THÈSE

En vue de l'obtention du

DOCTORAT DE L'UNIVERSITÉ DE TOULOUSE

Délivré par :

Institut Supérieur de l'Aéronautique et de l'Espace

Présentée et soutenue par :

Paulo Eduardo UBALDINO DE SOUZA

le jeudi 19 octobre 2017

Titre :

Vers une interaction humain-robot à une initiative mixe : une équipe coopérative composée par des drones et un opérateur humain

Towards mixed-initiative human-robot interaction: a cooperative human-drone team framework

---

École doctorale et discipline ou spécialité :

EDSYS : Robotique

Unité de recherche :

Équipe d'accueil ISAE-ONERA CSDV

Directeur(s) de Thèse :

M. Frédéric DEHAIS (directeur de thèse)
Mme Caroline PONZONI CARVALHO CHANEL (co-directrice de thèse)

Jury :

M. Gilles COPPIN Professeur IMT Atlantique - Président
M. Frédéric DEHAIS Professeur ISAE-SUPAERO - Directeur de thèse
M. Sidney GIVIGI Professeur Associé Royal Military College of Canada
M. Abdel-Illah MOUADDIB Professeur Université de Caen Rapporteur
Mme Caroline PONZONI CARVALHO CHANEL Professeur Associé ISAE-SUPAERO - Co-directrice de thèse
M. Frédéric VANDERHAEGEN Professeur Université de Valenciennes - Rapporteur

to Ian

Acknowledgments

Now, after completing this mission, I can say, without a doubt, that one of the most difficult parts of writing my thesis was finding the right words to express my gratitude to those who helped me get here. This incredible journey has been made possible and especially made pleasant by the experiences, conversations and relationships shared with all the people I had the privilege to meet along the way.

I would like to start by thanking my advisors, Frédéric DEHAIS and Caroline CHANEL, for accepting me as a PhD student. I came to Toulouse without much knowledge of decision theories, human factors, or even a clear idea of what it meant to conduct proper research. I learned so much under your tutelage and you provided me wise counsels every step of the way including knowing when to give me close guidance as well as when to give me the freedom to explore on my own.

I thank Frédéric VANDERHAEGEN, Abdel-Illah MOUADDIB, Gilles COPPIN and Sidney GIVIGI for accepting to be members of my committee.

My deep gratitude goes to Jean-Paul BRUYANT (Defence & Security Business Development - ONERA), Osvaldo CATSUMI (Institute for Advanced Studies - IEAV/DCTA) and Patrick FABIANI (ISAE), who opened doors for this quest to begin.

Heartfelt thanks go to Sidney for his constant wise guidance, humor and encouragement.

I was fortunate enough to share the Ph.D. experience with a number of fellow students and young doctors who all became my friends: Angela, Benoit, Corentin, Facundo, Igor, Jan, Leandro, Martin, Raphaelle, Raquel, Sebastien, Sergio, Soheib, Thibaut and all the others that I forgot to cite here. I enjoyed our conversations which have ranged from being academically stimulating to deeply profound to utter silly and everything in between. It was a privilege to work alongside such a group of bright and talented researchers.

I also tank all the 133 participants and the beta-testers in my experiments, without their "brains" I would not have gotten to the end of this project.

Finally, I would like to thank my family for the love and support they have provided me over the years. First and foremost, I would like to thank my wife Marina, for always pushing me and believing in me. Your care helped to encourage and motivate me, particularly at the moments during our simultaneous abroad Ph.D. when things were at their most difficult. Additionally, I would like to thank my eternal children: Aimée, Nathan and Ian. I consider myself to be blessed beyond all measure to be a member of such an amazing and loving family. Everything I have achieved in my life, I have done to make all of you proud.

This project has been financially supported by CNPq to whom I am sincerely grateful.

Contents

List of Figures

List of Tables

Table of Acronyms

3D	Dirty, dull, or dangerous
ACG	Anti-coordination game
AFE	Attribute framing effect
ALFUS	Autonomy levels for unmanned systems
BAG	“Be accurate” guideline
BFG	“Be fast” guideline
C	Contribution
CH	Contribution in Human factors
COG	Coordination game
CPG	Common-payoff game
CR	Contribution in robotics
DM	Decision maker
DPT	Dual process theory
DT	Decision theory
Dec-POMDP	Decentralized POMDP
EFG	Extensive-form game
ESA	European Space Agency
EUT	Expected utility theory
FE	Framing effect
GAN	Game against Nature
GFE	Goal framing effect
GLMM	Generalized linear mixed model

GT Game theory

GUARDIANS Group of Unmanned Assistant Robots Deployed In Aggressive Navigation by Scent

HLG High-low game

HO Human operator

HCI Human-computer interaction

HRI Human-robot interaction

IAC “In accordance” condition

JAXA Japanese Aerospace Exploration Agency

JPL Jet Propulsion Laboratory

LOA Levels of autonomy

LMM Linear mixed model

LRT Likelihood Ratio Test

MAS Multi-agent system

MDP Markov decision process

MEMS Micro-Electro-Mechanical Systems

MI-HRI Mixed-initiative human-robot interaction

MII Mixed-initiative interaction

MOMDP Mixed observability Markov decision process

MORSE Modular open robots simulation engine

MRS Multiple-robot system

NASA National aeronautics and space administration

NATO North Atlantic Treaty Organization

NCG Non-cooperative game

NDM Naturalistic decision making

NE	Nash equilibrium
NIST	National Institute of Standards and Technology
NS	Non-significant
NTC	“Neutral” condition
OMPFC	Orbital and medial prefrontal cortex
P	study report
POA	Price of anarchy
POI	Point of interest
POMDP	Parcially observable Markov decision process
PT	Prospect theory
RCF	Risk choice framing
RPAS	Remotely piloted aircraft system
RPSLS	Rock, Paper, Scissors, Lizard, Spock
RQ	Research question
SAR	Search and rescue
SEU	Subjective expected utility
SPN	Search pattern “Snail”
SPQ	Search pattern “Square”
SPT	Search pattern “Star”
UAV	Unmanned air vehicle
UMS	Unmanned system
USAF	United States Air Force
USAR	Urban search and rescue
UT	Utility theory
VCV	victim completely visible

VVS	Victim only visible by one side
VVT	Victim only visible from the top
WLU	Wonderful life utility
ZSG	Zero-sum game

Introduction

In theory, theory and practice are the same. In practice, they are not.

Anonymous

Human-robot interaction (HRI) is a field that is still in its infancy. In the recent past, we have seen robots develop into autonomous artificial agents capable of executing more and more complex tasks. In the future, robots will likely develop the ability to adapt and learn from their surroundings.

Robots designed for dirty, dull or dangerous ("3D") tasks have reliance, do not get bored and can operate in hostile and dynamics environments - all attributes well suited for space exploration, and emergency or military situations. They also reduce mission costs, increase design flexibility, and maximize data production. Moreover, multi-robot systems (MRSs) may potentially provide several advantages over systems with a single robot, namely speed, accuracy, and robustness [Bur+00]; [Bur+05]; [Vin+08].

On the other hand, when faced with unexpected events, robots fade-out in comparison with intuitive and creative human beings. For instance, military commanders and first responders are often required to make decisions under conditions of limited, incomplete or ambiguous information, and severe time pressure. These experts can take charge of life-threatening situations and decide how to use their crews and assets in a very effective way. However, in those situations, they have to work in very hard conditions, and are subject to cognitive and physical fatigue, which can lead to a reduction in the situational awareness and in the quality of their decisions. Thus, the future will require an intelligent balance between the human flexibility and creativity, and robust and sophisticated robotic systems.

Nonetheless, concerning the human-robot interactions, it is not easy to design a robust and efficient framework. Recently most of the scientific and technical efforts have focused on the implementation of smart sensors, complex embedded systems and autonomy to enhance the efficiency of the robots [Thr+04], especially when the human operator can not analyze or access visual data [Thr+04]; [SMT09]; [FO05]; [CM03]. However, these developments were generally achieved without questioning the integration of the human operators (HOs) *in the control loop* [SST03]: the HO is considered as a providential agent that will be able to takeover when sensors or automation fail [CM03]; [FO05]; [SMT09]. Yet, poor user interface design, the complexity of automation and high operational pressure can leave the HO ill-equipped when mental workload exceeds human capacity [Dur+14]. For instance, a careless design of authority sharing can lead to human-automation conflicts when the human operator misunderstands the automation behavior

[Deh+05]; [Deh+15]. The occurrence of such a situation is critical as long as it may cause cognitive dissonance (a contradictory information may produce discomfort caused by conflicting cognition or knowledge that controls or affects behaviors and attitudes) [Van14], and "mental confusion" (i.e. the HO is unable to glance and process the relevant parameters) [Deh+15] or "attentional tunneling" (i.e. the HO is excessively focused on a single display) [DCT11] yielding to irrational behavior [Deh+12]. Not surprisingly, a safety analysis report [Wil04] revealed that human factors issues were involved in 80% of accidents. This trend has led Cummings and Mitchell to state: *"Because of the increased number of sensors, the volume of information, and the operational demands that will naturally occur in a multiple-vehicle control environment, excessive cognitive demands will likely be placed on operators. As a result, efficiently allocating attention between a set of dynamic tasks will be critical to both human and system performance. - p. 451"* [CM08].

A promising avenue to deal with these issues is to consider that robot and human abilities are complementary and are likely to provide better performance when joined efficiently than when used separately. This approach, known as *mixed-initiative interaction* (MII) [AGH99]; [AC+04] is at the heart of this PhD dissertation. Specifically, we will focus our interest on decision making for both robots and humans.

Problem description

This thesis is concerned with the problem of constructing a robust framework for a team of aerial robots (a.k.a. drones) that must coordinate their actions among the other robotic team members and provide the HO sufficient data to make critical decisions that maximize the mission efficiency, according to some operational guidelines (see Fig. 1).

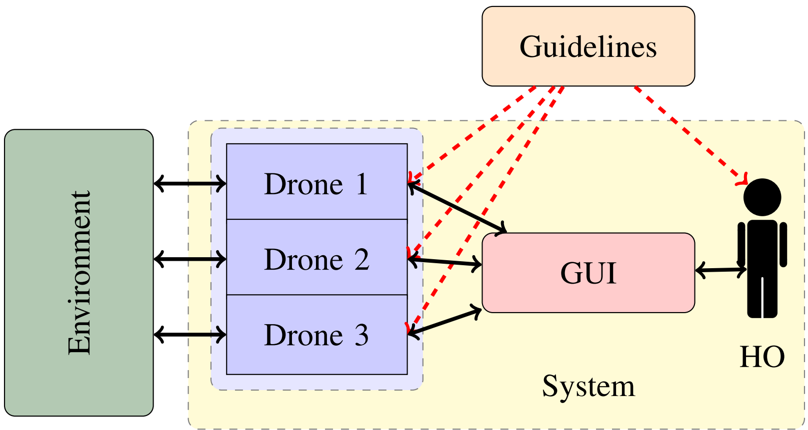


Figure 1: Framework architecture

In this way, this project meets the dual purpose of taking care of the effectiveness of the human-robot team (we will call it *robotic perspective*) and improving the human-decision process in such an operational context (*human perspective*).

Thesis statement

In this thesis, we consider the problem of designing the utility functions of utility-maximizing agents in a multi-robot system (MRS) with a (fallible and emotional) human operator (HO) in the loop, so that they work synergistically to maximize a global utility.

Thereby, one approach that we initially consider to make use was the decentralized (partially observable) Markov decision process (Dec-(PO)MDP), an extension of POMDP[1] framework for representing multi-agent coordination problems. Dec-POMDPs have been broadly used in artificial intelligence (AI) as a way of approaching fundamental differences in decision-making in decentralized environments [WVO12]; [MJM+12]; [Ama+13]. [Ama+14] argues that any problem where several robots share a single global reward or cost function can be formalized as a Dec-POMDP. As such, a Dec-POMDP solver could generate policies for decentralized control problems in the presence of uncertainty in position, sensors, and information about teammates. Unfortunately, this generality has a cost: Dec-POMDPs are typically unfeasible to solve, except for very small problems [Ber+02]; [AKK14]. This means that to update the state of each position at each timestep would be computational and memory excessively expensive and, then, impractical in real-world scenarios [Men08]; [PR11].

As [MG92] stated: "Real-life strategic situations are often extremely complicated. Game theory provides a model of this complexity". Hence, we decided to use a game-theoretic approach, which is an elegant way to model a decision-making process of an agent (a player) based on the others agents decisions in a decentralized and distributed way. A game involves multiple and sometimes different kinds of players that act under uncertainty based on partial views of the world. In a game, each player chooses an option (in parallel or sequentially) based purely on locally observable information, resulting in an immediate payoff [SLB08].

In the *robotic perspective*, in order to improve the overall performance, first we designed asynchronous games, in which the game occurs when a drone is available to play, independently of the situation of the other players; second, instead of playing a game at each timestep, our approach use "macro-actions" (i.e., the game occurs when a drone conclude its current task), which can be seen as a simple and efficient modeling for real systems.

The interaction between the drones and the HO is also a game, in which the human payoff (or utility) function is estimated by the drones. But the nature of human decision making is intensely

[1] Parcially observable Markov decision process

complex, hence, our approach in the *human perspective* is founded on the the *Prospect theory (PT)* [KT79]; [TK92], and the *Naturalistic decision making (NDM)* framework [Kle99]. In this sense, we do not consider the HO as a flawless and rational decision maker (DM) that can decide with logical consistency, regardless of the manner in which the options are presented. However, instead of attempting to "cure" the HO to have a logical and clear thinking, which consumes time and needs complete information (not always available), we make use of the human emotional and intuitive way of thinking to lead the HO to act as an expert and make the best possible decision under uncertainty and time stress.

Thesis overview

This thesis is divided into two parts, in the first one we present the literature review used to model our proposed system: Chapter 1 presents the theories about the human-robot interaction and some real cases about robots operating in *dirty, dull or dangerous* situations. Then, in Chapter 2 we contextualize the human decision making process, describe the *heuristics and bias theory*, in particular the *framing effect*, and introduce the *naturalistic decision-making framework*. Chapter 3 is dedicated to a general review, mainly about the *utility theory* and the *prospect theory*, that will help in understanding and relating later concepts in this manuscript. Following, Chapter 4 introduces essential knowledge about the *game theory* used in this thesis.

The second part presents the contributions of this thesis: in Chapter 5 we present a decentralized utility function to coordinate a drone team; In Chapter 6 we introduce the human operator in the team and a *framing effect* experiment in that context is conducted; the data produced in this previous experiment is also used to estimate a human utility in Chapter 7; and finally Chapter 8 put everything together, formalizing and evaluating the whole system.

In the end, it is presented in Appendix A our first study that acted as a exploratory research about "mixed-initiative" and decision-making processes such as MDP[2], POMDP and MOMDP[3]. It was reported in a conference paper with the title "MOMDP-based target search mission taking into account the human operator's cognitive state", presented at *IEEE International Conference on Tools with Artificial Intelligence*(ICTAI 2015). This exploratory study is not in the main core of this thesis.

[2]Markov decision process
[3]Mixed observability Markov decision process

Part I

Literature review

CHAPTER 1

3D robots

Contents

> The Three Laws of Robotics:
> 1: A robot may not injure a human being or, through inaction, allow a human being to come to harm;
> 2: A robot must obey the orders given it by human beings except where such orders would conflict with the First Law;
> 3: A robot must protect its own existence as long as such protection does not conflict with the First or Second Law;
> The Zeroth Law: A robot may not harm humanity, or, by inaction, allow humanity to come to harm.
>
> *Isaac Asimov*

Human safety is the utmost concern in the modern society, thus, *dirty, dull, or dangerous (3D)* tasks have been gradually transferred to robots. In this chapter, we point out some initiatives about these "3D" robots and their levels of autonomy. Then, we present the idea of a framework with a dynamic adjustment of the autonomy levels, accordingly with the mission phase, the type of interactions that can exist among robotic teammates and a framework to include a human as a member of the team.

1.1 Dirty, dull or dangerous (3D) missions

In these type of missions, the operating environment can be dynamic, uncertain, unstructured, and hostile (e.g., radiation, explosive material, chemical or biological contamination, extremely hot or extremely cold, outer space or in another celestial body). Nowadays, although several initiatives about autonomous systems [MSØ03]; [TL09], in general, real-life robots that operate in those contexts are remotely operated, such as the robots used in the World Trade Center and in the Fukushima nuclear plant [JA15], the military unmanned air vehicles (UAVs – or more precisely, remotely piloted aircraft systems RPAS) [EAS17]; [Col04], and the Mars rovers [JPL17]. Hence, the human operator (HO) and the robot must stay apart from each other and the distance can create a disconnection between them, which presents some challenges for effective collaboration within the human-robot team (e.g., situational awareness and time delay).

Following, we present two different types of missions that we will consider for our framework.

1.1.1 Search and rescue (SAR)

SAR[1] missions can be dirty, dull and dangerous, so, they are excellent candidates to a robot task. There are several types of SAR missions, they can be activated after an aircraft crash or when a ship loses its engines in the middle of nowhere, or even when some adventurous tourists get lost in the jungle or in mountain areas. There are also Urban SAR (USAR) missions that involve the rescue of victims from the collapse of man-made structures. In general, this environment is unstable and dangerous, with piles of concrete rubble, exposed metal, dust, and debris.

For instance, small mobile robots were used in the aftermath of the World Trade Center disaster and Fukushima nuclear plant meltdown, offering a valuable contribution to the efforts in those difficult environments in that they can go into places deemed too small or unsafe for people or dogs [JA15]. Another example is the European project GUARDIANS (Group of Unmanned Assistant Robots Deployed In Aggressive Navigation by Scent) that applies the concept of autonomous robots in USAR operations [Nag+08].

[1]Search and rescue

Robots involved in SAR operations must team with people both physically as well as perceptually [BM04]. For instance, [AT+15] proposed a Dec-POMDP Framework for human-robot teamwork coordination in SAR missions. Where robots and humans are teammates and the humans are considered as intelligent agents with their own observations and actions.

[BM04] argues that an effective HRI[2] in Urban SAR (USAR) missions currently requires a minimum 2:1 human-to-robot ratio, in order to maintain the HO situational awareness and reduce the cognitive and physical fatigue.

On the other hand, [Sch+04] affirms that completely autonomous robots for USAR are not feasible in the near future. So HOs must work as teammates with the robots, with all parties contributing according to their skills and capabilities.

1.1.2 Sample-return mission

Since the National Aeronautics and Space Administration (NASA) Apollo Program we have collected samples from other "worlds". However, due to the high risks and high costs, the humans were replaced by robotic systems. In 2003, the sample return mission of the Japanese Aerospace Exploration Agency (JAXA) *Hayabusa*, was launched to collect samples from the asteroid 25143 Itokawa and return them to Earth [Tsu+11]. The peregrine falcon (Hayabusa) safely returned to the Earth on June 13, 2010. Launched in December 2014, Hayabusa 2 will be Japan's (and the world's) second asteroid sample-return mission.

Figure 1.1: Hayabusa asteroid-sample capsule recovered in Outback - By JAXA

Although technologically challenging, bringing samples of celestial bodies (asteroids, comets, moons or planets) back to Earth is essential for answering scientific key questions about habitability and life, that cannot be addressed by purely in situ missions [ESA16].

For instance, NASA and the European Space Agency (ESA) are working together in a *Mars Sample Return* mission to return samples from the surface of Mars to Earth. The mission would use multi-robots systems and a Mars ascent rocket to collect and send samples of Martian rocks,

[2]Human-robot interaction

Figure 1.2: Mars sample return concept - By JPL/NASA

soils and atmosphere to Earth for detailed chemical and physical analysis [MM11]; [ESA16]; [JPL17].

1.2 Multi-robot systems (MRS)

The recent advancement in decision making techniques for robots has significantly increased the number of applications for a team of autonomous agents. In certain scenarios, MRSs are more desirable than a single robot due to their robustness, stability, adaptability, and scalability [Men08]; [Bur+00]; [Bur+05]; [Vin+08]. For instance, search and rescue (SAR) missions [Mur+08]; [SM11]; [XZZ11], autonomous infrastructure inspection [Sca+14], autonomous patrolling systems [ABG09]; [PR11]; [HCB+13], and exploration mission [MJM12].

A MRS can have different types of interactions among the teammates (robots). [Par08] proposed to categorize distributed intelligence systems according to the type of those interactions, underlining also the differences that exist within distributed robotic systems. These systems can thus be:

- *Collective* - Robots are not aware of the presence of other robots but share goals and their actions contribute to the actions of other robots. For instance, a robot swarm.
- *Coordinative* - Robots are aware of the presence of the other robots, they have no common purpose and their actions do not contribute to the satisfaction of the aims of the other robots, but, they must coordinate their actions to avoid interferences.
- *Collaborative* - Like before, robots are aware of the presence of the other robots, they have individual goals and their actions contribute to the satisfaction of the goals of the other robots.

- *Cooperative* - The robots are aware of the presence of the other robots, they share goals and their actions contribute to the actions of the other entities.

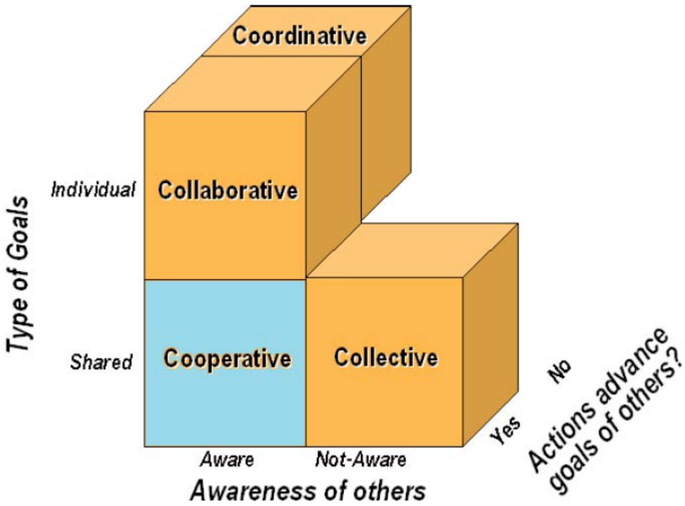


Figure 1.3: Types of interactions of multiple-robot systems [Par08].

However, in our case, where we intend to put a HO in the robot team, the situation is not that simple. According to [BM04], despite much of the literature on human-robot teams is predicated on the assumption that a single person will be able to control or supervise multiple robots. In these cases, robots tend to be perceived as mindless, obedient entities that will go and do as commanded with a minimum of attention or effort required from their human taskmasters. In reality, this is proving not to be the case. For instance, the Global Hawk UAV[3] (Fig. 1.4a), in use by the United States Air Force (USAF), requires a minimum of two operators, despite the high degree of onboard navigation [Col04]. The Jet Propulsion Laboratory (JPL) Mars Rovers (Sojourner, Spirit, Opportunity, Curiosity – Fig. 1.4b), currently keep a staff of hundreds employed for their missions on Mars [JPL17]. This subject has been the focus of recent research, in which this traditional paradigm of n *to* 1 (n HOs to one robot) is changing to a new paradigm of 1 *to* n (one HO to n robots) [Che+13].

One possible solution for this situation might be to put the HO at the same authority level of the robots and let the team member (human or robot) who knows the best achieving the mission phase objectives take the lead of that mission phase execution (as showing in Section 1.3.2.1).

[3]Unmanned air vehicle

(a) Global Hawk – by USAF

(b) JPL Mars rover family – by JPL/NASA

Figure 1.4: Robots operated by humans.

1.3 Robots interacting with humans

Nowadays the great majority of military UAVs are remotely operated [EAS17]. Despite in the last few years, the USAF trained more RPAS pilots than traditional pilots, the RPAS pilot turnover rates in many units are typically high [USA17]. In order to describe how complex their operations are, consider, for example, the *MQ-9 Reaper*, an armed, multi-mission, medium-altitude, long-endurance RPAS[4] that is employed (by USAF, US Navy and Royal Air Force) primarily against dynamic execution targets and secondarily as an intelligence collection asset (Fig. 1.5a) [USA17].

(a) MQ-9 Reaper – by USAF

(b) MQ-9 Reaper crew – by USAF

Figure 1.5: Robots operated by humans.

Its *remote split operations* employ a launch-and-recovery ground control station, housed in a hangar beside the runways, for take-off and landing operations at the forward operating location;

[4] Remotely piloted aircraft system

while a three-member crew, based a thousand miles apart, executes the remainder of the mission via beyond-line-of-sight satellite links. Both teams have a pilot and a sensor operator sit in front of several video screens, with a keyboard and a joystick (Fig. 1.5b), the remote team has also a mission coordinator. This concept of operation results in a smaller number of personnel deployed to a forward location, however, it requires several remote teams (supported by meteorologists, communications specialists, intelligence analysts and so on), each operating for six fatiguing hours in a 12 hours shift, for keeping a minimum of aircraft aloft 24 hours per day, seven days a week [USA17]; [MPR09].

In flight, the RPAS pilot, likewise a traditional pilot, must control the aircraft, communicate with air traffic agencies, and maintain situational awareness of flight parameters, system health, atmospheric conditions, restricted airspaces, and other aircraft in the vicinity. But, through six flat displays with information in different formats, without "feeling" the aircraft. Fatigue is not the only complaint of the pilots. They argue that it is difficult to focus in their "top secret" mission when on duty, making critical decisions that involve life and death, and, afterward, return home to fix the heater or to play soccer with their kids [MPR09].

Despite this demanding environment, there is a vision to broaden the use of RPAS by having a small crew operating multiple UAVs (from 3 to 50 drones). However, considerable research and development must be done to reach this capability [Cal+16].

1.3.1 Levels of autonomy (LOA)

Currently, an unmanned system (UMS) can be remotely controlled (tethered or wireless), assisted by a human operator, totally autonomous, or somewhere in between. While, on one hand, some researches have tried to avoid all human behavior complexity, delegating all decisions to complete autonomous systems based on Artificial Intelligence (AI) algorithms [Mur+08]; [SM11]; [XZZ11]. On the other hand, others have tried to enhance robots and computer interfaces to help human users in the execution of their missions [Hea99]; [Nag+08]; [Sch+04].

In order to formulate a logical framework for characterizing the UMS autonomy, covering issues of levels of autonomy (LOA), mission complexity, and environmental complexity, the US National Institute of Standards and Technology (NIST) created in 2003 the workgroup Autonomy Levels for Unmanned Systems (ALFUS) [Hua+05]; [Hua07]. Figure 1.6 illustrates the ALFUS detailed model.

In this framework, the autonomy level of a particular UMS can be represented with a triangular surface fitted through the values on the three axes. This model suggests vectors, as opposed to a single scale, to characterize unmanned system autonomy levels. Observe that the *human interface* in Fig. 1.6 is inversely proportional to the autonomy level, in other words, how much a UMS is independent of an interaction with humans.

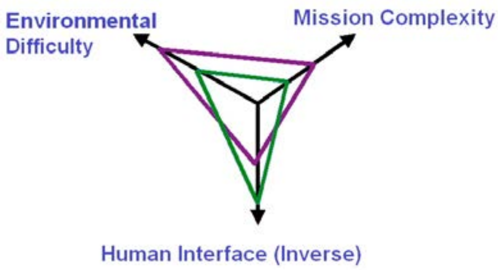


Figure 1.6: Three dimensions determining the autonomy level for unmanned systems [Hua+04]

For example, consider the project of the *Optionally-Piloted Black Hawk* (OPBH) helicopter [Ong14] (Fig. 1.7). It could provide the commander with the flexibility to determine autonomous, remotely-operated or piloted operations, according to the complexity of the mission and the environment. The idea is to maximize the mission efficiency. The great advantage would be the capability to spare pilots boring, repetitive, and relatively simple phases of a mission (e.g., to return to the base for refueling on a sunny day). They could instead focus their energies on more demanding missions involving difficult weather and human lives.

Figure 1.7: Optionally-piloted Black Hawk - By Sikorsky

In this case, although the LOA can variate, the initiative always comes from the human beings. HO (the pilot) is like a flawless god (for the machine) and decides when the helicopter can or cannot "take decisions".

1.3.2 Initiative modes

Sometimes it is interesting to change not only the LOA of an artificial system but also the initiative mode, allowing it to define its own LOA. In the recent literature, three approaches are highlighted in dynamically controlling the LOA: (1) *adjustable autonomy*, in which the HO has the total control; (2) *adaptive autonomy*, where the artificial agent has exclusive control; and (3) *mixed initiative*, in which both agents collaborate to maintain the best-perceived level of autonomy [HG09].

Adjustable autonomy occurs when only the HO can control the artificial agent autonomy. For example, only the commander of the *Optionally-Piloted Black Hawk* (OPBH) helicopter (See Fig. 1.7) can decide its LOA [Ong14]. In another example, [Jea10] presents a decision-theoretic approach to create an adjustable autonomy system using Mixed Markov Decision Processes (MI-MDPs). And [ZPV11] presents a model of human-robot cooperative control that helps to improve the resilience of the human-machine system by making the level of autonomy adjustable. The main disadvantage of this approach is that the overall system performance may decrease when the HO reacts too slowly or wrongly [TD12].

On the contrary, *adaptive autonomy* mainly enables the capacity of the artificial agent to ask for HO's help. One advantage of this approach is that the artificial agent can react faster than under human control. However, the drawback is that the HO cannot assume the control whenever she wants. Our experiment in Chapter 8 is a good example of adaptive autonomy, in which all initiatives come from the robots.

The aim of *mixed initiative* is to take advantage of the skills of both agents. For instance, the mixed-initiative framework highlighted in [SCD15] shows the relevance of taking into account the cognitive state of the operator, which permits to the robot to compute a policy for the sequential decision problem, in order to prevent re-planning when unexpected (but known) events occur.

Theoretically, the mixed initiative seems to be better than the other alternatives, but it must be well-tuned to present its benefits in practice [HG09]; [TD12].

1.3.2.1 Mixed-initiative human-robot interaction (MI-MRI)

Mixed initiative interaction (MII) first appeared in the domain of *human-computer interaction (HCI)* for building intelligent conversational agents. The first known reference to the term *mixed initiative* was by [Car70], in which the term was associated with a computer-assisted instruction system, designed to maintain a dialogue with students. After, [AGH99] defined MII as *"a flexible interaction strategy where each agent can contribute to the task that it can do best. Furthermore, in the most general cases, the agents' roles are not determined in advance but opportunistically negotiated between them as the problem is being solved"*. And later, [JA15] proposed a more comprehensive definition (MI-HRI[5]), since it both succinctly captures the key idea of an opportunistic intervention of MII and clearly defines what initiative means in a robotic context:

[5]Mixed-initiative human-robot interaction

> A collaboration strategy for human-robot teams where humans and robots opportunistically seize (relinquish) initiative from (to) each other as a mission is being executed, where initiative is an element of the mission that can range from low-level motion control of the robot to high-level specification of mission goals, and the initiative is mixed only when each member is authorized to intervene and seize control of it.

Thus, MI-HRI is a framework where HO[6] and a robot can collaborate as peers in an effective team. Both have their own respective limitations when operating under extreme conditions, however, they each also have a set of complementary skills [JA15]. Here we can see the advantages of a MI-HRI system, where the HO do not have and do not need to have a complete situational awareness in order to optimize the results of a mission. In this case, the artificial system must be able to decide for itself and take over the initiative when necessary.

Particularly, in complex missions, an MI-HRI system should require some level of supervision but not necessarily continual monitoring [BCJ15]. In these cases, a single operator may be responsible for multiple unmanned systems, thus, expanding the HO's role to even harder tactical or ethical decision. For example, [Bev+15] presented a mixed-initiative planning and execution framework for human-multi-drones interaction during SAR missions.

1.4 Summary

This chapter was dedicated to describe our view about "3D" robots and point out some MRS[7] missions used in our experiments and to illustrate our proposition throughout this thesis.

Initially, we listed some researches and initiatives involving robots in SAR and Sample-return operations. Following, we introduced the MRS, the different types of interactions among the robotic teammates, and the challenges to change the traditional paradigm of n operators to 1 robot to a new paradigm of 1 operator (or a few operators) to n robots. In this sense, we briefly described the current USAF operation of the MQ-9 Reaper RPAS. Then, we presented the ALFUS[8], a framework for dynamical adjustments of the autonomy levels, and the categorization of initiative modes.

Finally, we defined MII and MI-HRI, frameworks where humans and artificial agents can collaborate as peers in an effective team. These concepts were used in our studies as overarching goals to be pursued.

[6] Human operator
[7] Multiple-robot system
[8] Autonomy levels for unmanned systems

Next, we will address the human decision-making process and its theories.

CHAPTER 2

The "H" factor

Contents

A compelling narrative fosters an illusion of inevitability.

Daniel Kahneman

Decision making is a critical issue for humans cooperate with intelligent robots. While some theories of decision making affirm that many cognitive biases affect human judgments, leading to suboptimal or irrational decisions, and tend to emphasize the use of analytical processes in guiding human decisions, others argues that intuitive and emotional responses can play a key role in human decision-making process under time constraints and limited information conditions [DM+06]. In this chapter, we introduce these theories in order to make use of them to put the human operator (HO) in the loop as a teammate of the drones.

2.1 Human decision making process

The introduction of highly automatized systems has radically changed the role of human operators from direct controllers to a system supervisor and decision maker. As a matter of fact, there is a need to better understand theoretical models of human decision-making process to optimized HRI and to implement mixed-initiative interactions. The models and theories of this process can be separated into two classes: prescriptive (or normative) and descriptive [Bar07]; [Kah11].

The first category explores how people should make decisions. These theories typically assume ideal circumstances, as for instance, complete information, awareness of all options, an abundance of time to decide, and so on, in order to model the best and most rational path a person can take in order to come to the most suitable decision [TG00]. They assume that DM[1]s have a stable set of preferences and they are always trying to maximize their satisfaction [Suh07].

Prescriptive models are useful in highlighting how real-world decision-making processes might be improved and in efforts to make computers and robots think (e.g., Expected utility theory, Subjective expected utility theory, Behavioral decision theory, and others). However, they remain theoretical in nature, because people rarely, if ever, operate under the circumstances that such theories propose [TG00].

In contrast to prescriptive theories, descriptive models describe how people actually make decisions in the real-life situations, regardless of their rationality, elegance or efficacy [Suh07] (e.g., Heuristics and biases, Naturalistic Decision Making, Team cognition and others). Descriptive theories acknowledge that there are finite bounds to human cognition that frequently result in irrational decisions. Table 2.1 shows some examples for comparison and better understanding.

2.2 Bounded rationality

As said before, prescriptive models have tended to view human DMs as possessing supernatural powers of reason, limitless knowledge, and endless time. Conversely, instead of operating under those perfect circumstances, *bounded rationality theory* proposes that human DMs in the real world have to function under three crucial constraints that effectively limit human's rationality: (1) limited access to information, (2) cognitive limitations inherent to the human mind, and (3) limited time to make a decision [Sim55]; [Sim57]. This theory overturns the notion that humans process information and make decisions in a purely rational way, notably in situations that involve risk and uncertainty.

Some of the most important works in this regard has been conducted by Amos Tversky and

[1] Decision maker

Table 2.1: Examples of decision making theories

Theory	Features
Expected Utility	- Prescriptive theory - Assumes that decision maker has a “utility function” - All choice alternatives are known to the decision maker - Maximize utility from a stable set of preferences
Subjective Expected Utility	- Prescriptive theory - Assumes that decision maker has a “utility function” - All choice alternatives are known to the decision maker - Makes it possible to assign probabilities subjectively
Heuristics and Bias	- Descriptive theory - Heuristics are rules of thumb used to make decisions under conditions of uncertainty - They are highly economical and usually effective - However, they can lead to cognitive biases (predictable errors)
Naturalistic Decision Making	- Descriptive theory - Seeks to understand human cognitive performance - Focuses on expertise - Reflects conditions such as complexity and uncertainty - Highlights the importance of intuition

Daniel Kahneman in the field of behavioral economics, when they developed the *heuristics and biases* theory.

2.3 Dual process theory (DPT)

In the recent decades, psychologists have been intensely interested in the two main modes of thinking among humans: intuitive and analytical. In [Kah11], Kahneman informs that this typology of cognition has helped researchers better understand how people approach problems and make decisions in real-life circumstances. Kahneman also affirms that intuitive thinking (also called *System 1*) operates automatically and quickly, with little or no effort and totally unconscious. It allows people to multitask in a complex world. The crucial benefits of *intuitive thinking* are that it is time efficient and requires relatively little allocation of mental resources. By generalizing circumstances, it allows us to reduce the complexity of a situation, recognize patterns (real or perceived) and make decisions quickly according to past experiences or the logic of those recognized patterns. However, while this mode of thinking is exceptionally efficient and very often accurate, it makes us more vulnerable to errors [Kah11].

On the other hand, *analytical thinking* (a.k.a. *System 2*) requires conscious mental effort. The nature of this mode is *slow, effortful and deliberate*. Analytical thinking allows us to process information deliberately, consciously consider multiple options, debate with others, contemplate alternative perspectives, and come to logical and, ideally, thorough and effective conclusions [Kah11]. Table 2.2 compares both types of thinking.

Table 2.2: Comparison between intuitive and analytical thinking.

	Intuitive thinking	**Analytical thinking**
Characteristics	- Fast - Every-day decisions - Unconscious - Associative - Looks for patterns - Automatic - Emotive	- Slow - Complex decisions - Conscious - Deliberative - Effortful - Logical
Advantages	- Repetitive tasks - Creative - Crisis situations	- Math and statistics - Options - Pros and cons - Consequences
Disadvantages	- Jumps to conclusions - Emotional responses - Poor judgments	- Demands attention - Tiring - Requires time

Both modes of thinking are continuously active in people's minds, but analytical thinking is typically relegated to simply monitoring on-going cognitive activities and can be called upon when necessary. It is activated when *stakes are high, when we detect an obvious error or when rule-based reasoning is required* [Kah11].

2.4 Heuristics and biases

Since this notion that people can make decisions irrationally, much effort has been made to search for the bounds of human rationality. Among these theories there is the *heuristics and biases* approach, which argues that people make use of cognitive shortcuts based on mental illusions to make decisions under conditions of uncertainty and not necessarily try to maximize their satisfaction [TK75]; [Bar07].

Heuristics have developed over the course of human evolution as a means of ensuring survival. They are highly economical and usually effective in generalizing situations and allowing people to multitask, and make quick and fair accurate decisions despite time constraints or imperfect information. However, sometimes they result in predictable errors in judgment (cognitive biases) [TK75].

[TK75] initially described three general-purpose heuristics: (1) availability, (2) representativeness, and (3) anchoring, that underlie many intuitive judgments under uncertainty.

The *availability* is the perceived likelihood that an event will occur based upon how easy it is for an individual to recollect instances of that phenomena happening in their mind, i.e., it is the notion that the more examples one can recall of a particular outcome to a situation (i.e. how "available" those memories are), the more likely one will judge that outcome happening again in a similar situation in the future. For instance, for a person that lives in Lima (Peru), where it has not rained in a long time, it is reasonable to believe that it won't rain tomorrow. In contrast, for someone that lives in Manaus (Brazil), where it rains every day, it is also reasonable to believe that it will rain tomorrow. These individuals may reach completely logical but totally opposite conclusions regarding some third situation such as the weather in Toulouse (France). This will occur due to the availability of different experiences that they can recall. Cognitive biases associated with the availability heuristic include: *retrievability bias* (classes whose instances are more easily retrievable will seem larger), *search set bias* (the effectiveness of the search might not relate directly to the class frequency), and *imaginability bias* (instances often need to be constructed on the fly using some rule; the difficulty of imagining instances is used as an estimate of their frequency).

The *Representativeness* entails taking the characteristics of one object or person and applying them to a similar object or person. This cognitive shortcut serves us well in terms of survival in that we are able to quickly recognize patterns or similarities and react according to past experiences. Here we can identify some characteristics from experts (individuals who have achieved exceptional skills in some particular domain), they can quickly associate the current situation to another happened in their past. The main shortcoming of representativeness is that people tend to overestimate representative evidence and underestimate other influencing factors [BE01]. Some example of cognitive biases resulting from the representativeness: *base rate fallacy* (tendency to ignore general information and focus on specific information), *insensitivity to sample size* (tendency to under-expect variation in small samples), and misconception of change (tendency to expect random sequences to be "representatively random" even locally).

The *anchoring* heuristic relates to how individuals estimate a value. The first or initial guess is the anchor. It is typically related to how people estimate value. For instance, knowing today's temperature is an effective starting point (anchor) for estimating tomorrow's temperature. But it is not infallible. Cognitive biases associated with the anchoring shortcut: *insufficient adjustment*, *evaluation of conjunctive and disjunctive events*, and *assessing subjective probability distributions*.

2.4.1 Endowment effect

The *endowment effect* is defined as a tendency that people have to attribute more value to an object when they own it, that when they do not own it. [TK92] postulates that individuals perceive the separation of property owned as constituting a greater loss than the potential gain generated by the purchase of another item of the same value (loss aversion).

However, [Mor+09] argues that it is the *ownership* that causes the endowment effect. To prove this hypothesis, they carried out two experiments in which sellers were distinguished from owners. In the first experiment, buyers were willing to pay just as much for a mug as sellers demanded if the buyers already own an identical mug. In the other experiment, buyers' brokers and sellers' brokers agreed on the price of a mug, but both brokers traded at higher prices when they happened to own mugs that were identical to the ones they were trading. According to them, if *loss aversion* drives the endowment effect, sellers should value the object more than buyers do, regardless if those buyers already own a similar object or not. On the other hand, if *ownership* drives the endowment effect, then owners should value the object more than non-owners do, regardless of whether they are selling or buying. As their results showed.

In an interesting case involving human-robot interaction, [MBJ15] conducted an experiment, where a humanoid robot replaces the experimenter to study the endowment effect. Their findings suggested that there was no endowment effect in that HRI.

Another cognitive bias of our interest occurs when people react to a particular choice in different ways depending on how it is presented. It is called *Framing effect* and will be presented next.

2.4.2 Framing effect (FE)

The *Framing Effect* is a key aspect of *Prospect theory* (see Sec. 3.5), which states that different descriptions of formally identical problems can result in different choices [Kah11]; [TK75]. The core concepts in explain it resides in the combination of beliefs, fears, values, desires, mental models, and so on, which human beings use to perceive a situation. People effectively look through this frame in the way they would look through colored sunglasses. The frame significantly affects how we infer meaning and hence understand the situation.

In the classical experiment, [TK81] explored how different phrasing affected participants' responses to a choice in a hypothetical life and death situation. In this experiment, participants were asked to choose between two treatments for 600 people affected by a deadly disease. Treatment A was predicted to result in 400 deaths, whereas treatment B had a 33% chance that no one would die but a 66% chance that everyone would die. This choice was then presented to participants either with *positive framing*, i.e. how many people would *live*, or with *negative framing*, i.e. how many people would *die*, as shown in Table 2.3.

Table 2.3: Kahneman and Tversky framing effect experiment.

Framing	**Treatment A**	**Treatment B**
Positive	Saves 200 lives	A 33% chance of saving all 600 people, 66% possibility of saving no one.
Negative	400 people will die	A 33% chance that no people will die, 66% probability that all 600 will die.

Treatment A was chosen by 72% of participants when it was presented with positive framing, and dropping to only 22% when the same choice was presented with negative framing.

Cognitive neuroscientists have linked the framing effect to neural activity in the amygdala, and have identified another brain-region, the orbital and medial prefrontal cortex (OMPFC), that appears to moderate the role of emotion on decisions [Bar07]. Using functional magnetic resonance imaging (fMRI) to monitor brain-activity during a financial decision-making task, [DM+06] observed greater activity in the OMPFC of those research subjects less susceptible to the FE. In [Gon+05], participants were asked to choose between a certain and a risky alternative, in response to problems framed as gains or losses. fMRI revealed that the cognitive functions used by the DMs were localized in the prefrontal and parietal cortices of the brain, which suggests the involvement of working memory and imagery in the selection process. Their findings indicate that the cognitive effort required to select a *sure gain* was considerably lower than the effort required to choose a *risky gain*. In contrast, the effort expended in choosing a *sure loss* was equal to the effort expended in choosing a risky loss. Moreover, they proposed a cognitive–affective tradeoff model, in which the FE occurs due to a tradeoff between the cognitive effort (required to calculate expected values of an alternative) and the affective value of the alternative.

Other researches have shown that losses evoke stronger negative feelings than gains and choices are not reality-bound because *intuitive thinking* is not bound to reality [Bar07]. Reframing is effortful and *analytical thinking* is normally lazy. Unless there is an obvious reason to do otherwise, most people passively accept decision problems as they are framed [Kah11].

Kahneman [Kah11] also affirms that people dispose of a limited budget of attention that can be allocated to activities, and they will fail if try to go beyond their budget. Intense focusing on a task can make people effectively blind, even to stimuli that normally attract attention (attentional tunneling) [DCT11]; [Rég+14].

In [LSG98] a typology is presented to distinguish among three different kinds of FEs: (1) Risk Choice Framing (RCF) [TK81], which involves options differing in level of risk and described in different ways; (2) Attribute Framing (AFE), which affects the evaluation of the characteristics of an event or object; and (3) Goal Framing (GFE), which affects the persuasiveness of a communication. AFE seems to be the simplest case of framing, where only a single attribute is the subject of the framing manipulation and the evaluation can be measured by choices between yes or no. AFEs are also less likely when dealing with extremes [LSG98].

In another study and using a within-subjects framing manipulation and applying a difference score between positive and negative conditions as the unit of analysis for each type of framing, [Lev+02] presented new ways of looking at FEs. For instance, they illustrate that even more can be learned by going beyond aggregate results and examining individual differences in the effects being examined.

2.5 Improving decision making

Despite the vast body of research since the $1970s$, there remains a lack of consensus on appropriate and effective methods of "debiasing". [GGK02] suggests that understanding biases might decrease their effects. Another proposed strategy for overcoming cognitive biases is to deliberately shift people from intuitive thinking to analytical thinking. This involves promoting meta-cognitive skills to help people replace intuition with more deliberate analytic processes [Mor+15], and consumes time. [MCB09] explains that it may be possible to achieve this cognitive shift through several approaches, for instance, taking an outsider's perspective and considering the opposite of whatever decision the decision-maker is about to make.

However, this comes into direct conflict with the nature of many of the decision making scenarios that military and first-responder professionals (doctors, nurses, firemen, police officers, and so forth) expect to face. The complexity and uncertainty of these situations may not afford individuals the luxury of time or collaboration that the methods detailed above require, particularly for soldiers operating at the tactical level where commanders must rely on quick, and often inherently intuitive, decisions [Kle89]. For example, [TG00] describe the following situation "A man is rushed to a hospital in the throes of a heart attack. The doctor needs to decide whether the victim should be treated as a low-risk or a high-risk patient. He is at high risk if his life is truly threatened, and should receive the most expensive and detailed care. Although this decision can save or cost a life, the doctor must decide using only the available cues, each of which is, at best, merely an uncertain predictor of the patient's risk level". To resolve this kind of problem, they explored *fast and frugal heuristics* approach [GT99], which, according to them, can enable both living organisms and artificial systems to make smart choices quickly and with a minimum of information by exploiting the way that information is structured in particular environments.

One such approach to developing intuitive expertise and thereby mitigating or even eliminating the effects of cognitive biases is based on the Naturalistic decision making (NDM) approach.

2.5.1 Naturalistic decision making (NDM)

The NDM deals with how people make decisions in demanding real-world situations, under time pressure and uncertainty, with team constraints, unstable conditions, and varying amounts of experience [Kle99].

As a descriptive theory, NDM attempts to describe what people do, instead of trying to discover deviations from optimal strategies. The proponents of NDM argue that the benefit of selecting an optimal choice may not be so clear, because of Fredkin's paradox (that states that "in a choice situation, as the options become more closely matched on utility, the decision becomes more difficult, but the consequences become less significant"). Then, when you have to make a choice, you spend some time weighing the options (for simplicity let us say that there are only two options to be weighed). If one option is obviously better the time you spend pondering will be minimal. As the two options get closer and closer to each other in quality, the time you spend considering them will increase.

Whereas prescriptive models have the strength of being generic, they cannot be grounded within the context of a specific domain. That is an advantage of NDM. For instance, a domain-specific and context-restricted strategy is used by air-traffic controllers to detect early signs that an aircraft may soon be violating separation criteria. Seems that have not much value teaching expected utility methods or Bayesian statistics to air-traffic controllers [Kle97].

On the other hand, contrary to the arguments from other descriptive theories that humans are limited and fallible, and need medicines (like training to learn how to think logically and clearly), NDM denies the need to mitigate biases at all, and instead, proposes to appropriate them in order to improve decision making [Kle97]. Klein and his colleagues argue that heuristics highlight specific human strengths of cognition that are "hard-wired" into us [Kle99]. Consequently, their research suggests that it is possible to take advantage of cognitive biases (and emotions) in order to improve decision making.

Another positive aspect of NDM is that it can use the strategies of skilled DMs (a.k.a. experts) to serve as criteria for evaluating novices. For instance, in [KH93] they list the ways that experts see the world differently from novices.

Overall, it shows that emotions can play a role in decision making when information is incomplete or too complex, serving as a time-critical rules of thumb.

2.6 Summary

In this chapter, we described how the human decision-making process is theorized. Then, we focus on the descriptive theories, the dual-process theory, and the heuristics and biases theory. In the latter, we presented two cognitive biases very important for our study: the endowment effect and the framing effect. Finally, we described the NDM and its assumptions.

In this thesis, our approach is to explore the FE, instead of attempting to debias the decision behavior, in order to make novices act and decide like experts, leading the former to repeat patterns and strategies used by the latter.

Next, we will address in Chapter 3 some formal prescriptive models in the decision theory, like the Expected utility theory (EUT), and at the end the Prospect theory (PT), a descriptive model that attempts to be an alternative to EUT.

CHAPTER 3

Decisions and utilities

Contents

Money has no utility to me beyond a certain point.

Bill Gates

In this thesis, we consider situations where robots and human have to take critical decisions under uncertainty. As shown in the previous chapters, robots may fail to adapt to new situations and the HO may experience decision biases. Therefore, we need to define a formal framework to optimize human-robot decision making under such circumstances. The goal of this chapter is to present the field of decision theories that could be applied to such a problem.

3.1 Decision theory (DT)

Decisions often involve conflict. There may be a conflict between goals or the desirability of an outcome [Bar07]. The best answer to this conflict depends on the costs and benefits (consequences) of each alternative and the probability that it happens.

In this sense, the aim of DT is to help decision makers (DMs) who face complex problems, choosing between different possible alternatives, taking into account the consequences of each decision and their preferences. Then, the two central concepts in DT are *prospects* (or options) and *preferences*. Roughly speaking, an agent prefers the option A over B. It is intuitive that preference is a comparative attitude. The numerical representations (or measurements) of preferences are known as utility functions [SS16].

3.2 Utility theory (UT)

In economics, *utility* is a measure of satisfaction (rewards) gained from a good or a service [Bar07]. For instance, the reward might be the amount of money earned in a financial investment. In robotics, for instance, the reward could indicate the amount of remaining battery after a mobile robot goes from a place to another. In other applications with humans, the reward may be subjective, based on the enjoyment or misery in performing a task. For example, what is the reward for washing dishes, in comparison to making the diner? In this case (and others), different people can have different preferences.

The idea behind *utility theory* is simple: for each object on which the DM has preferences, it is assigned a real number, in such a way that the higher the number, the preferred the object. Then, comparing objects amounts to comparing their associated numbers, which is a trivial task for a computer. The DM expresses her preferences through a set of attributes. Each attribute can take a certain number of values (a.k.a. levels of satisfaction). [Gon07].

Definition 3.1
Let X be the set of objects over which the DM has preferences. DM prefers x_i to x_j or is indifferent between x_i and x_j. $U : X \to \mathbb{R}$ is a utility function if and only if

$$\forall x \in X, x_i \succeq x_j \iff U(x_i) \geq U(x_j)$$

When there are multiple attributes, the set of objects X can be represented as $X = X_1 \times \ldots \times X_n$.

Moreover, when there are conflicting goals (for example, speed and accuracy), a utility function can specify the appropriate trade-off [RN09].

Utility functions are computationally very attractive because they provide easy and fast ways to extract the DM's preferences [Gon07]. However, elicitation of a DM's utility function is challenging. Since Nicolas Bernoulli described the St. Petersburg paradox in 1713 [SS16], several theories presented their solutions. We will discuss some of them in the next sections.

Following we present some utility functions used in this thesis.

3.2.1 Additive utility

Computationally, in general, utilities require as much memory as pairwise comparison tables (n-dimensional set) [Gon07]. For example, suppose that there are 5 attributes and that each one has 10 levels of satisfaction, then the outcome set X is a set with $5^{10} = 9765625$ elements and, to store the utility function into memory, up to 9765625 bytes may be needed.

Definition 3.2
A utility function U is said to be additively separable (or an additive utility) if and only if it is a utility function and there exist functions $u_1, ..., u_n$ such that $U(x_1, ..., x_n) = U_1(x_1) + ... + U_n(x_n)$.

In words, x_i and x_j are orthogonal to each other. It means that the amount of good x_i that you consume does not have any impact on the enjoyment you get from consuming any amount of good x_j. Back to our example, if the utility function is additively separable, then storing each $U_i(x_i)$ requires only 10 bytes, and the whole utility is stored in at most 50 bytes.

Remark
when utility is additively separable in x_i and x_j, then $U(x_i)$ does not depend on the level of x_j, and vice-versa.

Note that, since utility functions are not unique, it is sometimes possible to transform functions which are not additively separable into equivalent functions which are.

Example 3.2.1
Some examples:

- $U(x_i, x_j) = ax_i + bx_j \iff a \cdot u(x_i) + b \cdot u(x_j)$
- $U(x_i, x_j) = x_i^a \cdot x_j^b$ *is not additively separable, but as an ordinal representation of preferences, it's isomorphic to the additively separable utility function*

$$U(x_i, x_j) = a \cdot \log(x_i) + b \cdot \log(x_j)$$

where $a, b \in \mathbb{R}$ are scaling constants and do not indicate the relative importance of attributes.

Generally, mixing addition, multiplication and exponentiation will destroy additive separability.

3.3 Expected utility theory (EUT)

EUT is a normative model of decision making when outcomes are uncertain (probabilistic), that is, the theory of how we should choose among possible actions under ideal conditions. In this sense, it deals with the analysis of choices among *Lotteries* (risky projects) [Bar07]. For a lottery L with many possible options:

$$EU(L) = \sum_{i=1}^{n} U(x_i)p_i \tag{3.1}$$

where x denotes the possible outcomes and p_i the probability of the outcome x_i, with $\sum_i p_i = 1$, denoting the probability of each outcome to happen.

The first important use of EUT was that of Von Neumann and Morgenstern [VNM07], who used the assumption of expected utility maximization in their formulation of *Game theory*. They addressed situations in which the outcomes of choices are not known with certainty, but have probabilities attached to them.

In this way, EUT requires that the agent specifies preferences among probability distributions $p_i \in P$ of outcomes and being *rational* when assigning those preferences, i.e., the agent's preferences must be in accordance with the *rationality axioms* here after recalled [LaV06]:

Axiom 3.1
completeness - If $p_1, p_2 \in P$, then either $p_1 \preceq p_2$ or $p_2 \preceq p_1$.

Axiom 3.2
transitivity - If $p_1 \preceq p_2$ and $p_2 \preceq p_3$, then $p_1 \preceq p_3$.

Axiom 3.3
independence - If $p_1 \prec p_2$, then $\alpha p_1 + (1-\alpha)p_3 \prec \alpha p_2 + (1-\alpha)p_3$, for any $p_3 \in P$ and $\alpha \in [0,1]$.

Axiom 3.4
continuity - If $p_1 \prec p_2 \prec p_3$, then there exists some $\alpha \in [0,1]$ and $\beta \in [0,1]$ such that $\alpha p_1 + (1-\alpha)p_3 \prec p_2$ and $p_2 \prec \beta p_1 + (1-\beta)p_3$.

3.3.1 Existence of a utility function

If it is possible to determine the preferences in a rational way, then it can be shown that a utility function U always exists. This means that there exists a function $U : X \to \mathbb{R}$ such that

$$p_1 \prec p_2 \iff EU_{p_1} < EU_{p_2}, \forall p_1, p_2 \in P \tag{3.2}$$

Where EU_{p_i} denotes the expected value of U under the probability distribution p_i.

The existence of U implies that it is safe to determine the best action by maximizing the expected utility [LaV06].

Hence, a rational agent has clear preferences, models uncertainty via expected values of variables, and always chooses to perform the action with the optimal expected outcome for itself from among all feasible actions.

However, establishing the existence of a utility function does not provide a systematic way to construct it. In general, a trial-and-error process is used to design U.

3.3.2 Risk aversion

EUT takes into account that individuals may be risk-averse [VNM07]. Risk aversion implies that utility functions are concave and show diminishing marginal wealth utility (see Fig. 3.1).

Figure 3.1 shows that the risk behavior is directly related to the utility function curvature: risk neutral individuals have linear utility functions, while risk-seeking individuals have convex utility functions and risk-averse individuals have concave utility functions. The degree of risk aversion can be measured by the curvature of the utility function.

3.3.3 Criticism

Despite the mathematical correctness of EUT, it is not guaranteed that this is a reliable guide to human behavior or optimal practice. In empirical applications, several violations have been shown to be systematic. For example, Prospect theory [KT79] showed empirically how preferences of individuals are inconsistent among the same choices, depending on how those choices are presented (see Section 3.5).

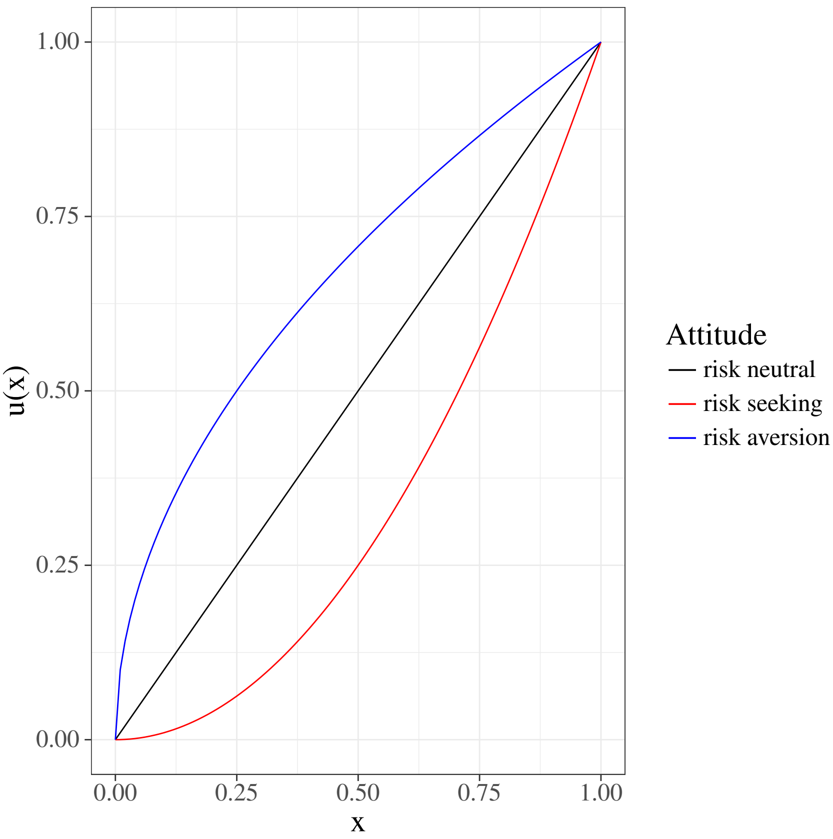


Figure 3.1: Graphical Representation of Risk Preferences in EUT.

3.4 Subjective expected utility theory (SEU)

Typically, in DT the problem consists in making a choice between different alternatives. If the outcome for each alternative is known, the decision is made under certainty. If not, then the situation is made under risk or uncertainty. [Kni12] proposed to reserve the term “uncertainty” for cases where the degree of uncertainty cannot be quantified (“Knightean uncertainty”). “Decision under risk” refers to the quantifiable cases, in which the outcomes probabilities are given or can be estimated.

SEU refers to situations under uncertainty and combines two subjective concepts: z is a subjective probability distribution and $u(x)$ is a personal utility of a possible outcome x. Then

$$SEU(X) = \sum_i u(x_i)z_i \tag{3.3}$$

Here, the utility function represents the agent’s desires, and the probability function represents her beliefs.

3.5 Prospect Theory

Kahneman and Tversky [KT79]; [TK92] formulated the *(Cumulative) Prospect Theory (PT)* as an alternative descriptive model to EUT. PT shows how intuitive and analytical thinkings affect human decisions. Mainly, how intuitive thinking influences people's immediate reaction to a risk or gamble they are facing.

PT describes the decision process in two stages: editing and evaluation [Bar13]. In the first stage – *editing* – , decision outcomes are intuitively ordered according to a certain heuristic, set a reference point and then consider lesser outcomes as losses and greater ones as gains. In the second stage – *evaluation* –, people behave as if they would compute an expected utility, based on the potential outcomes and their respective probabilities, and then choose the alternative having a higher utility. The PT expected utility function [KT79], is recalled here as:

$$EU(X) = \sum_{i=1}^{n} pv(x_i)w(p_i) \tag{3.4}$$

where, $EU(X)$ is the expected utility of the outcomes, pv is a value function that assigns a personal value to outcomes $X = \{x_i...x_n\}$, p_i is the respective probability of an x_i, and $w(\cdot)$ is a subjective *probability weighting* function. Kahneman and Tversky [KT79]; [TK92] emphasize that this transformed probability function do not represent erroneous beliefs, rather, they are decision weights. $w(\cdot)$ is a strictly increasing function that satisfies $w(0) = 0$ and $w(1) = 1$ and that may differ between gains and losses [KR06].

The value function $pv(\cdot)$, defined in Equation 3.5 and shown in Fig. 3.2, passes through the reference point, is continuous for all objective values x, strictly increasing s-shaped and asymmetrical, leading people to be risk-averse for gains and risk-seeking for losses and, also, showing that losses hurt more than gains feel good. This *loss aversion* is defined by the λ constant factor (see Eq. 3.5).

$$pv(x) = \begin{cases} x^{\alpha} & x > 0 \\ -\lambda(-x)^{\beta} & x \leq 0 \end{cases} \tag{3.5}$$

This formulation (Eq. 3.5) illustrates three elements of PT and corresponds to Kahneman and Tversky's explicit or implicit assumptions [KT79] about their value function:

- *Reference dependence* - people derive utility from gains and losses, measured relative to

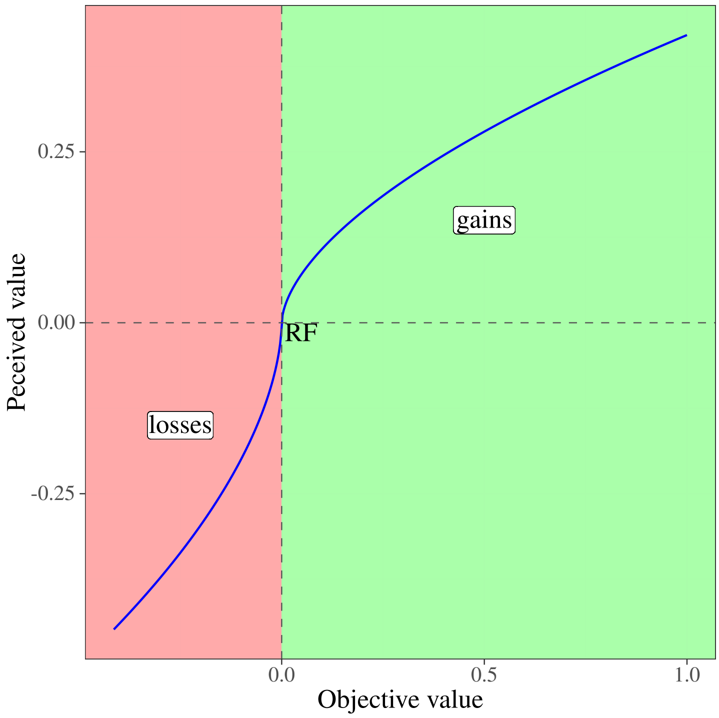


Figure 3.2: Prospect theory typical value function.

some reference point, rather than from absolute levels of wealth.

- *Loss aversion* - loss aversion is generated by making the value function steeper, modeled by the λ constant, in the region of losses than in the region of gains. If $y > x > 0$, then $pv(y) + pv(-y) < pv(x) + pv(-x)$.
- *Diminishing sensitivity* - the value function is concave ($pv''(x) \leq 0$ for $x > 0$) in the region of gains but convex ($pv''(x) \geq 0$ for $x < 0$) in the region of losses. It is modeled by the constants α and β. The concavity over gains captures the finding that people tend to be risk averse over probability gains. However, people also tend to be risk seeking over losses.

It is important to notice that the *probability weighting* function, the forth PT element, (see Eq. (3.4)) models the fact that people do not weight outcomes by their objective probabilities p_i but rather by transformed probabilities or decision weights $w(p_i)$ [TK92]. In this sense, a delicate issue is how to approach such personal weighting function.

Recently, several researchers have used PT to explain the decision-making process. For instance, [NBV16] argues that for hypothesis testing a human agent decision making can be model by PT. In [Zha16], an emotion-driven behavior selection mechanism based on the PT's Value Function is suggested in order to understand the autonomous behavior selection of artificial life. Ren and her colleagues [RXH16] propose a method to deal with the emergency decision making based on PT, applying thermodynamics concepts such as energy and entropy to take the quantity and the quality of the decision values into account.

Moreover, Kőszegi and Robin [KR06] propose a formal framework for applying PT in economics. They argue their proposal is both disciplined and portable across different contexts. The idea is that the reference point people use to compute gains and losses is fully determined by their expectations (instead of the status quo). In particular, they propose that people derive utility from the difference between consumption and expected consumption, for instance, a salary of $\$50,000$ to an employee who expected $\$60,000$ will not be assessed as a gain relative to status-quo wealth, but rather as a loss relative to expectations of wealth. They also assume that expectations are rational, in that they match the distribution of outcomes that people will face if they follow the plan of action that is optimal, given their expectations. Then, according to them, a person's utility depends on her multi-dimensional consumption bundle c and also on a reference bundle r, combining classical consumption utility with reference dependence utility by assuming people care about both. For instance, they don't just react to the sensation of gaining or losing a mug, they also care whether they have a mug to drink from. Thus, this *personal Utility (U)* is given by:

$$U(c|r) = m(c) + n(c|r) \tag{3.6}$$

where, $m(c)$ is an intrinsic "consumption utility" (typically stressed in economics) that corresponds to the personal outcome-based utility, and $n(c|r)$ is a *gain–loss utility*, that should be, in accordance with PT, given by:

$$n(c|r) = \mu(m(c) + m(r)) \tag{3.7}$$

Their model allows for both stochastic outcomes and stochastic reference points and assumes that a stochastic outcome is evaluated according to its expected utility. For instance, if c is drawn according to the probability measure F, the person's utility is given by:

$$U(F|r) = \int u(c|r)dF(c) \tag{3.8}$$

However, considering the gain-loss utility $n(c|r)$, they impose some simplifying assumptions, like linear utility for gains and losses and no probability weighting, which differs from the proposed *gain–loss utility* presented in Equation (3.4).

Using a different approach, Abdellaoui and his peers [Abd+16] introduced a method to measure loss aversion under ambiguity or risk without making simplifying assumptions about prospect theory's parameters, extended the trade-off method [WD96] in order to measure the utility for gains and losses simultaneously, and thus loss aversion. According to them, under Binary Prospect Theory (BPT), the DM's preferences over gain and loss risky prospects are evaluated by:

$$U(x|y) = w^{+}(p)U(x) + w^{-}(1-p)U(y) \tag{3.9}$$

where, $U(x|y)$ is an overall utility function that includes loss aversion. w is a probability weighting function, p is the probability value, x is a *gain* and y is a *loss*, thus, $-U(y) > U(x)$.

However, in this thesis, we will explore the Kőszegi and Robin approach [KR06], deriving the personal utility from consumption and the reference bundles, but without making simplifying assumptions about PT.

3.6 Summary

In this chapter we described situations where a rational DM chooses among several actions (Section 3.1 – *Decision theory (DT)*) based on their preferences (Section 3.2 – *Utility theory*), highlighting the *additive utility*. Following, Section 3.3 provided the fundamentals of *Expected utility theory (EUT)*, that is addressed to the analysis of choices among decisions under risk. After, we talked about decisions under uncertainty in Section 3.4 – *Subjective expected utility theory (SEU)*. And, finally, Section 3.5 presented the *Prospect theory (PT)*, that describes how people decides under uncertainty in the real life. These theories will pave the way for the following chapters.

Next, we will focus on problems involving multiple DMs, in which the decisions of each interfere with the outcome of the other DMs, the *Game theory*.

CHAPTER 4

Shall we play a game?

Contents

’It is better to have loved and lost than never to have loved at all.’ In other words, love is a dominant strategy.

Avinash K. Dixit

This chapter describes the *game theory* (*GT*), i.e., how to model problems that involve more than one decision maker (DM), focusing on making a single decision in the presence of other DMs that may interfere with the outcome. The objective is to provide the reader with enough GT background to understand our approach in this thesis. It may be safely skipped by those familiar with game theory.

It is important to state that this chapter is not intended to be an exhaustive overview of GT. There are many books that provide a good introduction to GT (e.g. [SLB08]; [LBS08]; [VNM07]). In short, GT is a mathematical theory designed to model phenomena that can be observed when two or more *rational* DMs interact with each other. A DM is said to be rational if she chooses her actions in order to maximize her satisfaction, happiness, or a utility function.

Game Theory is an interesting tool for understanding how decisions affect the players [Bar02]. [DS] stated three uses for GT:

- *Explanation* - when the situation involves the interaction of DMs with different aims, GT supplies the key to understanding the situation and explains why it happened.
- *Prediction* – when looking ahead to situations where multiple DMs will interact strategically, people can use GT to foresee what actions they will take and what outcomes will result.
- *Advice or Prescription* - GT can help one participant in the future interaction, and tell her which strategies are likely to yield good results and which ones are liable to lead to disaster.

At its inception, GT attracted little attention (ancient records date back to the 18th century). But, the mathematician John von Neumann changed this situation, and, in 1944, with the economist Oscar Morgenstern, published the classic "The Theory of Games and Economic Behavior" [VNM07]. And with that, GT invaded economics and applied mathematics.

Nowadays, GT is used to study subjects such as auctions, the balance of power, genetic evolution, political science, psychology, linguistics, sociology, etc [LBS08]; [Bar02]. However, GT is studied mainly in its pure mathematical aspects and, in applications, it is used as a tool or allegory that aid in the understanding of more complicated systems (e.g., multi-agent systems, network communication) [SLB08].

4.1 What is a game?

A game could be defined as a choice of optimal decisions under conflict or cooperation conditions. The dominant approach to model an agent's interests is the *Utility theory* [SLB08] (see Section 3.2). And the "game" begins when the world contains two or more utility-maximizing agents whose actions can affect each other's utilities [LBS08]. For instance, consider the following example.

Example 4.1.1
Consider a driver who decides on the route from home to job.

Alternatives: (1) take the shortest route through the tunnel or (2) follow the highway along the lake.

As the driver wants to minimize the time to arrive at the job, one strategy for her is: If the weather is rainy or if the tunnel is congested, then, she will take the longest route along the lake. Otherwise, she will take the tunnel.

The basic element in a game is the set of *players* that participate in it. Where each player has a set of *strategies*. A strategy depends on information that is not under the player's control – it can be deterministic or stochastic. When each player chooses their strategy, then we have a situation (*profile*) in the space of all possible situations. Each player has their own preferences for each situation in the game. In mathematical terms, each player has a *utility function* that assigns a real number (the player's gain or *payoff*) to each game situation.

Definition 4.1
Game - A N-player finite game Γ is a tuple $(N, \mathbb{A}, u)$, where:

- $N = \{1, \cdots, n\}$ *is the finite set of n players, indexed by i;*
- $\mathbb{A} = A_1 \times A_2 \times \cdots \times A_n$*, where A_i is a finite set of all options (or actions) available to player i. Each vector $a = (a_1, \cdots, a_n) \in \mathbb{A}$ is called a profile;*
- $u = (u_1, \cdots, u_n)$ *is the payoff function, where $u_i : \mathbb{A} \to \mathbb{R}$ for each player i.*

In this work we will adhere strictly to the *non-cooperative games* (NCG) – a.k.a. *strategic games* –, i.e., in which *self-interested* agents interact.

Note that this does not necessarily mean that they want to hurt each other, or that they only care about themselves. Instead, it means that each agent has his or her own preferences – which can include good things happening to the others – and that he or she acts in accordance with these preferences.

Definition 4.2
Non-cooperative game - A game is non-cooperative or strategic if each player seeks to maximize his or her own utility. They can not agree among themselves to form coalitions.

It is important to emphasize that it is possible to play a non-cooperative game among teammates (a *team game*) without forming coalitions.

Remark
A game with only one player is a classical optimization problem.

4.2 Normal form games

The normal form game (the most common representation of strategic interactions in GT) is a representation of every player's utility for every state of the world, where those states of the world depend only on the players' combined actions. It is assumed that both players will reveal their choice simultaneously [LBS08].

A intuitive way to represent games is via an n-dimensional matrix (see Table 4.1). Where, for instance in a two-player game, each row corresponds to a possible action for player X, each column corresponds to a possible action for player Y, and each cell corresponds to one possible outcome. Each player's utility (x or y) for an outcome is written in the cell corresponding to that outcome, with player X's utility listed first.

Table 4.1: Normal form game

		Player Y	
		A	B
Player X	A	(x_1, y_1)	(x_2, y_2)
	B	(x_3, y_3)	(x_4, y_4)

Following, we will present some types of normal-form games that will be interesting for our study.

4.2.1 Common-payoff games (CPG)

As the name suggests, these are games in which, for every action profile, all players have the same payoff [LBS08]. They are also known as *pure coordination games* or *team games*.

Definition 4.3
Common-payoff game - It is a game in which for all action profiles $a \in A_1 \times \cdots \times A_n$ *and any pair of agents* i, j*, it is the case that* $u_i(a) = u_j(a)$.

Example 4.2.1
Imagine two people walking towards each other on the sidewalk. They must independently decide whether to go on the left or on the right. If both of them choose the same side (left or right) they have some high utility, and otherwise, they have a low utility. The game matrix is shown in Table 4.2.

Remark
It is usual in CPG to present a single utility value in the outcomes of the game matrix, since $y = x$.

Table 4.2: Common-payoff game

		Player Y	
		$Left$	$Right$
Player X	$Left$	1	-1
	$Right$	-1	1

Observe that in this game there is no agreement among the players. Each is a self-interested agent trying to maximize her own utility.

4.2.1.1 Hi-Lo games (HLG)

This particular type of pure coordination game is called *Hi-Lo game*, where the players have the same interest and both prefer the same outcome [SLB08].

Example 4.2.2
Ian and Emily are going to the same cinema, and each one is expecting the other to be there, but they have not seen each other yet (and surprisingly they do not have smartphones). There are two movies playing in the afternoon: "Star wars" and "Star trek". They both hope to see each other – if not they will have no fun, and both of them prefers "Star wars" over "Star trek". They must decide what to do before knowing where the other is going. The payoff matrix is in Table 4.3

Table 4.3: Hi-Lo game

		Ian	
		Star trek	Star wars
Emily	Star trek	1	0
	Star wars	0	2

In this case, it is intuitive that they will meet at the new episode of "Star wars".

We will use this game to model the human-robot interaction (HRI) of our framework (see 8.6).

4.2.1.2 Anti-coordination games (ACG)

In this game, it is mutually beneficial for the players to play different strategies [LBS08]. In this way, it can be seen as the opposite of a *pure coordination game*.

The popular example is the *chicken game* [LBS08].

Example 4.2.3
Consider two drivers, Dumb and Dumber, both headed for a single-lane bridge from opposite directions. The first to swerve away (chicken out) yields the bridge to the other. If neither player swerves (C) and drives straight (D), the result is a costly deadlock in the middle of the bridge or a potentially fatal head-on collision. In this classic game, each player would prefer to win over tying, to tie over losing, and to lose over crashing (see Table 4.4).

Table 4.4: Chicken game

		Dumber C	Dumber D
Dumb	C	(tie,tie) (0,0)	(loose, win) (-1,1)
Dumb	D	(win, loose) (1,-1)	(crash, crash) (-10,-10)

In this thesis, this game will model the interaction among the drones (see 8.4.1).

4.2.2 Zero-sum games (ZSG)

In contrast with *Common-payoff games* there are the *Zero-sum games* (or more general *Constant-sum games*) [SLB08], which are *pure competition games*, that is, when a player wins the other necessarily looses.

Definition 4.4
Constant-sum game - is a (two-player) game in which for each strategy profile $a \in A_1 \times A_2$ there is a constant k where $u_1(a) + u_2(a) = k$.

For convenience, usually it is assumed that $k = 0$ (then, a zero-sum game) [SLB08].

Example 4.2.4
Rock, Paper, Scissors, Lizard, Spock - The game is an expansion on the game "Rock, Paper, Scissors", in which each player picks a variable and reveals it at the same time. The winner is the one who defeats the others. In a tie, the process is repeated until a winner is found. The rules are simple:

- *Scissors cuts Paper*

- *Paper covers Rock*
- *Rock crushes Lizard*
- *Lizard poisons Spock*
- *Spock smashes Scissors*
- *Scissors decapitates Lizard*
- *Lizard eats Paper*
- *Paper disproves Spock*
- *Spock vaporizes Rock*
- *(and as it always has) Rock crushes Scissors.*

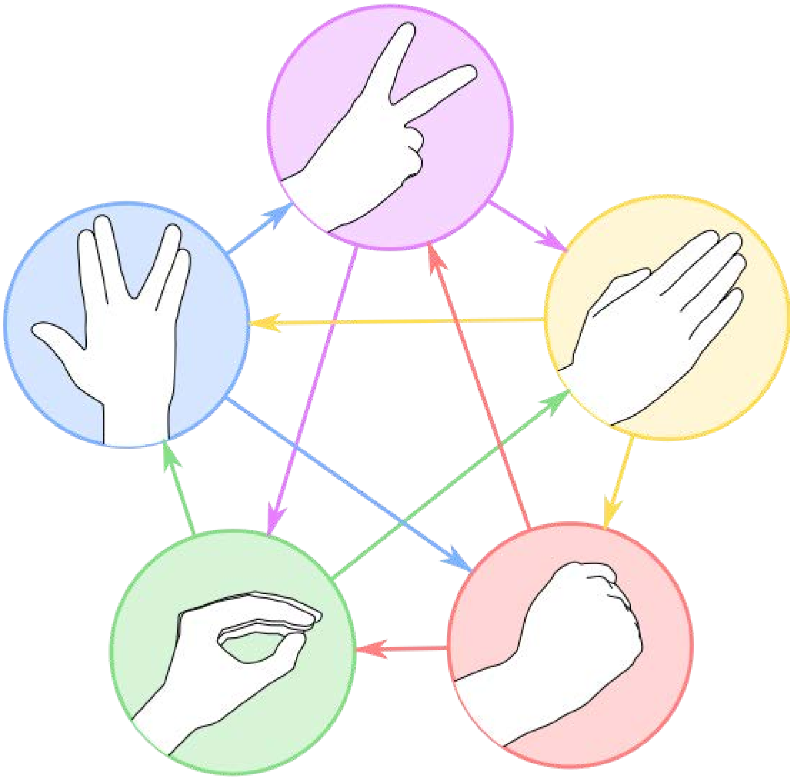


Figure 4.1: Rock, Paper, Scissors, Lizard, Spock. – by The Big Bang Theory Wiki

Example 4.2.5
A less trivial game - Consider the payoff matrix showed in Table 4.6.

Table 4.5: Zero-sum game

		Player Y				
		Rock	Paper	Scissors	Lizard	Spock
Player X	Rock	0	-1	1	1	1
	Paper	1	0	-1	-1	1
	Scissors	-1	1	0	1	-1
	Lizard	-1	1	-1	0	1
	Spock	1	-1	1	-1	0

Table 4.6: A less trivial game

		Player Y		
		A	B	C
Player X	A	0	1	-2
	B	-3	0	4
	C	5	-6	0

Looking to Tables 4.5 and 4.6, it is easy to see that no player has a winning pure (deterministic) strategy (any fixed strategy can be exploited by the opponent). The solution for both players would be to randomize their strategies.

Remark
In a Zero-sum game, it is usual to show only the payoff of Player X, since $y = -x$.

4.2.3 Strategies

The simplest strategy of a player is to select a single action and play it. This kind of strategy is called *pure strategy* [SLB08].

Definition 4.5
Pure strategy - is a single action (or choice) j of a player i:

$$a_j \in A_i$$

And, we call a choice of pure strategy for each agent a *pure-strategy profile*.

Definition 4.6

Pure-strategy profile - is a vector with all pure strategies of each player:

$$a = (a_1, \cdots, a_n) \in \mathbb{A}$$

A less obvious possibility is to randomize over the set of available actions according to some probability distribution. This is called *mixed strategy* [LBS08]. Let us define it

Definition 4.7
Mixed strategy

- *Let (N, A, u) be a normal-form game.*
- *For any set Z let $\Pi(Z)$ be the set of all probability distributions over Z.*
- *Then, the set of mixed strategies for player i is $S_i = \Pi(A_i)$.*

and

Definition 4.8
Mixed strategy profile - is simply the Cartesian product of the individual mixed-strategy sets, $S_1 \times \cdots \times S_n$.

Remark
A pure strategy can be seen as a special case of mixed strategies in which the distribution of probabilities corresponds to the Dirac delta function *of the chosen action.*

4.2.4 Payoffs

In a Normal-form game it is easy to see the utility of each pure strategy profile of a player, they are stamped in the payoff matrix [LBS08]. For mixed strategies, we recall a basic element of Decision theory: EUT[1] (see Section 3.3) – the gain is now a function of a probability distribution instead of actions.

Definition 4.9
Expected utility of a mixed strategy - Given a normal-form game (N, A, u), the expected utility u_i for player i of the mixed-strategy profile $s = (S_1 \times \cdots \times S_n)$ is defined as

$$u_i(s) = \sum_{a \in A} u_i(a) \prod_{j=1}^{n} s_j(a_j)$$

[1]Expected utility theory

Example 4.2.6
Consider the Zero-sum game in Table 4.7.

Table 4.7: Mixed strategy game example

		Nathan	
		C	D
Aimee	A	2	-1
	B	0	3

Aimee can choose the mixed strategy $p = (1/3, 2/3)$ *which corresponds to play action* A *with a probability of* $1/3$ *and action* B *with* $2/3$*. Similarly, Nathan can choose* $q = (1/4, 3/4)$ *which corresponds to play action* C *with a probability of* $1/4$ *and* D *with* $3/4$*.*

Calculation of Aimee's gain:

- *if Nathan choose* C*, Aimee wins on average:*

$$\frac{1}{3} \cdot 2 + \frac{2}{3} \cdot 0 = \frac{2}{3}$$

- *if Nathan choose* D*, Aimee wins on average:*

$$\frac{1}{3} \cdot -1 + \frac{2}{3} \cdot 3 = \frac{5}{3}$$

- *therefore, the Aimee's payoff is*

$$\frac{1}{4} \cdot \frac{2}{3} + \frac{3}{4} \cdot \frac{5}{3} = \frac{17}{16}$$

4.2.5 Game solution

A game solution (a.k.a. the value of a game) is a prediction about the outcome of the game. There are several different concepts of a solution. Here, we will present the most common concepts: *Dominance (or Pareto optimality)*, *Maxmin and Minimax value*, and *Nash equilibrium*.

Definition 4.10
Solution - The solution to a game is the strategy profile that is consistent with each player's beliefs.

4.2.5.1 Dominance

Definition 4.11
Dominance - For a player i, a strategy s_{ik} is said to be strictly dominated (or weakly dominated) by the strategy $s_{ik'}$ if and only if $u_i(s_{ik}, s_{-i}) < u_i(s_{ik'}, s_{-i})$ (resp. $u_i(s_{ik}, s_{-i}) \leq u_i(s_{ik'}, s_{-i})$), where

$$s_{-i} = (s_{1j_1}, \cdots, s_{(i-1)j_{i-1}}, s_{(i+1)j_{i+1}}, \cdots, s_{nj_n}) \in S_{-i} = S_1 \times \cdots \times S_{i-1} \times S_{i+1} \times \cdots \times S_n$$

(A strategy choice for all players except the player i).

Remark
*A strategy is **strictly dominant** if all other strategies are strictly dominated by it.*

Example 4.2.7
Let us go back to Ian and Emily. They both enjoy each other's company, but neither can communicate with the other before deciding whether to stay at home (where they would not see each other) or go to the park this afternoon (where they could see each other). Each prefers going to the park to being at home, and prefers being with the other person rather than being apart. Table 4.8 represents this game.

Table 4.8: Hang out game

		Ian	
		Home	Park
Emily	Home	$(0,0)$	$(0,1)$
	Park	$(1,0)$	$(2,2)$

In this HLG[2], going to the park is a (strictly) dominant strategy for each player, because it always yields the best outcome, no matter what the other player does. Thus, if the players are both maximizing their individual expected utilities, each will go to the park. So, Park-Park is a dominant strategy equilibrium for this game. Because of this, Ian and Emily do not need to cooperate (make an agreement) ahead of time. Each can just pursue their own interest, and the best outcome will occur for both.

Example 4.2.8
Now, imagine Bob and Emily. Bob likes Emily, but Emily does not like Bob that much. Each one of them knows this, and none wants to call the other before deciding what to do this afternoon: stay at their respective homes or go to the movies. Table 4.9 shows this game.

In this case, Emily's best strategy depends on what Bob does. But if she assumes Bob is

[2] High-low game

Table 4.9: Asymmetrical friends game

		Bob: Home	Bob: Movies
Emily	Home	$(2, 0)$	$(2, 1)$
	Movies	$(3, 0)$	$(1, 2)$

rational, she will reason that he will not stay home, because going to the movies is a dominant strategy for him. Knowing this, she can decide to stay home (because of $2 > 1$*). This is called* iterated dominance.

Thus, *Dominance* is nothing more than a process where *strictly dominated strategies* are iteratively eliminated.

Remark
The existence of a solution is not always guaranteed with this method.

4.2.5.2 Maxmin and Minimax strategies

Some pessimistic people always expect the worse. The *Maxmin value* (or Security level) of a player i is the largest value she can be sure to get when the other players respond with actions that minimize her gain (worst-case payoff).

Example 4.2.9
Imagine a game where two cars (driven by Dumb and Dumber) arrive at the same time at an intersection. Drivers must choose between proceeding (P) or wait (W). See the payoff matrix in Table 4.10.

Table 4.10: Intersection game

		Dumber: P	Dumber: W
Dumb	P	(-1,-1)	(2,0)
	W	(0,2)	(1,1)

Dumb looks for a strategy that maximizes her guaranteed gain $\underline{v_i}$*. If she chooses to proceed (P), her minimal payoff is* -1*, otherwise,* 0*. Then, in this case, pessimistic Dumb should wait (*$\underline{v_i} = 0$*).*

Definition 4.12
Maxmin value - Player i *can guarantee a gain of* $\underline{v_i}$ *if there exists a strategy whose utility is at*

least $\underline{v_i}$ whatever the other players strategies s_{-i}:

$$\underline{v_i} = \max_{s_i \in S} \min_{s_{-i} \in S} u_i(s_i, s_{-i})$$

Remark
To make use of Maxmin strategy a player does not need to know the payoffs of the other players.

Maxmin strategy is an interesting choice for a conservative player who wants to maximize her expected payoff without making any assumptions about the other players' strategies (for instance, if they are rational and want to maximize their utilities or if they are just playing arbitrarily).

In contrast to Maxmin, in a two-player game, Minimax strategy of Player i keeps the maximum payoff of the adversary j at a minimum (*Minimax value*). In a ZSG[3] is equivalent to minimize the loss of Player i.

Definition 4.13
Minimax value - In a two-player game, Player j's Minimax value is

$$\overline{v_i} = \min_{s_i \in S} \max_{s_j \in S} u_j(s_i, s_j)$$

Remark
In two-player games, a player i's Minimax value is always equal to her Maxmin value: $\underline{v_i} = \overline{v_i}$ [VNM07].

In cases of knightean uncertainty (where is not possible to predict the adversary's strategy), another approach can be useful: *Minimax regret strategy* in order to minimize a worst-case loss, rather than maximize a worst-case gain. Thus, a player's Minimax regret action is an action a_i that yields the smallest maximum regret:

$$\operatorname*{argmin}_{a_i \in A_i}[\max_{a_{-i} \in A_{-i}}([\max_{a_i^* \in A_i} u_i(a_i^*, a_{-i})] - u_i(a_i, a_{-i}))]$$

Example 4.2.10
Consider the following game in Table 4.11

In this example, the payoffs of Player Y (a, b, c, d) are unknown. according to Maxmin strategy suggests that pessimistic Player X should select the action B (maximum worst payoff). Nevertheless, if Player X is not that pessimist, she might make use of a Minimax regret strategy and choose T in order to minimize her worst-case loss.

[3]Zero-sum game

Table 4.11: Minmax regret

		Player Y L	R	Worst payoff	Worst regret
Player X	T	(100,a)	(1,b)	1	1
	B	(3,c)	(2,d)	2	97
	Best payoff	100	2		

Those strategies have been extended to decisions where there is no other player, but where the consequences of decisions depend on unknown facts – stochastic outcomes – (see Section 4.7).

4.2.5.3 Nash Equilibrium (NE)

Now let us look at games from a player's point of view, instead of from the privileged point of an outside observer. This will lead us to the most prominent solution concept in game theory, the *Nash equilibrium*.

As known as *strategic solution*, the NE of a game is a point where none has the interest to change his or her strategy if the other players do not change their owns.

Observe that, if a player knew how the others were going to play, her strategic problem would become a simple single-agent problem of choosing a utility-maximizing action. Thus, if the players other than i were to commit to playing s_{-i}, a utility-maximizing agent i would face the problem of determining her *best response*.

Definition 4.14
Best response - Player i's best response to the strategy profile s_{-i} is a mixed strategy

$$s_i^* \in S_i \mid u_i(s_i^*, s_{-i}) \geq u_i(s_i, s_{-i}), \forall s_i \in S_i$$

The *best response* is not necessarily unique. Actually, the number of best responses is infinite, except in the case in which there is a unique *pure strategy*. For example, if there are two pure strategies that are individually best responses, any mixture of them is necessarily also a best response.

It is intuitive that a *best response* is not a solution concept. Typically a player does not know the strategies that the others will play. However, it can be used to support the *Nash equilibrium*.

Definition 4.15
Nash equilibrium

*- A strategy profile $s = (s_1, \cdots, s_n)$ is a **Nash equilibrium** if and only if, for all agents i, s_i^* is a best response to s_{-i}.*

Thus, any unilateral deviation of a player lowers her utility and increases the utility of the other players.

Theorem 4.1
(Nash, 1958) - Every game with a finite number of players and action profiles has at least one Nash equilibrium.

Remark
In zero-sum games (ZSG), the Minimax solution is the same as the Nash equilibrium.

4.3 Potential games

A game is a potential game if the incentive of all players to change their strategies can be expressed using a single global *Potential function* [MS96]. That is, if a player unilaterally changed her action, the change in her objective function would be equal to the change in the potential function.

Definition 4.16
A game $\Gamma = (N, \mathbb{A}, u)$ is a potential game if there exists a function

$$f : \mathbb{A} \to \mathbb{R} \mid \forall i \in N, \forall a_{-i} \in A_{-i}, a_i, a_i' \in A_i,$$

$$u_i(a_i, a_{-i}) - u_i(a_i', a_{-i}) = f(a_i, a_{-i}) - f(a_i', a_{-i})$$

Example 4.3.1
Consider the game in Table 4.12.

Table 4.12: Prisoner dilemma - Potential game

			Player Y			
		L	R		L	R
Player X	T	(1,1)	(9,0)	T	4	3
	B	(0,9)	(6,6)	B	3	0
		(Payoffs)			(Potentials)	

In this game, we can observe that

$$u_X(a_X^T, a_Y^L) - u_X(a_X^B, a_Y^L) = f(a_X^T, a_Y^L) - f(a_X^B, a_Y^L) = 1$$

$$u_X(a_X^T, a_Y^R) - u_X(a_X^B, a_Y^R) = f(a_X^T, a_Y^R) - f(a_X^B, a_Y^R) = 3$$
$$u_Y(a_X^T, a_Y^L) - u_Y(a_X^T, a_Y^R) = f(a_X^T, a_Y^L) - f(a_X^B, a_Y^L) = 1$$
$$u_Y(a_X^B, a_Y^L) - u_Y(a_X^B, a_Y^R) = f(a_X^T, a_Y^L) - f(a_X^B, a_Y^L) = 3$$

The existence of pure strategy Nash equilibrium is guaranteed in potential games, and multiple Nash equilibria may exist.

Theorem 4.2
Every finite potential game has a pure-strategy Nash equilibrium [MS96]; [SLB08].

This theorem will be applied to simplify the calculations in the interactions among the drones since they would have actions aligned with a global utility, thus, they only need to optimize their own choices.

4.3.1 Wonderful life utility (WLU)

In WLU, the utility of a player is the marginal contribution to the global utility as a result of her action, meaning that, the player's utility is the change in the global utility as a result of her action as opposed to she not act at all.

$$WLU_i = f(Z) - f(Z_{-i}) \tag{4.1}$$

where Z denotes the set of all players, Z_{-1} is the collection of all players except player i, $f(\cdot)$ denotes a global utility function. [Wol04]

Remark
WLU leads to a potential game, where the global utility function is the potential function.

Accordingly to [SLB08], in a multi-agent system (MAS) each player's objective function should be appropriately "aligned" with the objective of the global planner. In this sense, in Chapter 5 we will invoke the WLU to support our utility choice.

4.4 Repeated games

In repeated games, a given game is played multiple times by the same set of players. The game being repeated is called the *stage game* [LBS08].

Definition 4.17
Fictitious play - Sometimes, in a repeated game, a player may guess that the frequency of choices played by her opponent in the last trials might be his current mixed strategy, and play a best response to that (presumed) strategy.

Fictitious play is an important definition to our framework and will be useful for designing the HRI, in order to a drone estimates the HO's next action, based on statistical data previously collected.

4.5 Stochastic games

A stochastic (or Markov) game is a collection of games. the agents repeatedly play games from this collection, and the particular game played at any given iteration depends probabilistically on the previous game played and on the actions taken by all agents in that game.

Stochastic games generalize both Markov decision processes (MDPs) and repeated games. An MDP is a stochastic game with only one player, while a repeated game is a stochastic game in which there is only one state (or stage game).

In our approach, stochastic games can appear in any type of interaction, when there are several NE[4] or the opponent is not a "rational" player.

4.6 Extensive-form games (EFG)

Some games are not necessarily played simultaneously. The normal-form game representation does not incorporate any notion of the sequence of the players' actions. The extensive form is an alternative representation that makes the temporal structure explicit [LBS08].

EFGs are sequential games represented by "trees", in which the root represents the first player to move, the branches are the actions, the nodes are decision points of one of the players (alternately) and the outcomes are the leaves, specifying the players' payoffs. In this type of game, a

[4]Nash equilibrium

player choose her action first and the other observes her decision before decide.

Consider the *chicken game*:

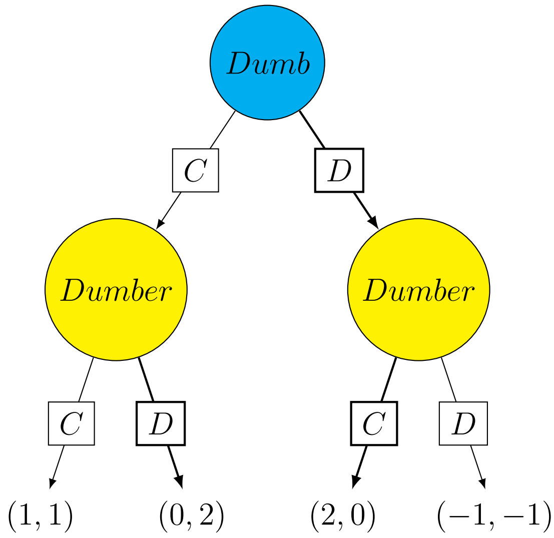


Figure 4.2: Sequential version of *chicken game*

Fig. 4.2 presents the *game tree* of a sequential version of chicken game, where Dumb decides first. In this case, it is easy for Dumber to choose. What it is not necessarily an advantage, if Dumb chooses to drive (D), the best response for Dumber is chicken out (C). The rational decisions are indicated by thicker arrows.

4.7 A game against Nature (GAN)

Individual decision problems with stochastic outcomes, also known as *lottery*, can be considered "one-player games", in which a special adversary called "Nature" can be used to model uncertainties. Nature is fictitious in the sense that it is not a real and rational agent that makes decisions for its own benefit. Instead, Nature "acts" randomly, referring to events that happen independently of the agent's decisions (for instance, if it rains or not). Then, the introduction of Nature is just a convenient tool to express different forms of uncertainty.

This kind of stochastic-outcome decision problems can be resolved using different approaches (which could lead to different solutions). For instance, *Markov decision process (MDP)* makes use of EUT to infer the next action, given a fixed probability distribution [TBF05], while Minimax strategy considers the worst case over a set of "adversarial" options.

Example 4.7.1
Planning a party

Emily is planning a party, and she is worried about whether it will rain or not. The utilities and probabilities for each state and action can be represented as follows:

		Nature's states	
		Rain ($p = 1/3$)	No rain ($\neg p = 2/3$)
Emily's party	Outside	1	3
	inside	2	2

Acording with EUT:

$$EU(Outside) = (1/3)(1) + (2/3)(3) = 2.33$$

$$EU(Inside) = (1/3)(2) + (2/3)(2) = 2$$

Therefore, Emily should choose the action with the higher expected utility: Outside.

However, if Emily is risk averse, she could make use of Maxmin (or Minimax) strategy and select an action that maximizes her minimum gain, that is: Inside.

Note that the probability of a state can depend on the agent's choice of action, although, in the above example, it does not.

In real-live decision situations, people often have to rely on their subjective estimates or perceptions of probabilities. SEU[5] (see Section 3.4) plays an important role within this context [Bec08]. In a GAN, and according to SEU, the action must be made in order to maximize the subjective expected utility of a choice:

$$\max\left(\sum_{i=1}^{n} u_j(x_i)z_{ij}, \sum_{i=1}^{m} u_j(y_i)z_{ij}\right), x_i \neq y_i \tag{4.2}$$

Where z is the agent's subjective probability.

Remark
What characterizes a GAN is that the subjective probability values are independent of the agent's decision.

As shown in Example 4.7.1, if Emily is pessimist or risk-averse, she can try to maximize her minimum payoff using a Minimax strategy. However, in cases where the probabilities for

[5]Subjective expected utility

different outcomes in Nature are not known (Knightian uncertainty), it may make sense to use mixed strategies, although GANs are not exactly strategic situations [Bec08].

In fact, Minimax approach may be advantageous in these situations, but, selecting the worst case, may also overestimate extremely unlikely (but costly) events (see *The black swan theory* in [Tal07]), severely affecting the strategies in such scenarios.

By using the mixed strategy solution in a repeated game (in a single-shot game it is impossible to tell if a player is using a mixed strategy), the player decides on the presumption that Nature would attempt to deceive her and would be totally against her. This approach can be seen as a Minimax strategy under total uncertainty, and it leads to an insensitivity about wrong risk estimates. That is, Nature can do what it wants and the actor can be guaranteed not to fall under the expected value of the mixed strategy (which is greater than the pure strategy Maxmin *security level*). Note that, this is not true for a single trial, but, it is in an expected long-term outcome or the case where a decision can be divided simultaneously into many sub-decisions (stochastic games) [Bec08].

In our framework, we will use GANs in the interactions between a drone and the environment.

4.8 Summary

In this chapter, we described some key concepts from game theory (GT) that we used to model the interactions among our players in our framework.

In Chapter 5, the interaction among the drones will be model as a repeated *anti-coordination game* (ACG) in order to spread the drones in a optimal way, then, we will show that they have a *wonderful-life utility* (WLU), thus, we can simplify it to a *potential game*.

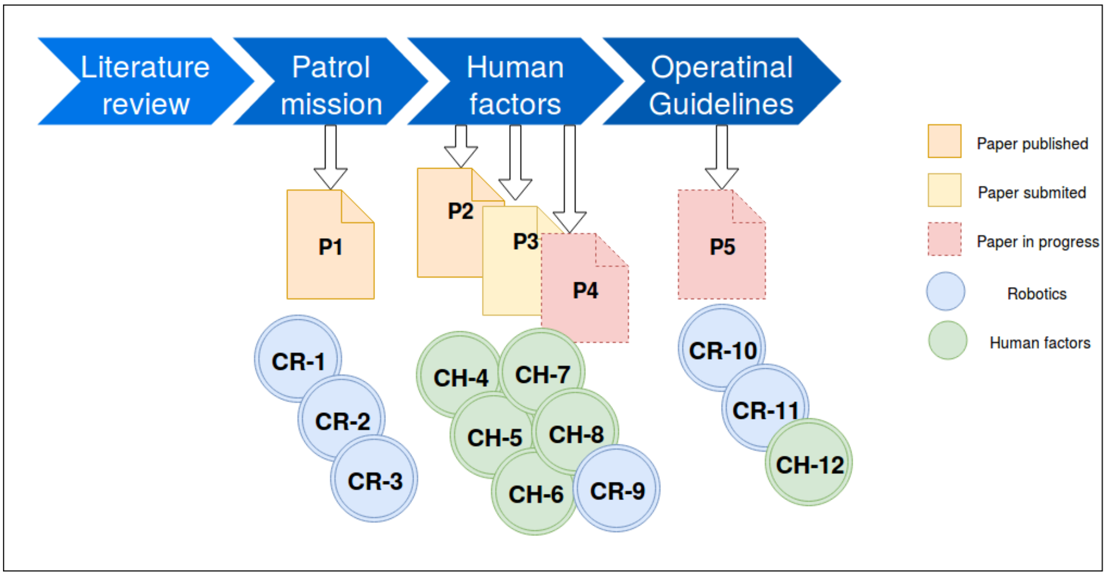
In Chapter 8 we will define a *stochastic game*, where each stage game is a *game against Nature* (GAN), in order to select a search pattern in a SAR mission; and for the HO-drone interaction we will use a *fictitious play*, based on the *human utility* proposed and presented in Chapter 7, to design a sequential *high-low game*.

Part II

Contributions

In the first part of this manuscript, we introduced the state-of-the-art technologies in robotics for dirty, dull or dangerous tasks, and presented the concepts used to formulate our framework. Chapter 1 was devoted to some real cases about modern robots operating in complex missions (such as SAR and sample-return). These cases were used to illustrate our experiments. After, the theories about MRS and HRI were presented. Then, in Chapter 2, we contextualized the human decision-making process, describe the *heuristics and bias theory*, in particular the *framing effect* (FE), and introduce the *naturalistic decision-making framework*. Our idea is making the robots explore the FE in order to lead the HO to choose the optimal option, given operational guidelines. Chapter 3 was dedicated to a general review about formal models of decision making, such as SEU and PT[6]. And Chapter 4 introduced key concepts about the *game theory* for our framework.

This second part, we will devote to the results of our research and our contributions.



Thesis design.

Although, (P/MO)MDP frameworks are an elegant way to model and solve sequential decision problems under uncertainty, even in a complex framework, they require fine-tuning in the rewards (observations, latency, and so on) and considerable time to calculate the policies ($O(2^n)$, where n is the number of agents).Thus, in order to avoid this complexity and with a focus on real-life emergency or another unexpected situation missions, we choose to explore the game theory (GT) in this kind of sequential decision problem under uncertainty (uncertainty in GT is intrinsic, and probabilities are not always known), as an alternative to (P/MO)MDP. The idea was to simplify the framework, in the sense of being easier and faster to set up the system in such kind of situation.

Therefore, as presented in Chapter 5, we elaborate the paper (P1) "A Game Theoretical For-

[6]Prospect theory

mulation of a Decentralized Cooperative Multi-Agent Surveillance Mission", presented at Workshop on Distributed and Multi-Agent Planning (DMAP 2016), which provided the design of a robotic patrol utility. The main contributions of this work were:

- CR[7]-1 – the formulation of an original player's utility function composed by three parameters that are independent of the action choices of the others players;
- CR-2 – the demonstration that the game solution is a Nash equilibrium, and that this equilibrium can be obtained by optimizing separately and individually the single player's action choice;
- CR-3 – the proposal of a decentralized algorithm used to conduct the mission, which works considering minimum communication among players.

With this, we had a proposition for a team of drones to patrol a known area. We then focused our work on the integration of the human operator (HO) in the system. In this regard and in order to better understand the effects of human cognitive biases in operational contexts and to optimize (HRI), we conducted an experiment involving a framing effect (FE) paradigm for two different robotic missions: a SAR mission (earthquake) and a Mars sample-return mission, detailed in Chapter 6, and reported in paper (P2) entitled "Towards human-robot interaction: a framing effect experiment" presented at IEEE Systems, Man and Cybernetics conference (SMC 2016). In addition, we are preparing a journal paper more focused to the human-factors related issues (P4). The main contributions of this work are:

- CH[8]-4 – the observation of the FE in the addressed context;
- CH-5 – the emotional commitment influence on the FE efficiency;
- CH-6 – the time-to-answer influence on the FE efficiency;
- CH-7 – the interference of the use of colors, as a complementary visual framing, in the "power" of the FE.

Hence, in Chapter 7, we used the data collected in this previous experiment to design an "utility function" to the HO in order to enable the drones to decide how to interact with her. The third paper (P3) "Applying Prospect Theory for Human Operator's Utility Function Modeling in a Cooperative Human-Robots Scenario" has been submitted to the *Special Issue on Autonomous Cognitive Robotics and Systems* of *IEEE Transactions on Systems, Man, and Cybernetics: Systems*. The main contribution of this study is:

[7]Contribution in robotics
[8]Contribution in Human factors

- CH-8 – the HO's utility function approximation founded on PT.
- CR-9 – a decisional model based on the economics approach of multi-dimensional consumption bundle and Prospect Theory.

We have another paper in progress (P5), reporting the results of the last experiment (Chapter 8) that will be submitted to *IEEE Transactions on Systems, Man, and Cybernetics: Systems* within the best delay. It will present our last contributions:

- CR-10 – the operational guidelines driving drones utilities.
- CR-11 – the decisional model proposed in CR-9 is explored to align HO decisions with the operational guidelines, allowing to close the loop in an "optimized" way.
- CH-12 – the FE leading HOs to decide in accordance with the operational guidelines.

CHAPTER 5

The patrolling problem

Contents

Disobey, and you die.

A.R.I.I.A. - Eagle Eye

This chapter presents the research to design a heuristic utility function for a drone team patrolling mission. The results of this work were presented in the conference paper P1 (“A Game Theoretical Formulation of a Decentralized Cooperative Multi-Agent Surveillance Mission”) at the Workshop on Distributed and Multi-Agent Planning (DMAP) 2016.

5.1 Motivation

Among MRSs, the robot team autonomous patrolling problem is very challenging: the robots must navigate through the environment so different locations that are scattered in the operational space, and they have to coordinate their actions in order to optimize the time spent to cover all the desired points of interest (POI) [PR13a]. One of the critical issues of a surveillance mission for a MRS is how to coordinate their behaviors in order to optimize the global performance [Men08]. For example, monitoring an area of interest requires that the robots move repeatedly through the environment, and the difficulty is to decide on the paths while optimizing some performance criteria [PFB10]. Moreover, since surveillance implies the maximization of the number of visits to each node in a given environment, a good surveillance strategy must reduce the time interval between visits to the same location [Che04].

With the aim of evaluating surveillance strategies, a comparative study using distinct topological environments and different team sizes is presented in [PR13b]. That work analyzes the performance and scalability of each patrolling approach. For that, [PR13b] proposed as an evaluation metric the *average idleness of the graph* (Idl_G). In the same point of view, [Che04] demonstrates that minimizing *worst idleness* will also lead to a smaller average idleness. In any case, the smallest the idleness, the better is the performance.

Another crucial point argued by some authors is that, for security reasons, it should be suitable to consider irregular time intervals to perform visits on POIs while optimizing the strategy, in order to avoid that a potential intruder could observe the movement of the patrol members for some time and derive an accurate belief of their strategies [HCB+13]; [Ami+10]. The key idea is to make it more difficult for an intruder to predict the motion strategy of the team members.

In this kind of surveillance application, it is well known that the minimal refresh time patrolling problem is *NP-hard* [PFB10]; [PR11]; [ZK15]. This means that to update the state of each position at each timestep would be computational and memory expensive and impractical in real-world scenarios [Men08]; [PR11]. This is so because in order to improve the efficiency of the collective searching strategy, the action of each robot does not only depend on its own situation, but also on other robots decisions.

In this sense, recent papers have based their approaches on *Game Theory* [Ami+10]; [HCB+13]; [Men08]; [Pes+00]; [An+12]; [Kha07]. An example of such a Game Theory application is presented in [HCB+13], where Game Theory models of the multi-robot patrolling problem are solved with the use of dynamic and decentralized collaborative approach. Another interesting solution is proposed by [Ami+10] based on Game Theory, which develops a surveillance strategy to drive mobile robots around a known environment in order to avoid intrusions while implementing a non deterministic strategy for their movements in order to make more difficult the task of intruders for they do not know a priori the stochastic distribution of such motions. Others examples can be found in [Men08], which proposed an N-agent cooperative nonzero-sum game to achieve an optimal overall robots behaviors; [Pes+00] described a gradient-descent policy-search algorithm for cooperative multi-agent domains, where they all share a common payoff; and, [An+12] that investigated the use of zero-sum games for the protection of critical infrastructures.

5.2 Objective

With the purpose of evaluating the team coordination performance (without the human operator's intervention), a cooperative surveillance mission based on Game Theory (GT) was designed, in which two metrics were defined: (1) *idleness* – the time interval expended by the patrols to revisit each POI[1], and (2) *predictability* – the difficulty in predicting the next move of the drones.

In this sense, this work addresses the problem of monitoring a closed area by a team of drones minimizing the POIs idleness while keeping some kind of randomness of motion in order to render movements less predictable.

Note that, this is neither a coverage problem nor an adversarial problem, but a mix of them. The issue is the development of a dynamic and decentralized approach to multi-aerial-robot cooperation in order to solve the patrolling problem by implementing game theoretical models.

5.3 Problem formulation

This mission can be defined as a frequent visitation problem of all preset points (POI) for a drone team in the lowest possible time interval without having a cycling behavior in order to make the motion model less predictable.

The idea of this chapter is to present a method of coordination between drones, based on Game Theory, that is capable of carrying out a patrolling mission on a known *topological model* represented as a graph $\mathbb{G} = (\mathbb{S}, \mathbb{E})$. In this graph $\mathbb{G}$, $\mathbb{S}$ is the set of nodes representing the POIs in the environment (i.e. positions), and where the edges $\mathbb{E} \subseteq \mathbb{S} \times \mathbb{S}$ define adjacency relationships between the nodes $s \in \mathbb{S}$. Each edge $e \in \mathbb{E}$ has a cost that represents the time required to move from one node to another. These costs are fixed.

In order to reduce the computational complexity, the following approach for the solving algorithm is proposed: (1) a fixed path between nodes in the graph and its cost are generated offline, considering that the graph does not change during the mission; and (2) the communication between the drones and a new game occur only at the destination of a drone, instead of at every

[1] Point of interest

timestep (i.e. the communication is asynchronous).

To define the game problem, some assumptions were taken:

- For simplicity, time was discretized in turns (timesteps), and a timestep represents the time to go from a position to another adjacent one;
- Each node s is considered as a POI that should be observed, i.e. looking for an intruder;
- Each destination node is a point where the communication among the drones team occurs;
- Each drone will select, only once it reaches its destination point, the next point to visit, based on the available information of the others. This means that a new action selection problem will be considered by a drone only when this one has reached the destination point, instead of each timestep t;
- The drones are defined as "Conscientious Cognitive" agents [PR11], i.e., they choose the next point to visit in the global graph, instead of in their neighborhood. So, at each time interval, each drone can move from one node to another adjacent, without necessarily selecting a new point of interest;
- All drones have perfect knowledge of the graph model, of their own positions in the graph, the last position informed by the others and their destinations in the graph;
- We assume that each drone can avoid obstacles and collisions;
- The horizon of the mission is considered as infinite.

Therefore, under these assumptions, a Game-theoretic formulation of the problem is proposed.

5.4 Moving game

Consider a graph $\mathbb{G} = (\mathbb{S}, \mathbb{E})$, where $\mathbb{S}$ is the set of nodes representing the POIs in the environment and where the edges $\mathbb{E} \subseteq \mathbb{S} \times \mathbb{S}$ define adjacency relationships between the nodes $\mathbb{S}$, i.e., the possible paths between the POIs. Each edge has a cost that represents the time required to move from one node to another. These costs are fixed.

During a mission, in order to each drone selects the next sector to visit, a dynamic ACG was designed, where the payoffs at each timestep depend on the minimal distance between POIs (represented as nodes in a graph), the current position (node) of all drones and the last time since each POI was visited. Formally, it can be defined as a N-player finite game $\Gamma = (N, \mathbb{A}, u)$, where:

- $N = \{1, \cdots, n\}$ is the finite set of n players, indexed by i;
- $\mathbb{A} = A_1 \times \cdots \times A_n$ represents all possible actions to be taken by all players;
- $u = h(u_1, \cdots, u_i, \cdots, u_n)$ is the payoff function (which in turn is function of the payoff of each single player), with $u : \mathbb{A} \rightarrow \mathbb{R}$, and $u_i : A_i \rightarrow \mathbb{R}$ for each player i.

In conformity with the GT[2] formulation, $\bar{a} = [a_1, \cdots, a_n]$ is defined as the vector of actions for all $n \in N$ drones and $A_i = \{a_i^1, \cdots, a_i^q\}$, where q is the number of actions at the disposal of $Drone_i$. Observe that the sets of actions A_i do not need to be equal for all drones. However, in the scenario we are modeling, we will consider the possible actions to be all equals since each drone can select any destination $s_k \in \mathbb{S}$ as an action. Then, one may conclude that $\mathbb{A} = A^n$ and the cardinality $|A| = q$. Thus, the set A is equal to the set of states (nodes of the graph) $\mathbb{S}$.

According to the positions/destinations of the drones at timestep t, σ^t is defined as the summation of the utilities of all players involved in the game, i.e.,

$$\sigma^t(\bar{a}, \bar{s}^t) = \sum_{\bar{a} \in \mathbb{A}} \sigma_i^t(\bar{a}, \bar{s}^t, m) \tag{5.1}$$

where $\bar{a}$ is the vector of actions of all drones and $\bar{s}^t$ is the state (position) of the drones at timestep t.

5.4.1 Patrol mission

In this type of mission, the drone team has to monitor a closed area, minimizing the time to revisit the POIs, while keeping some kind of randomness of motion in order to render movements less predictable for a potential intruder. Thus,

$$\sigma_i^{t*}(a_i, \bar{s}^t) = \max_{a_i \in \mathbb{A}} \left(-[\delta_i^t(a_i, s_i^t) + \theta_i^t(a_i, \bar{s_{-i}}^t) - \rho_i^t(a_i)] \right) \tag{5.2}$$

where:

- cost to move: $\delta_i^t(\cdot)$ is the distance for $Drone_i$ to move from its current position s_i^t to all its possible future locations $a_i^k \in A_i$, with $k \in \{1, \cdots, q\}$. Therefore, considering that $f^*(s_i^t, a_i^k)$ is the optimal distance cost that refers to the optimal (or sub-optimal, when the optimal cannot be calculated) path from node s_i^t to a_i^k, one gets:

$$\delta_i(a_i^k, s_i^t) = f^*(s_i^t, a_i^k) \tag{5.3}$$

[2] Game theory

cost for not moving: infinity. The idea is to force $Drone_i$ to move to another place, then

$$\delta_i^t(s_i^t, s_i^t) = \infty$$

.

- $\theta_i^t(\cdot)$ is the cost relative to the proximity of the other drones:

$$\theta_i^t(a_i, s_{-i}^{-t})) = \frac{\sum_j^{n-1}(\max(\delta_j^t) + \min(\delta_j^t) - \delta_j^t)}{n-1}, i \neq j \tag{5.4}$$

  $\theta_i^t(\cdot)$ is the weighted sum of all other drones "inverted distance", where *inverted distance* is defined as a value that is equal to the maximum distance for the nearest point and decreases with the distance. The idea here is to make the sectors more distant from the other drones more attractive for $Drone_i$.

- $\rho_i^t(a_i^k)$ is the *expected reward* to $Drone_i$ reaches the node $a_i^k \in A_i$. These values are collected (turn into zero) when a drone passes over the position and increase by a factor ηn each timestep that they are not visited, where $\eta \in [0, 1]$ is a normalizer constant and n is the number of drones:

$$\rho_i^{t+1}(a_i^k) = \rho_i^t(a_i^k) + (\eta n) \tag{5.5}$$

Note that since all action sets A_i are equal to A, the *expected reward* is equal for all drones.

In this way, $\rho(\cdot)$ is an *attractor* to POIs with lower number of visits (greater *idleness*).

5.4.2 Potential game

A potential game, as defined in Section 4.3, requires perfect alignment between the global goal and the players' local objective functions, meaning that if a player unilaterally changed her action, the change in her objective function would be equal to the change in the potential function.

In our case, based on the definition of the utilities, the optimal global utility for this game would be:

$$\sigma^{t*}(\bar{a}, \bar{s}^t) = \max_{\bar{a} \in \mathbb{A}} \sigma^t(\bar{a}, \bar{s}^t) \tag{5.6}$$

Observe that the $Drone_i$'s utility ($\sigma_i^t(\cdot)$) is only directly dependent on a_i and only indirectly takes into consideration the actions of all other drones (through $\theta_{-i}(\cdot)$). So, individual's utility functions are composed by three parameters that are, by definition, independent from the choices of the others players. In this sense, (5.6) may be rewritten as:

$$\sigma^{t*}(\bar{a}, \bar{s}^t) = \max_{a_1 \in A_1} \sigma_1^t(a_1, \bar{s}^t) + \cdots + \max_{a_n \in A_n} \sigma_n^t(a_n, \bar{s}^t) \tag{5.7}$$

Therefore, the maximum global utility strategy solution for $Drone_i$, σ_i^{t*}, is adopted for the decoupled game as described in:

$$\sigma_i^{t*} = \operatorname*{argmax}_{a_i \in A_i} \sigma_i^t(a_i, \bar{s}^t) \tag{5.8}$$

It means that for this formulation the action choice for $Drone_i$ is independent from the action choices of the others drones. Now, we can enunciate and prove the following theorem:

Theorem 5.1
The N-player finite game $\Gamma = (N, \mathbb{A}, u)$ *with utility functions defined in* (5.1) *and* (5.2) *possess a pure-strategy equilibrium.*

Proof. Let us consider a *Wonderful Life Utility* for $Drone_i$.

$$WLU_i = \phi(z) - \phi(z_{-i})$$

where z is the set of all drones and z_{-i} is the collection of all drones except $Drone_i$. It is clear, that if one considers $\phi = \sigma^t(\cdot)$, then

$$WLU_i = \sigma_i(\cdot)$$

Therefore, the game Γ becomes a *Potential Game*, i.e., the drones' utilities $\sigma_i(\cdot)$ are aligned to the global utility $\sigma(\cdot)$. Therefore, it is guaranteed to have a pure-strategy equilibrium according to *Corollary 2.2* of [MS96]. □

Moreover, it may be verified that this pure-strategy equilibrium is indeed a NE of the game [PGJS14], for:

$$\sigma^t(\bar{a}^*, \bar{s}^t) \geq \sigma^t([a_1^*, \cdots, a_{j-1}^*, a_j, a_{j+1}^*, \cdots, a_n^*], \bar{s}^t), \ \forall j \in N.$$

Finally, notice that this decentralized approach, where the action selection is formalized as a *potential game*, allows to drones to take decisions in an asynchronous way, as each drone selects the next action only once it reaches the destination point based only on available (last) information.

Algorithm 1 Patrol mission for $Drone_i$

1: **while** True **do**
2:   **if** status == $NotBusy$ **then**
3:     **report** current position
4:     **read** messages
5:     **assign** infinity to current position cost - $f^*(s_i^t, s_i^t) = \infty$
6:     **compute** the utility vector σ_i^t (Eq. (5.2))
7:     **find** and **select** the maximum utility strategy (Eq. (5.8))
8:     **report** destination
9:     **assign** $Busy$ to its current status
10:     **start** navigation
11:   **else**
12:     **if** position == destination **then**
13:       **assign** $NotBusy$ to its current status
14:     **else**
15:       **continue** navigation
16:     **end if**
17:   **end if**
18: **end while**

5.4.3 Algorithm for communication and coordination

Consider a *patrol mission*, in which the drone team is monitoring some POIs $s \in \mathbb{S}$. Algorithm 1 presents the process inside each drone. To better explain this algorithm we introduce two execution status on which drones' action selection relies. Before a $Drone_i$ starts to move, it changes its status to *Busy* and when it arrives at the destination point it changes to *NotBusy*.

When $Drone_i$ is *NotBusy*, i.e., when it is ready to leave the current point s_i^t, (line 2 of Alg. 1), it broadcasts a message of its current position and updates its knowledge of the position of the *NotBusy* drones and the destination position for the *Busy* ones (lines 3 and 4). Then, $Drone_i$ changes the cost of its current position s_i^t to ∞ which forces it to move to somewhere else (line 5). After, it proceeds all calculations to compute the utility vector σ_i^t, and it selects the strategy that maximizes its utility (lines 6 and 7), applying the proposed approach. As explained before, this is a *potential game*, then, when $Drone_i$ computes its *maximum utility*, it also computes the parcel of the *global maximum utility* concerned to it, knowing that the others will do the same. In this way, using a potential game to predict what others will do, coordination arises. Finally, it broadcasts its next destination to the others, changes its status, and starts to navigate again (lines 8-10).

When the drone is *Busy*, it only continuously verifies if the destination point is reached, if is the case, it changes its status to *NotBusy*, if not, it continues to navigate (lines 11-15).

Remark
This procedure is "cheap" and robust. If $Drone_i$ does not receive the updated position of $Drone_j$ ($i \neq j$) because they are very far apart, $Drone_i$ will consider revisiting the current position of $Drone_j$ sooner, which will increase the difficulty of prediction of the next position of the patrols. On the other hand, if $Drone_j$ crashes, the other drones will no longer receive its updates, then, they will adjust their patrol to cover the absence of $Drone_j$ and eventually find it.

To evaluate the proposed approach an application case is presented next.

5.5 Simulation Experiments

5.5.1 Setup

The topological model considered for these experiments is shown in Figure 5.1. This model is represented by the graph $\mathbb{G} = (\mathbb{S}, \mathbb{E})$ in that the nodes $\mathbb{S} = S \cup D$ represent some positions in the environment, with $S = \{s_1, ..., s_q\}$ the set of positions inside the rooms and corridors (POIs) and D the set of doors. The edges $\mathbb{E} \subseteq \mathbb{S} \times \mathbb{S}$ define adjacency relationships between the nodes $\mathbb{S}$, i.e., the possible paths. Each edge has a fixed cost associated with, here, the time required to move from one node to another.

To evaluate the approach, a patrol simulator was developed in Python 2.7.8. In this simulation model there are 25 POIs ($s_k \in S$), the 7 doors are considered as connection points ($d_m \in D$) and 60 edges, i.e. $|S| = 25, |D| = 7, |\mathbb{E}| = 60$ respectively, as shown in Figure 5.1. Please note that the set of actions A_i of $Drone_i$ is equal to S.

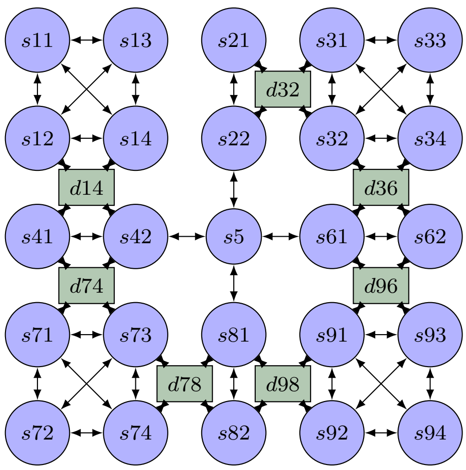


Figure 5.1: Topological model with the points of interest and all possible transitions.

Figure 5.2 shows a moment during the mission with three drones. In this simulation, the color of the floor is related to the *idleness* of the point, the blue areas are associated with greater rewards ρ^t.

We note that, as commented before, the approach presented in this paper is neither a coverage problem nor an adversarial problem, but a mix of them. The mixed problem proposed, as far as we know, is for the first time studied, and for this reason, a comparison to previous approaches is not straightforward possible.

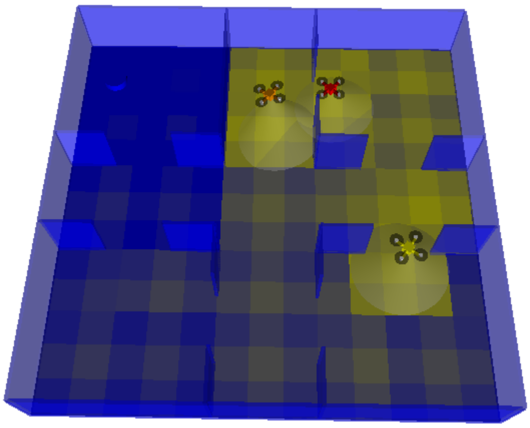


Figure 5.2: Geometric model.

In this context and in order to verify the performance of the patrolling algorithm considering different numbers of drones in the team and the influence of each component of the utility function (δ, θ and ρ from eq. 5.2), five "scenarios" were designed:

- *complete Utility* - where all components of the utility function were used;
- *no Reward* - where ρ was removed from the utility function;
- *no Inverse* - where θ was removed from the utility function;
- *only Distance* - where ρ and θ were removed from the utility function;
- *random* - where the drones select their destinies randomly.

1000 missions for each scenario were played and each patrol mission ran until each point of interest was visited at least fifty times.

Next, we define formally the metrics used to evaluate the performance of our approach.

5.5.2 Metrics

This study has been focused on (1) the interval between visits (*idleness*) and (2) the difficulty of prediction of the next position of the patrols (*predictability*). For the first one the *average idleness of the graph* Idl_G [PR13b] was used as a metric, and for the second one, the Ljung-Box test [BJR08] results were considered.

The *average idleness of the graph* (Idl_G) proposed by [PR13b] is defined as:

Starting with the *instantaneous idleness* (Idl_{t_k}) of a position $s_i \in S$ in the time step t_k:

$$Idl_{t_k}(s_i) = t_k - t_{last_{visit}}$$

where $t_{last_{visit}}$ corresponds to the last time step when that point s_i was visited by a drone. Consequently, the *average idleness* (Idl_m) of a point s_i in a total time T is defined as:

$$Idl_m(s_i) = \frac{\sum\limits_{k=0}^{T} Idl_{t_k}(s_i)}{T}$$

And, finally, the *average idleness of the graph* (Idl_G) is defined as:

$$Idl_G = \frac{\sum\limits_{i=0}^{|S|} Idl_m(s_i)}{\mid S \mid} \tag{5.9}$$

where $\mid S \mid$ represents the cardinality of the set S.

On the other hand, to evaluate how “unpredictable” the drone paths were, the *Ljung-Box test* was used. This statistical test allows the measurement of the "overall randomness" based on a number of lags of a time series by means of a single value Q:

$$Q = p(p+2) \sum_{l=1}^{m} \frac{\hat{\rho}_l^2}{p-l}$$

and:

$$\hat{\rho}_l = \frac{\sum\limits_{k=1}^{p-l} (Y_i - \bar{Y})(Y_{i+l} - \bar{Y})}{\sum\limits_{k=1}^{p} (Y_i - \bar{Y})^2} \tag{5.10}$$

where p is the sample size, m is the number of lags being tested, $\hat{\rho}_l$ is the autocorrelation function

(ACF) at lag l and $Y = (Y_1, \cdots, Y_p)$ are the measurements. For a significance level α, the critical region for rejection of the hypothesis of randomness is given by the percentile $(1 - \alpha)$ of the chi-squared distribution with m degrees of freedom:

$$Q > \chi^2_{1-\alpha,m} \tag{5.11}$$

Thus, if Eq. 5.11 is *TRUE* it is possible to say that exists a linear correlation, in other words, the information of past positions allows an inference of future positions. Moreover, Q weights the correlation process, i.e., the higher the value the greater the correlation.

Obviously, all tested scenarios have a high degree of autocorrelation between adjacent and near-adjacent positions, due to the movement model of the drones. Even though, Q can identify an appropriate time series model even when the data are not random.

In the end, in order to use this values as a metric of predictability (π) in the present work, Q for each scenario c was normalized by the worst value (per number of drones n):

$$\pi_c^n = \frac{Q_c^n}{max(Q^n)} \tag{5.12}$$

In this work, for a specific number of drones, the degrees of freedom m were selected among all scenarios as the smallest median number of steps necessary to complete a cycle (i.e., to visit all positions at least once) with an $\alpha = 0.05$.

5.5.3 Results

Figure 5.3 shows that increasing the number of drones implies the convergence of idleness, which, in an unusual and somehow unrealistic situation, will be zero when the number of drones reaches the number of POIs. Nevertheless, looking to these charts it is possible to infer the minimal number of drones to achieve the goal of the mission in an efficient way, defined as the ratio $\frac{|N|}{Idl_G}$ (best cost-benefit ratio).

Interestingly, in the *no Inverse* scenario, differently from the others, the idleness seems to be almost steady with two drones or more. The reason for that must be interpreted with caution, but it seems that when they do not need to coordinate their moves (and that is in essence what θ do), they can reach a local optimum very fast; however, these values will eventually decrease to zero. Also, it can be seen that the variance decreases with the number of drones, except for the *no Inverse* scenario. Together these results provide important insights into the approach presented. It is easy to observe the importance of each cost variable and their contribution to idleness.

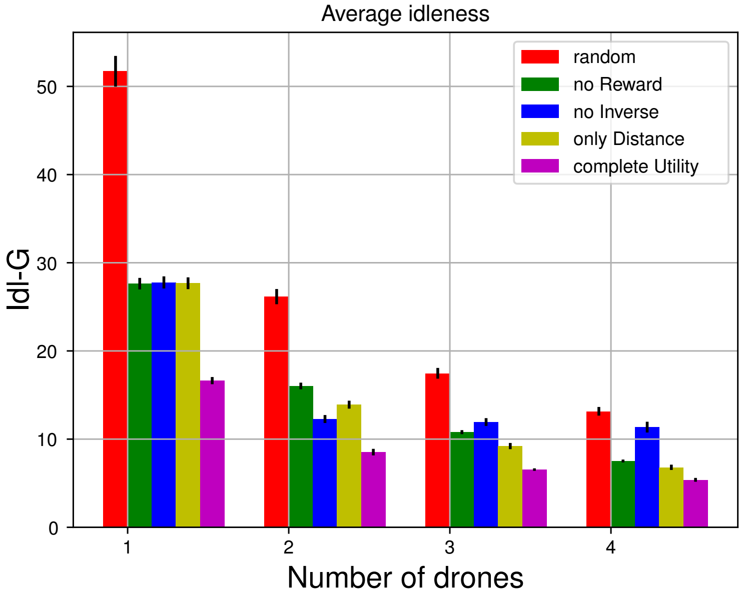


Figure 5.3: Average idleness of the graph per number of drones.

The increase of the mission performance with the rise in the number of drones in all scenarios for both metrics, *idleness* and *predictability*, is shown in Figure 5.4. The results also indicate that when ρ was not used (*no Reward*) the paths became more predictable (greater values of π). With a single drone the scenarios *no Reward* and *only Distance* achieved the same value, as expected, since, in this case, they have the same utility function.

On the other hand, still looking at the single drone case, a very predictable path can be identified for *no Inverse* and *complete Utility* scenarios. A possible explanation for these results may be that they tried to maximize the reward earned at each iteration. Interestingly, for more than one drone, the *no Reward* scenario appears to maintain predictable paths. Overall, these charts indicate that the best scenario is the *complete Utility*.

The charts in Figure 5.5 present a slice of the surveillance mission for three drones with 100 arbitrarily collected steps from all scenarios, where each line represents the path of a drone.

What is interesting here is that in *complete Utility*, *no Reward* and *only Distance* the drones tend to maintain themselves in a separated sector from the others. The *Random* scenario presented, as expected, the worst results as the drones moved randomly around the environment. In *complete Utility* and *no Inverse*, the path was longer than the others and with almost no local cycles, indicating global movement in contrast with some "sawtooth" path in the others charts. Another interesting behavior is observed in the *no Inverse* scenario where it seems like that the drones are following each other, maintaining almost the same path. The most striking observation to emerge from the data comparison is that the *complete Utility* generated longer and clearer

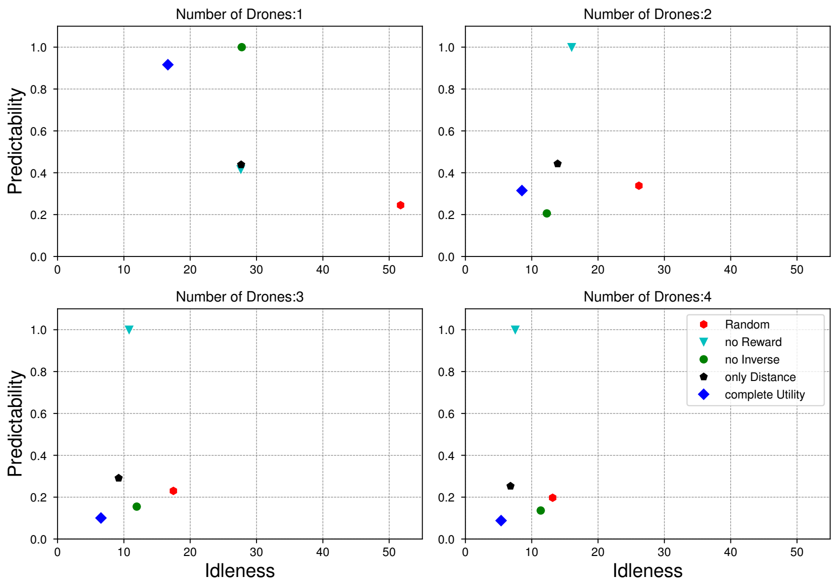


Figure 5.4: Predictability versus idleness.

paths, maintaining the drones separated for almost all time and changing the patrol sectors once in a while.

5.6 Discussion

As it is well known, depending on the type of game used, the computational complexity would become intractable with a large-scale team. This was the reason why a potential game was proposed.

It is important to recall that our decentralized patrolling strategy was not only to minimize the time interval between revisits of each POI, but also make the patrol movings less predictable. A similar context is difficult to find in the literature, generally researches are exclusively addressed to find the minimal visiting interval (e.g., [NK08]; [CDL11]) or to handle with a intruder (e.g., [IHC11]; [BGA09]). The dual objective of satisfying patrolling constraints (to minimize the revisit time) and reducing the patrol predictability to possible intruders separates our problem from many patrolling problems investigated in the literature. Therefore, it was not possible to compare our results with other researches.

Overall, the results indicate that the proposed *utility function* can minimize the *idleness* while also minimizing the patrol *predictability*.

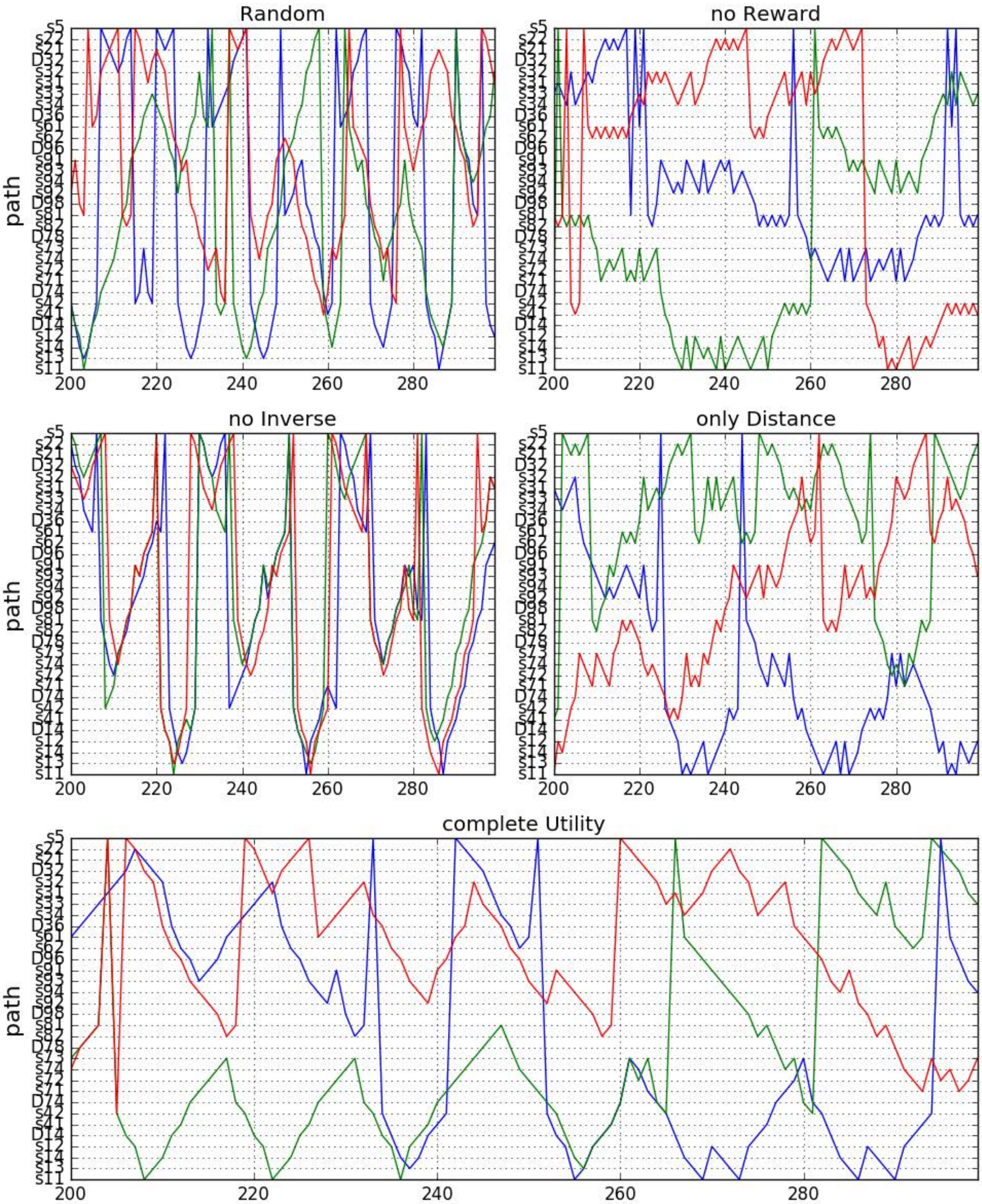


Figure 5.5: Paths generated with three drones. The “path” axis contains the nodes of the graph.

5.7 Summary

This chapter presented a multi-aerial-robot coordination game theoretical approach to performing a surveillance mission in a well-structured environment. Such a mission consisted in constantly visiting a set of points of interest while minimizing the time interval between successive visits (idleness).

The proposed approach optimized the agents' action selection based on an N-player ACG framework. The main contributions were:

- CR-1 – the formulation of an original player's utility function composed by three parameters that are independent of the action choices of the others players;
- CR-2 – the demonstration that the game solution is a Nash Equilibrium (NE), and that this equilibrium can be obtained by optimizing separately and individually the single player's action choice, i.e., it is a *potential game*;
- CR-3 – the proposal of a decentralized algorithm used to conduct the mission, which works considering minimum communication among players.

In other words, an original heuristic utility function was presented, where not only the path travel cost was considered, but also the current positions of the other players and the last time since each point of interest was visited. And, based on this utility function, an *anti-coordination game* (ACG) was generated, where the NE solution guides the player's behavior towards the team goal.

Simulations evaluated the different policies obtained, which were compared using as metric the average idleness of all points of interest (POI). The proposed framework allowed the decrease of the idleness of watched points compared to random action selection while keeping some kind of randomness of motion (measured by a predictability metric), which might be desired to curb the prediction of the team surveillance strategy by an intruder.

In this way, we concluded this study about the *moving game* for a patrol mission. In the next chapter, we will present the first step to put a human operator in the drone team, observing in a carried out experiment how the participants reacted in function of the way the problem was presented to them and their emotional involvement with the situation in question.

CHAPTER 6

The framing effect

Contents

An evil gain equals a loss.

Syrus

In the Chapter 5 we presented a decentralized algorithm for an autonomous patrolling drone team. However, there are some kind of missions that, for ethical or operational reasons, it is compulsory to have a human being in the loop, working side-by-side with the robots.

However, decision making is a critical issue for humans cooperate with intelligent robots. Moreover, it is well admitted that many cognitive biases affect human judgments, leading to suboptimal or irrational decisions. The framing effect is a typical cognitive bias causing people to react differently depending on the context, the probability of the outcomes and how the problem is presented (loss vs. gain), as explained with more details in Chapter 2.

In this chapter, we present the results of framing effect experiments carried out in order to better understand the effects of human cognitive biases in operational contexts and to optimize HRI. These results were reported in the conference paper P2 "Towards human-robot interaction: a framing effect experiment" presented at the *IEEE International Conference on Systems, Man, and Cybernetics (SMC 2016).*

6.1 Motivation

Human beings make daily decisions with limited time and incomplete information using a restricted cognitive budget. How could one be rational in those circumstances? What about in an emergency situation, when lives are at stake?

While classical models (such as expected utility theory) see human decision makers as unfailing machines with all knowledge needed and the eternity to decide in order to maximize cost-benefit decisions, other models try to avoid all human behavior complexity betting all their chips in totally autonomy systems using Artificial Intelligence (AI). AI tries to model the way a human should think in perfect conditions in order to create a computer system that can perform intelligent actions. On the other hand, Human-Computer Interaction (HCI) makes use of computer interfaces to help human users in the execution of intelligent actions [Hea99].

In [Fon+05] it is argued that for humans and robots to work effectively together, they should collaborate as peers instead of a "master-slave" relationship in space mission tasks, where, for several reasons (such as risk and cost mitigation) the human team must be kept small. In this approach, the robots can make their own decisions autonomously but query humans as needed.

Moreover, research suggests that when human decision-makers have to make critical decisions under uncertainty and imperfect information conditions or in situation where they are emotionally involved, like during natural disasters, emergencies, military operations or any other unpredictable and diffuse environment, people are more susceptible to make predictable errors in judgment caused by *cognitive biases* [Kah11]. In order to overmatch these situations and remain adaptive and effective amid a complex and ambiguous environment, it is important to understand and deal with these *hard-wired* human processes [Kle97].

Hence, in order to better understand the framing effect on the human decision-making process in a cooperative-mission context, the study presented in this chapter was carried out. Next, we detail the experiments.

6.2 Experimental design

We conducted two experiments whereby participants had to make decisions under uncertainty in the context of HRI. In the first one, the participants were facing two possible scenarios: (1) assisting victims of an earthquake and (2) sampling rocks on Mars. They had to decide either to launch a first-aid kit in the scenario (1) or to collect rocks, in scenario (2). The decision to made was based on incomplete information where the probability of the outcomes and the framing (positive or negative) were manipulated.

In the second experiment, new participants were placed in the earthquake scenario context. Similarly to the work of [Cho+13], we also manipulated the text color of the frame presented to the operator.

Such experiments were designed in order to answer some research question hereafter presented.

6.2.1 Research questions

The goal of this study is to answer the following research questions:

- *RQ1 - Is there the Framing Effect present in this context?*
- *RQ2 - Does the emotional commitment influence the Framing Effect efficiency?*
- *RQ3 - Has the Time to answer any influence over the Framing Effect efficiency?*
- *RQ4 - Do the operator's levels of confidence and satisfaction increase when the framing is aligned to a "good choice"?*
- *RQ5 - Is there a choice of framed questions that could provide a predictable decision regardless the Probability value presented*?
- *RQ6 - Is the use of colors as complementary visual framing can interfere in the "power" of the Framing Effect?*

In this sense, the study here presented uses the attribute framing effect (AFE) [LSG98] and the visual framing effect [Cho+13] influences in a drone operation situation.

6.2.2 Drones' environment and mission simulation

A simulation with a graphical interface (see Fig. 6.1) common to both scenarios was set up in Python 2.7.11. The left panel has a 3D environment where operators can change the point of view as they wish. During the simulation, three drones (2) depart from the base (1) to the search zone (3). The control panel at right shows (4) the status of the drones, where the buttons change colors when any of them needs an operator decision; (5) the battery level of each drone; (6) the sectors already visited, here the gray intensity is correlated to the type of search pattern used by the drone; and (7) the number of kits or storage places available for the mission in a given moment.

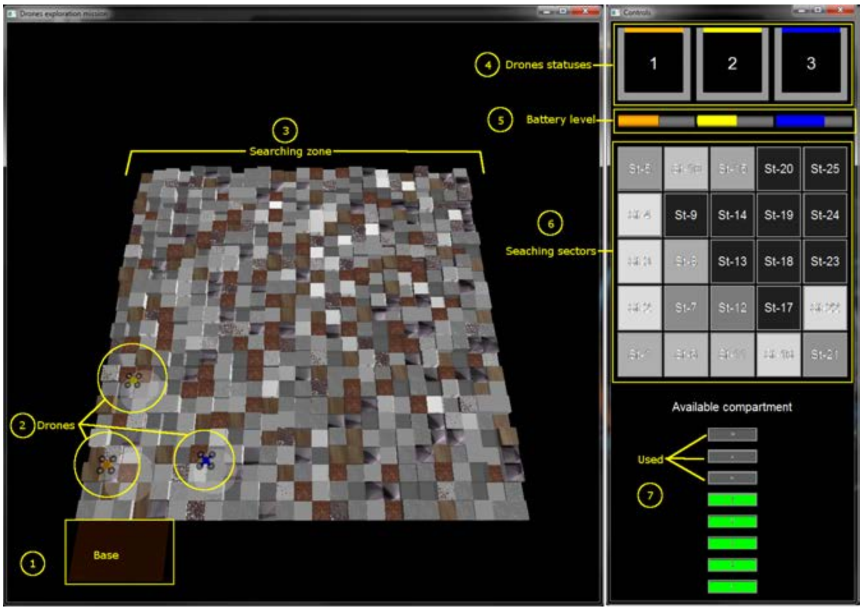


Figure 6.1: Operator's graphical interface.

6.3 Experiment I

6.3.1 Participants

Twenty volunteers (34.81% female, mean age: 30.73, sd: 7.54), participated in the experiment. They were, unknown to them, randomly split into two groups (one for each scenario). They were not rewarded for the participation.

6.3.2 Experimental protocol

Each participant randomly executed 10 missions (repetitions) for a given scenario (earthquake or Mars rock sampling). Each mission had a duration of around three minutes. During the evolution of a given mission, when the drones found something, 10 different types of sentences (2 types of *text frames* $\times$ 5 levels of probabilities) were randomly presented and the operator was requested to decide. For the probability levels *low*,*middle-low*, *middle-high* and *high* every two of the sentences had the same level of *Probability*, one with a positive framing and the other with a negative framing. The *extreme* levels were used as a "coherence check": first, one sentence was presented with a positive framing with an *extreme low* probability and, next, a negative framing sentence was presented with an *extreme high* probability, expecting a negative answer for both. The participants had 10 seconds to decide between say *YES*, i.e, take a *positive action* (release a kit or collect a rock), or *NO*. After this time period, the drone who asked should consider the operator's decision as a *NO*. Thus, the only thing the operator had to do was to answer the questions made by the drones by clicking in YES or NO on the pop-up window (Fig. 6.2).

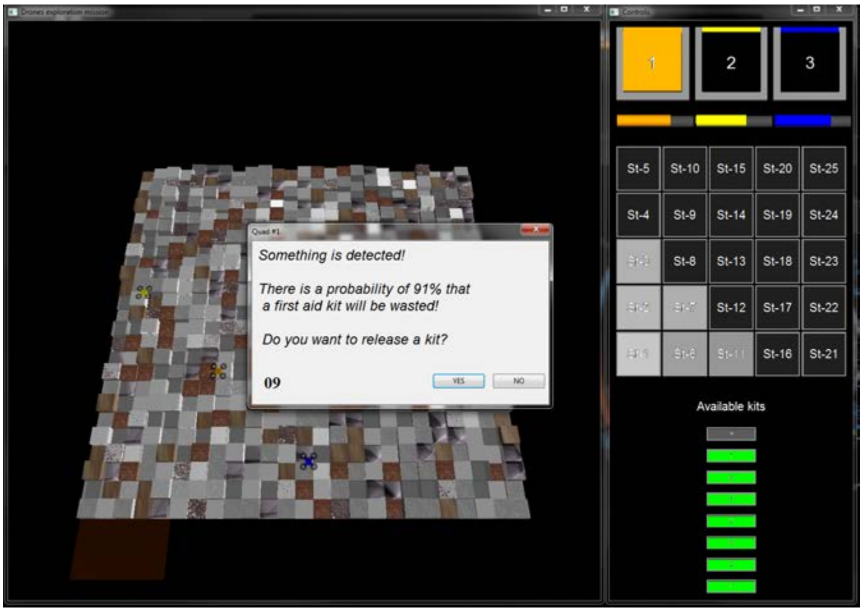


Figure 6.2: Operator's graphical interface.

Notice that, it was not possible to know the real result of every single mission, i.e., the operator could not know how many victims were helped or "good" rocks were collected during the experiment.

6.3.3 Statistical analysis

In order to evaluate the results of this experiment, two explanatory variables have been used: (1) *Text Framing* and (2) the *Probability* that a kit would be useful or not (earthquake scenario) or the target would be or not a "good" rock.

The *Text Framing* is the way how the sentences were presented (positive or negative). In the earthquake scenario, for the *Positive framing* a sentence was presented like: "There is 70% of chance that the kit will be **useful**" and for the *Negative framing* it was: "There is 30% of chance that the kit will be **wasted**". In the case of the Mars rock sampling scenario, for the *Positive framing* a sentence was presented such as: "There is 70% of chance of being a **'good' rock**" and: "There is 30% of chance of being a **'bad' rock**", otherwise.

For the *Probability*, four levels of interest were selected: *Low* (from 0.13 to 0.25), *Middle-Low* (from 0.37 to 0.49), *Middle-High* (from 0.51 to 0.63) and *High* (from 0.75 to 0.87). Each level represents a range of 12.5%. Two more levels were introduced with the intention of hiding these levels of interest, they were: *Extreme Low* (from 0.01 to 0.12) and *Extreme High* (from 0.88 to 0.99).

This experiment involved two factors with many levels (2 types of sentences and 4 probability levels). In general, *factorial designs* are most efficient for this situation [Mon12], because in each complete trial of the experiment all possible level combinations of the factors are investigated. In this sense, this factorial design required 8 runs for each combination (i.e. 2×4) to be tested in each scenario, consequently, each participant might take at least 8 different decisions during the experiment.

Because we have taken multiple measures per subject, which would violate the *independence assumption* of a linear model[1], a *Linear Mixed Model* was used [AK11] to deal with this situation. Adding some random effects for subject allows us to resolve this non-independence by assuming a different baseline for each subject. In this mixed design, we tested our hypotheses comparing the results of the two scenarios using a *Generalized Linear Mixed Model - GLMM* [Bat+15]. GLMMs are an extension of linear mixed models to allow response variables from different distributions, such as binary responses: "YES" or "NO".

In this study we have been interested in the relationship between operator's decision ($\boldsymbol{OD}$) and the main explanatory variables: Scenario ($\boldsymbol{S}$), Text framing ($\boldsymbol{TF}$) and Probability ($\boldsymbol{P}$) (see Eq. (6.1)).

$$\boldsymbol{OD} \sim \boldsymbol{S} + \boldsymbol{TF} + \boldsymbol{P} + (1|\boldsymbol{ID}) + \epsilon \tag{6.1}$$

[1] in fact, every person has some idiosyncratic factor that affects all responses from the same subject

where, part of the random factors ϵ, that was not possible to control experimentally, was unpacked in the variable $\boldsymbol{ID}$ (an assumption of a different intercept for each subject).

We started the statistical analysis with a model with all fixed effects available and dropped one by one until all unnecessary terms were removed, for instance: age and gender. In order to check the goodness of fit (GOF) of each model, the *Hosmer and Lemeshow test* [LKS16] was used. And, in the end, the model was checked to make sure that the data were not overdispersed [LL13].

Additionally, the subjective confidence and satisfaction levels of the participants about their performance after each mission were checked with a seven-point Likert-type scale.

6.3.4 Results

We collected 1982 observations from 20 subjects. Figure 6.3 shows a dot plot of the random effect term if this experiment. Here is possible to see the effects of each operator on the decision process as well as their standard errors to help identify how distinct the random effects are from one another. The plot shows that some participants (we suppressed their IDs) are more meticulous (negative values) than others in their choices.

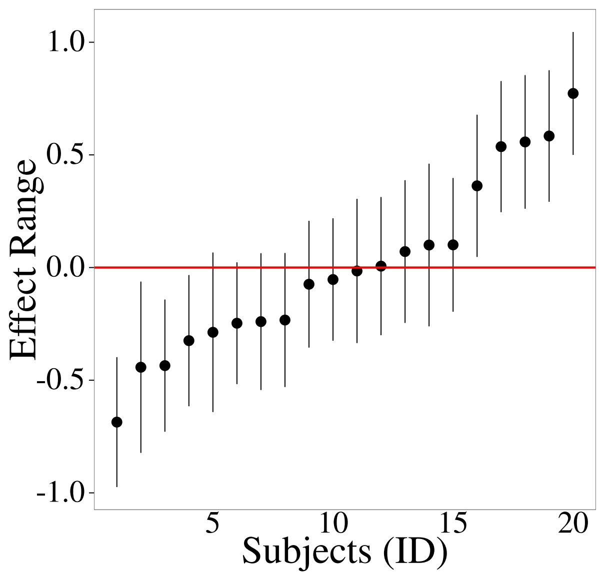


Figure 6.3: Random effects by subject.

In order to answer the research questions, some hypotheses were made and are presented next.

6.3.4.1 Hypothesis H1

To answer the first research question ($RQ1$), which was *“Is the Framing Effect present in this context?”*, we elaborated the following hypothesis:

- $H1_A$[2]: The operators’ decision are different, in a similar situation, according to the equivalent version of the choice presented, a negative or a positive one.

Here, there is a significant difference ($Positive : Estimate = 0.355, sd = 0.098, z = 3.621, p = 0.0002$) between positive (e.g., “There is 45% of chance that the kit will be **useful**”) and negative framing (e.g., “There is 55% of chance that the kit will be **wasted**”) in a GLMM[3] analysis. The p value indicates that we would reject the *null hypothesis* $H1_0$ in favor of $H1_A$. In this sense, we can confirm the presence of the FE in the experiment.

6.3.4.2 Hypothesis H2

Looking to $RQ2$: *Does the emotional commitment influence the FE efficiency?*, another hypothesis was defined:

- $H2_A$: The *positive frame* will be more effective in situations of emotional commitment (first scenario).

Results of the GLMM analysis show that there is a significant difference between the two scenarios ($Mars : Estimate = -0.475, sd = 0.233, z = -2.034, p = 0.042$). The negative estimated value (-0.475) refers to the *Mars* scenario and suggests that people are willing to take more risks when they are emotionally involved (*Earthquake* scenario). Figure 6.4 shows the influences of *Text framing* and *Scenario* variables in the operators’ decisions. The difference of behavior between the two scenarios demonstrates that the participants appeared to take more risks (saying YES even with low probabilities) when they were thinking about saving lives. The *positive frame*, in contrast with the negative one, was more effective in the *earthquake* scenario, confirming $H2_A$.

6.3.4.3 Hypothesis H3

In relation to the time to answer influence on the framing efficiency ($RQ3$), the following hypothesis was analyzed:

[2]The subscript “A” represents the alternative hypothesis, in contrast with the null hypothesis “0”.
[3]Generalized linear mixed model

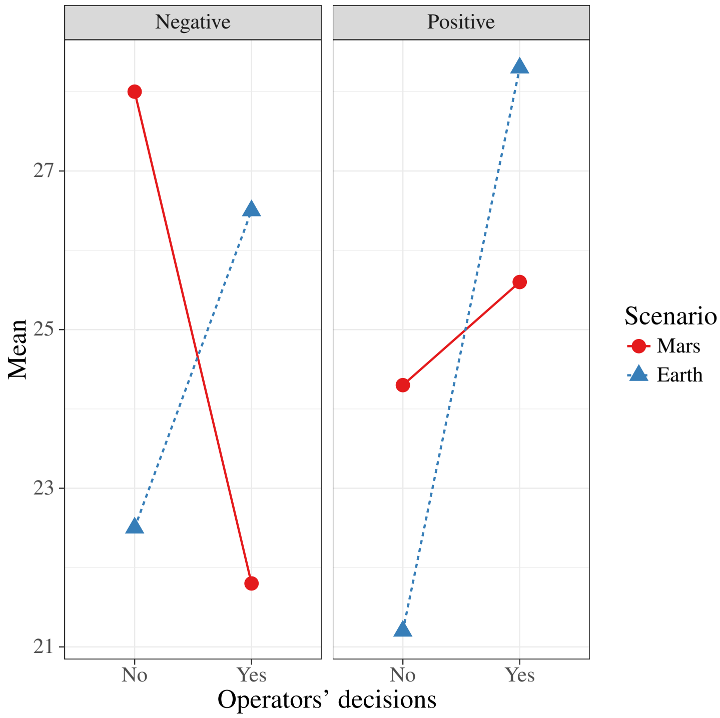


Figure 6.4: Average operators' decisions in function of the Text framing and the Scenario

- $H3_A$: The more time is devoted to answering a question the less effective is the FE.

In general when the participants answered not in accordance with the framing presented (e.g., saying NO after the sentence "There is 30% of chance that the kit will be **useful**") they expended more time than otherwise ($Estimate = -0.065, sd = 0.030, z = -2.154, p = 0.031$), indicating that we should accept $H3_A$. Maybe here they were using the analytical thinking mode instead of the intuitive one.

6.3.4.4 Hypothesis H4

For the purpose of observing the satisfaction and confidence levels in function of the operators' decisions ($RQ4$), we defined the following hypothesis:

- $H4_A$: The operators' subjective levels of *Confidence* and *Satisfaction* will increase when they believe that they made the best choice possible in a given situation.

Figure 6.5 shows those levels according to the number of *positive actions* executed (to release a first aid kit or to collect a rock). This criterion was used because, as already said before, it was not possible to know the results of the operators' actions (if they really helped some victims or collected some "good" rocks, respectively) at the end of every single mission. It is possible to see a significant correlation between these factors and their actions (Likelihood Ratio Test - LRT: *Satisfaction:* $\chi^2(2) = 266.47$, $p < 0.0001$ and *Confidence:* $\chi^2(1) = 196.58$, $p < 0.0001$), which indicates that we should reject $H4_0$ in favor of $H4_A$.

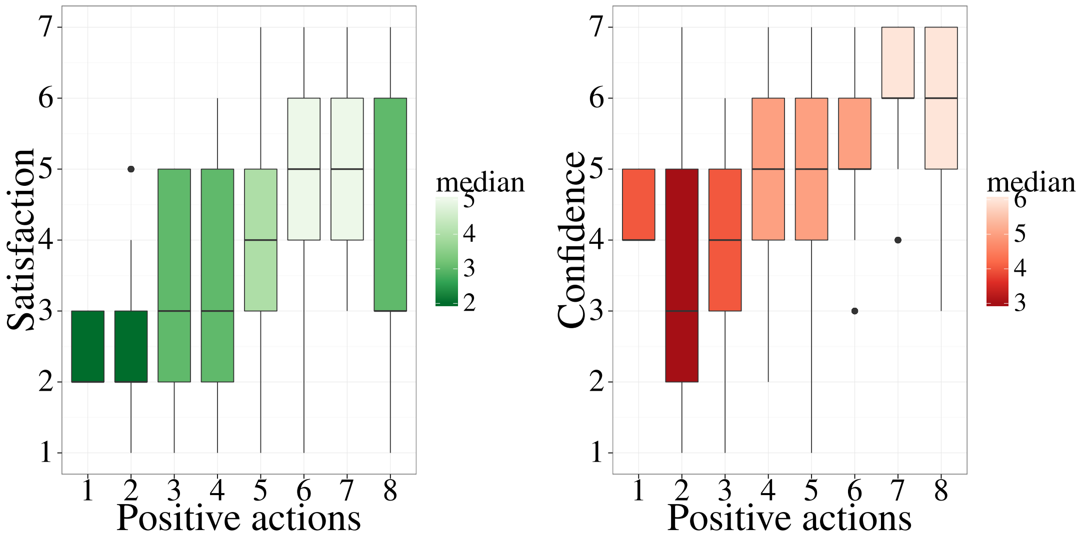


Figure 6.5: Satisfaction and confidence subjective levels in function of the operator's positive actions

6.3.4.5 Hypothesis H5

In order to answer $RQ5$: *"Is there a choice of framed question that could provide a predictable decision regardless the Probability value presented?"*, another hypothesis was proposed:

- $H5_A$: The higher the *Probability value* more the operator will be willing to say "YES" for the *Positive framing* and "NO" otherwise.

Looking to Figure 6.6, it is apparent that $H5_A$ is corroborated. Moreover, the negative framing could not overcome the emotional effect, that influences participants to be more risky, present in the *earthquake* scenario.

As expected, the attribute framing is only effective around the value of 50%, where there is a high level of uncertainty. Thus, the answer for the research question is "no", there is not a choice of framed questions that could provide a predictable decision regardless of the probability value.

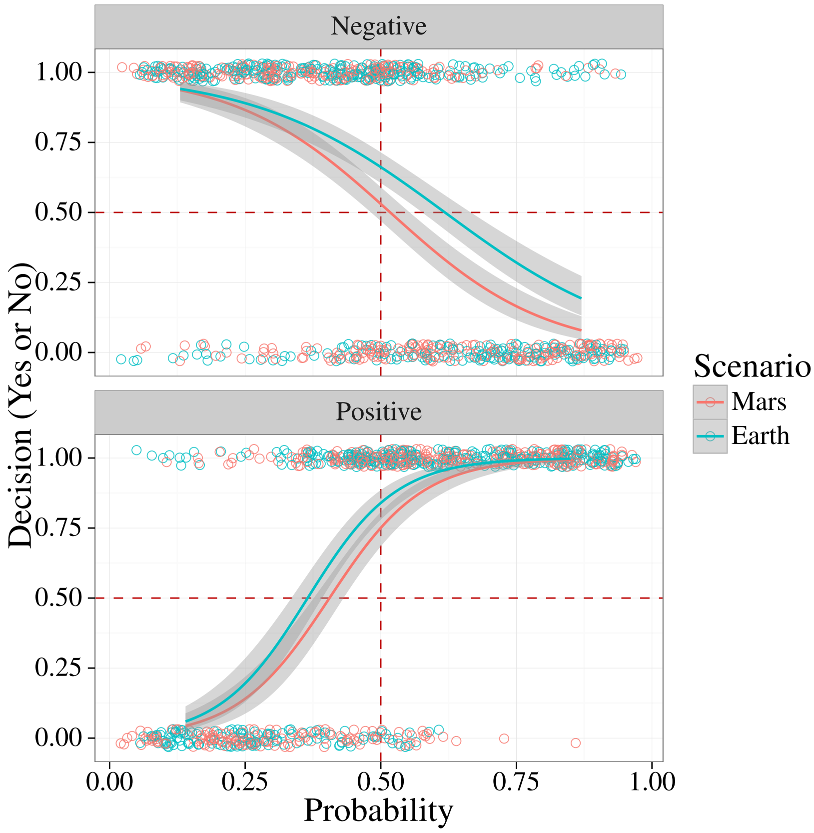


Figure 6.6: Operators' decisions in function of the framing, the scenario and the probability value.

6.3.4.6 Coherence check

Finally, the "coherence check" was observed (where, first, one sentence was presented with a positive framing with an *extreme low* probability value (< 0.13) – e.g., "There is 5% of chance that the kit will be **useful**" – and after a negative framing sentence was presented with an *extreme high* probability value (> 0.87) – e.g., "There is 95% of chance that the kit will be **wasted**", expecting "NO" as answer for both). Results showed positive answers ("YES") in 3.6% of the positive framing condition and 13.3% in the negative one. Demonstrating that, in the negative framing, the participants tended to underestimate the extremely high probability values.

6.4 Experiment II

In order to understand the *text color effect* over Human Operators' decisions, another experiment was carried out. At this time, only the *Earthquake scenario* was used. Here, the idea was to verify if a Visual Framing could change the tendency of reducing the probability value threshold, probably caused by the emotional commitment (less than 50% - see Fig. 6.6), observed in *Experiment I*.

The graphical user interface was the same used in the precedent experiment (cf. Fig. 6.1).

6.4.1 Participants

Twelve individuals (16.67% female, mean age: 24.75, sd: 4.89), all volunteers, participated in the experiment. The participants were, unknown to them, randomly split into two groups: (1) a control group with the texts written in black and (2) an experimental group with colored texts: GREEN - for a POSITIVE *Text framing* with a probability OVER 60% or for a NEGATIVE *Text framing* with a probability UNDER 60% and RED, otherwise. They were not rewarded for the participation.

6.4.2 Experimental protocol

Each participant randomly executed two missions, each one with 10 different types of sentences (2 types of text frames $\times$ 5 levels of probabilities). They were not previously informed about the existence of different colors in the text presented.

6.4.3 Statistical analysis

Similarly to the first experiment, in order to evaluate the results and to study the Human Operators' decisions ($\boldsymbol{OD}$) we used a *Generalized Linear Mixed Model - GLMM*, where the inherent difference of each participant ($\boldsymbol{ID}$) was used as a "random effect" and for the "fixed effect" variables were selected: *Text framing* ($\boldsymbol{TF}$), the *Probability* ($\boldsymbol{P}$) that a kit would be useful or not and *Visual framing* ($\boldsymbol{VF}$) that put colors (red or green) on the text (see Eq. (6.2)).

$$\boldsymbol{OD} \sim \boldsymbol{TF} + \boldsymbol{P} + \boldsymbol{VF} + (1|\boldsymbol{ID}) + \epsilon \tag{6.2}$$

6.4.4 Results

We collected 240 observations from 12 participants. Likewise in Experiment I, one last hypothesis was made.

6.4.4.1 Hypothesis H6

To answer the last research question ($RQ6$): *"Is the use of colors as complementary visual framing can interfere in the "power" of the Framing Effect?"*, one last hypothesis was proposed:

- $H6_A$: Different text colors can modify the participants' decisions.

Results show that the presence of the *Visual framing* (with a threshold of 60%) reduced Human Operators' willingness to release a first-aid kit (*Estimate*$= -0.763, sd = 0.321, z = -2.375, p = 0.017$), which affirmatively answer the research question.

Figure 6.7 shows that, in contrast with the control group, the experimental group reduced their willingness to say "YES" in both types of framing. Moreover, in the negative framing, it appears that they became confused trying to figure out the "right" answer for colored negative sentences in 10 seconds, which could explain that there are almost as many "YES" answers as there are "NO" ones in extreme probabilities.

6.5 Limitations

Before the discussion is presented and conclusions are drawn, it should be remembered that these studies had limited data. Therefore, generalization is limited to the population represented in the sample.

6.6 Discussion and Conclusions

In order to understand what could influence human operators while making critical decisions under uncertainty and imperfect information conditions, a framing effect experiment was carried out, followed by a visual framing experiment. With a software simulator, two different scenarios were presented to the participants: (1) helping victims of an earthquake and (2) sampling rocks on Mars. During the Framing Effect experiment, we manipulated the framing (positive vs. negative) and the probability values of the outcomes. Some hypotheses were defined to analyze the data collected. Results showed that the way the problem was presented (positively or negatively framed) and the emotional commitment (saving lives vs. collecting rocks) statistically affected the choices made by the human operators.

A second experiment, *the visual framing* was also carried out. In this experiment, only the earthquake scenario was played. Results showed that the presence of the *the visual framing*

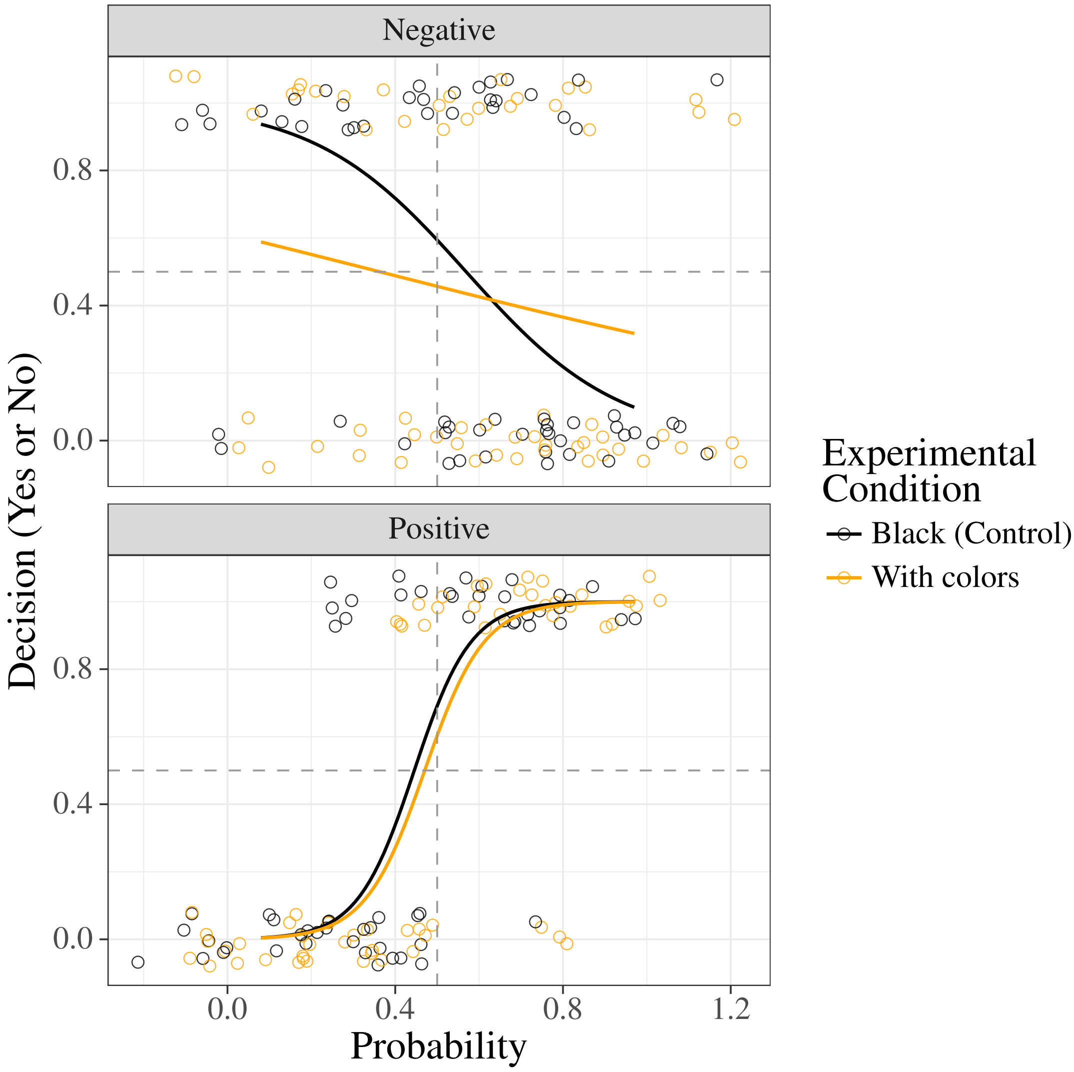


Figure 6.7: Operators' decisions in function of the 'text' and 'visual' framing

changed the average preference of the participants in say "YES" according to the probability value presented.

6.7 Summary

Decision making is a critical issue for humans cooperate with intelligent robots. Moreover, it is well admitted that many cognitive biases affect human judgments, leading to suboptimal or irrational decisions. The framing effect is a typical cognitive bias causing people to react differently depending on the context, the probability of the outcomes and how the problem is presented (loss vs. gain).

We recall that the aim of this study is to better understand the influences of the framing effect in operational contexts to optimize human-robot interactions.

Here, we conducted an experiment involving a framing paradigm in a search and rescue mission (earthquake) and in a Mars sample-return mission. We manipulated the framing (positive vs. negative), the probability of the outcomes and the text colors (visual framing). Statistical analyses were made.

Our findings revealed that the way the problem was presented (positively or negatively framed), the emotional commitment (saving lives vs. collecting the good rock) and the text colors statistically affected the choices made by the human operators.

The main contributions of this study were:

- CH-4 – the observation of the FE in this context;
- CH-5 – the emotional commitment influence in the FE efficiency;
- CH-6 – the time-to-answer influence in the FE efficiency;
- CH-7 – the interference of the use of colors, as complementary visual framing, in the "power" of the FE.

In the next chapters we will take into account these cognitive biases, using PT as a predictor of HO's decisions, to set the utility functions of the drones and to adapt dynamically HRI by automatically choosing which framing should be presented to the HO in order to maximize the chance the HO take an aligned decision regarding a mathematical criterion – expected value or cost – when performing the actions.

CHAPTER 7

The human utility

Contents

...the rarest of all human qualities is consistency.

Jeremy Bentham

In this chapter, we will look into ways and means of including the human agent as part of the team. In our approach, a drone has to calculate the optimum payoff (for the moment) and frame the information to share with HO in a way that maximizes the probability of HO to take a decision that leads to that common payoff. For that, it has to infer a "human utility" for making use of it (see Chap. 8).

7.1 Motivation

According to [TK86], the use of prescriptive models to predict and explain the human decision-making process has been defended by several arguments. In general, people attempt to be effective in pursuing their goals. Then, it appears to make sense to describe choice as a maximization process. But, descriptive alternatives have shown violations in those theories. [TK86] argues that these deviations are too big to be ignored and suggests that, when people have to make decisions under imperfect information conditions, they are more likely to make predictable errors in judgment caused by *cognitive biases*. This is true mainly in situations where they are emotionally involved, as for instance, during space missions, emergencies, natural disasters, military operations or any other complex situation.

In this sense, rather than idealizing the conditions of the human decision-making process, descriptive theories permit to better understand the internal process people use when making decisions. Hence, here we based our research on the *Prospect theory (PT)* [KT79]; [TK92] to consider human's cognitive biases, in particular, the framing effect (FE), in order to learn a function that fit (and help to predict) the HO utility.

7.2 Personal utility model

In order to calculate the utility function for HO, the Prospect Theory (PT) was used. Following, based on Equation 3.6, is presented our estimation for the intrinsic *consumption utility*, $m(c)$, and the gain-loss function, $n(c|r)$, terms. This step should allow us to define a personal utility function as proposed by Kőszegi and Robin [KR06] (see Section 3.5).

7.2.1 HO's intrinsic consumption utility

According to our hypothesis, HO has two personal *goods*: the *belief that her action could result in a good job* $h \in \{0, 1\}$ (e.g., helping victims or not – earthquake scenario – and collecting or not rocks on Mars) and the *perceived ownership value* of an asset ($pov \in \mathbb{R}$) at a given moment. Hence, she has a bidimensional consumption bundle $c = (h, pov)$. Note that, HO has to face conflicted emotions to decide: if she says *YES*, she wins the *satisfaction* (gain) of doing a good action (h^+, i.e. $h = 1$ in our case) against the probability (p) of loosing a precious asset. Otherwise, if she says *NO*, she can save the asset for a better future opportunity, but with the risk ($1 - p$) of living behind a victim (in a SAR mission) or a wanted rock (in a sample-return mission) – h^-, i.e. $h = 0$.

In this cost-benefit dilemma, supposing that HO wanted to do a good work, for instance by doing a *positive action* (say *YES*) in function of her consumption bundles, the function $m(c)$ could be defined in this application case as:

$$m(c) = \begin{cases} (h^+ - pov) \cdot p, \text{for a positive action} \\ (pov - h^-) \cdot (1 - p), \text{for a negative action} \end{cases} \tag{7.1}$$

where p is a given objective probability value, or the presented one, for instance.

7.2.2 The gain-loss utility

Following Equations (3.6) and (3.7) the term $n(c|r) = \mu(m(c) + m(r))$ represents the *gain–loss utility*, that should be in this study in accordance with PT (cf. Section 3.5). For this propose, we need to define the weighting $w(\cdot)$ and the perceived value $pv(\cdot)$ functions that are necessarily following Equation (3.4).

$$n(c|r) = \begin{cases} (h^+ - \gamma \cdot pov) \cdot w^+(p), \text{for a positive action} \\ (pov - \gamma \cdot h^-) \cdot w^-(1 - p), \text{for a negative action} \end{cases} \tag{7.2}$$

7.2.3 Proposed personal utility (Ψ)

Supposing again that HO wanted to do a good work, according to Equation (3.6), her personal utility $\Psi(\cdot)$ will depends on if she made a *positive action* (say *YES*) or not. In this sense, one can define $\Psi(\cdot)$ as follows:

$$\Psi(c|r) = \begin{cases} \psi^+(h^+, pov, p), \text{for a positive action, and} \\ \psi^-(h^-, pov, p), \text{for a negative action} \end{cases} \tag{7.3}$$

with,

$$\psi^+(h^+, pov, p) = (h^+ - pov) \cdot p + (h^+ - \lambda \cdot pov) \cdot w^+(p) \tag{7.4}$$

and,

$$\psi^-(h^-, pov, p) = (pov - h^-) \cdot (1 - p) + (pov - \lambda \cdot h^-) \cdot w^-(1 - p) \tag{7.5}$$

where p is the current objective probability, $w(\cdot)$ is a *subjective probability weighting function* and $\lambda > 1$ is the *loss-aversion coefficient* (see Sec. 3.5).

Supposing that HO would maximize her personal utility $\Psi(\cdot)$, one can link an HO's decision to her $\Psi(\cdot)$ by means of a maximization operator, and so predicting HO's decision, a positive (pos) or a negative (neg) action, as follows:

$$\phi(h,p) = \arg\max_{neg,pos}(\psi^-(h^-,pov,p),\psi^+(h^+,pov,p)) \tag{7.6}$$

Such a decision criterion should select which framing should be shown to HO in order to maximize the chance of having an appropriated decision, i.e., a decision aligned with the operational guidelines.

7.3 Previous Experiment

Based on data collected the experiment described in Section 6.3, a different statistical study is proposed here, in order to observe the utility function for gains and losses and the FE influence over the decision taken by the human operator (HO) in two different scenarios: (1) helping victims of an earthquake and (2) collecting rocks on Mars.

7.3.1 Statistical results based on the previous experimental data

In this study we have been interested in the relationship between HO's decision ($\boldsymbol{OD}$) and the main explanatory variables: Scenario ($\boldsymbol{S}$), Text framing ($\boldsymbol{TF}$), Probability ($\boldsymbol{P}$) and used Assets ($\boldsymbol{A}$) (see Eq. (7.7)). $\boldsymbol{A}$ was introduced in the statistical model to determine the HO *Reference point* (according to PT, see Sec. 7.4) and when she considered the action either as a gain or as a loss. First of all, the random factors ϵ, that was not possible to control experimentally, were unpacked in two different variables: $\boldsymbol{ID}$ and $\boldsymbol{Seq}$. The first one referred to the assumption of a different intercept for each subject and the second one referred to the sequence of the missions, which were shuffled for each subject, all the others "stochastic" differences have remained in the error term ϵ.

$$\boldsymbol{OD} \sim \boldsymbol{S} + \boldsymbol{TF} + \boldsymbol{P} + \boldsymbol{A} + (1|\boldsymbol{ID}) + (1|\boldsymbol{Seq}) + \epsilon \tag{7.7}$$

Table 7.1 shows the estimated coefficients and errors of the GLMM. Here, the positive value of an estimated coefficient denotes that the condition increases the preference in saying "YES" and vice-versa.

Table 7.1: GLMM summary

	Dependent variable:
	Decision (OD)
Earthquake (S)	0.323^{*}
	(0.192)
Positive frame (TF)	0.252^{**}
	(0.127)
Probability (P)	0.731^{***}
	(0.279)
Asset (A)	0.311^{***}
	(0.042)
Intercept	-0.938^{***}
	(0.235)
Log Likelihood	−735.662
Akaike Inf. Crit.	1,485.324
Bayesian Inf. Crit.	1,520.955
Note:	*p<0.1; **p<0.05; ***p<0.01

7.4 Proposed Prospect theory model

In a first step and based in these previously collected data, PT was explored in order to model the HO's utility. In a second step, we proposed a model, based in a decisional mathematical criterion, used to decide how to frame a question to HO, which should predict, or at least maximize the chances to induce the desired decision from her in such operational scenario.

7.4.1 Approximating the gain-loss utility

Considering Equations (3.6) and (3.7) the term $n(c|r) = \mu(m(c) + m(r))$ (from [KR06]) represents the *gain–loss utility*, that should be in this study in accordance with PT (cf. Section 3.5). For this propose, we defined the weighting $w(.)$ and the perceived value $pv(\cdot)$ functions, fitting all parameters to the ones previously presented in Eq. (3.4).

7.4.1.1 Definition of the probability weighting function - $w(\cdot)$

Because the dependent variable OD was represented by “1” and “0” (*YES* or *NO* resp.) instead of cardinal numbers, a *Binomial Logistic Regression* was used to describe the average preference of the participants in function of the probability values. Figure 7.1 shows the probability of saying *YES* versus the objective probability, according to the framing used, with the logistic regression curve fitted to the data. The analysis gave the output presented in Table 7.2.

Table 7.2: Logistic regression analysis

Framing	Scenario	variable	Coefficient	error
Positive	earthquake	Intercept	-5.924^{***}	0.983
		Probability	16.437^{***}	2.219
	rock sampling	Intercept	-7.403^{***}	1.311
		Probability	18.373^{***}	2.772
Negative	earthquake	Intercept	-3.442^{***}	1.178
		Probability	9.103^{***}	2.256
	rock sampling	Intercept	-5.287^{***}	1.269
		Probability	11.609^{***}	2.512

Note: *p<0.1; **p<0.05; ***p<0.01

Looking to their decisions OD in function of the objective probability P, the output indicates that the probability of saying *YES* is significantly associated with the probability of a kit be useful (in the earthquake scenario) or a rock be a *good one* (Mars scenario). Here, it is easy to observe the *framing effect* with a significant difference between the positive and the negative framing. Also, it is perceptive the *emotional commitment* influence in the subjects' decisions, comparing the results of the different scenarios. These statistical effects were already presented in Chapter 6.

Moreover, this curve is a strictly increasing function that satisfies $f(0) = 0$ and $f(1) = 1$ required by PT. From there, thus, it is possible to derivate their *subjective probability weighting function* $w(\cdot)$:

$$w(p) = \frac{1}{1 + e^{-(I+bp)}} \tag{7.8}$$

where I is the *Interceptor*, b is the estimated coefficient and p is the objective probability.

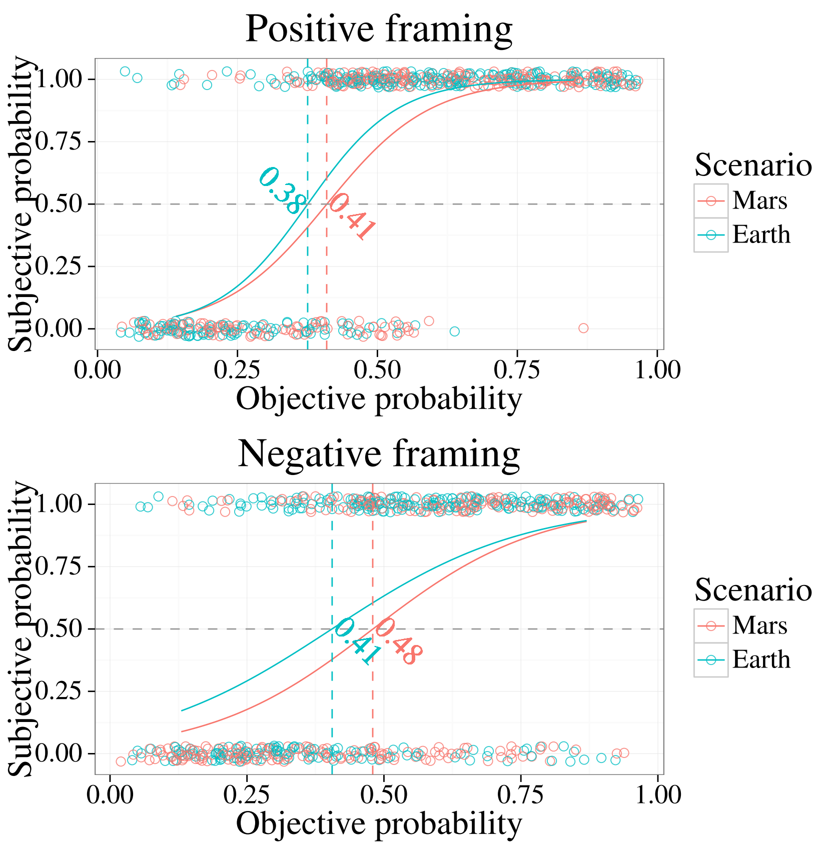


Figure 7.1: Probability of saying *YES* according to the objective probability.

7.4.1.2 Approximating a personal value function - $pv(\cdot)$

In Figure 7.2, HO's average preference was crossed against the number of assets used. A *Binomial Logistic Regression* was used again to describe this relationship. It suggests that, in the beginning, the participants had an *endowment effect* for the assets (they became *owners*) which decreased their willingness to make use of them. This attachment effect made them access the use of an asset as a *loss* and only accepted to give up it by a *high price* (high probability value). However, at a certain point they changed their mind and started to act as "sellers" (which do not assess *sales* as loss of inventory but as a gain of money). After that *reference point*, looks like they wanted to make the difference and use the assets as much as possible.

Such a hypothesis have already been observed in Section 6.3.4.4, where Fig. 6.5 presents the results of a questionnaire made after the experiment, demonstrating that the participants were more satisfied when they used more assets.

In this sense, one can assume a *reference point* RF where the preference of saying *YES* became greater than the preference of saying *NO*, thus, a curve that satisfies a *PT value function* $pv(\cdot)$ (see Eq. (3.4)) could be fitted over the positive framing curve in the *gain* region and over

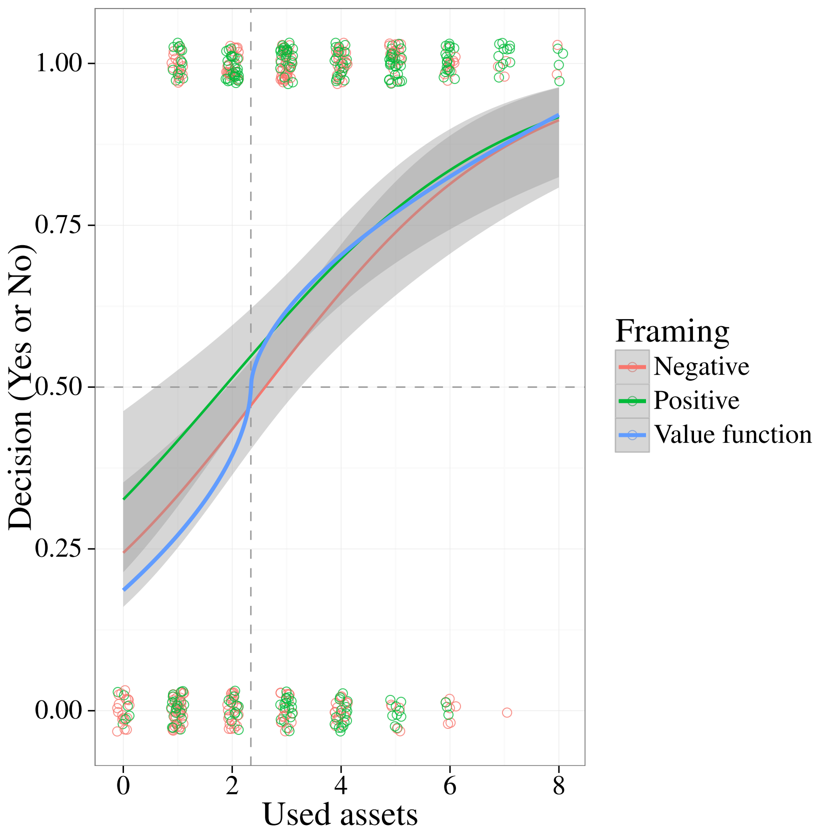


Figure 7.2: Probability of saying "YES" according to the number of used assets. The dark blue line is the approximated *personal value function* $pv(\cdot)$ of Equation (3.5).

the negative framing curve in the *loss* region.

Without loss of generality, it is reasonable to assume that the *perceived ownership value* $pov(\cdot)$ (see Eq. (7.1)) of an asset in a given moment is proportional to this *usefulness value* $pv(\cdot)$ at that moment, the bigger the former the smaller the latter, so

$$pov(x) = (1 - pv(x)) \cdot d \tag{7.9}$$

where $d \in [0, 1]$ is a normalizer constant.

7.4.2 Generating the proposed personal utility (Ψ)

The results for each scenario generate two surfaces (see Figure 7.3 - top-left): one for the positive framing and the preference in saying "YES" (green - $\psi^+(\cdot)$) and other for the negative one and the preference in saying "NO" (red - $\psi^-(\cdot)$). The top-right plot in Figure 7.3 shows the personal utility in function of the used assets for a given probability value (color intensity). The bottom-left plot Figure 7.3 shows the personal utility versus the probability for a given number of used assets. And, finally, the bottom-right plot Figure 7.3 presents the indifference curves (same utility lines) for both framings. These indifference curves were used to estimate the HO's decision, comparing the utilities of the framings (the greater one won).

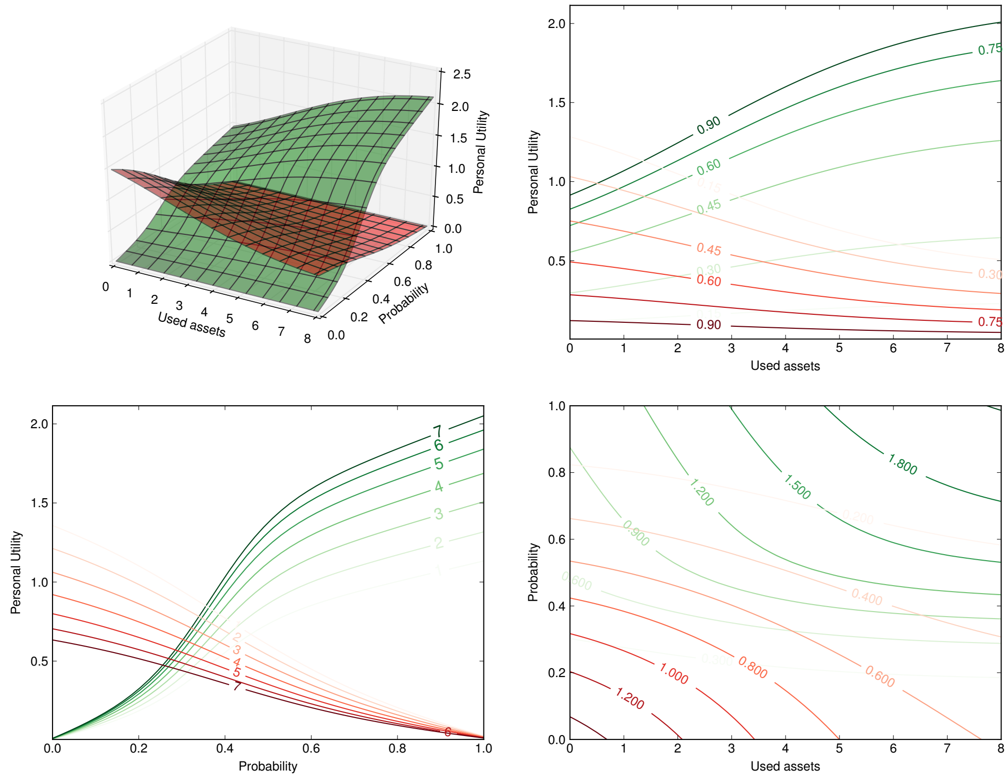


Figure 7.3: Personal utility in function of the framing for the earthquake scenario. The green color represents the positive framing ($\psi^+(\cdot)$) and the red color the negative framing ($\psi^-(\cdot)$).

7.4.3 Evaluation of the model

In order to validate the resulted model, a training subset with 75% of the data (homogeneously selected between the *text framings* and randomly among the individual data) were used for modeling and the remaining 25% were used to test the model.

Applying the decision criterion $\phi(\cdot)$ over the test subset in order to predict HO's decision and comparing with the actual decisions made by the participants, we could observe the results summarized in Table 7.3.

Table 7.3: Confusion Matrix and Statistics

Scenario	Probability range	Confusion matrix					
		Accuracy	Sensitivity	PPV	Prediction	Answer	
						NO	YES
Earthquake	0 - 100%	0.8131	0.9542	0.8013	NO	36	6
					YES	31	125
	40 - 60%	0.7647	1.0	0.7647	NO	0	0
					YES	20	63
Rock sampling	0 - 100%	0.8614	0.9576	0.8309	NO	61	5
					YES	23	113
	40 - 60%	0.7375	0.8966	0.7761	NO	7	6
					YES	15	52

In Table 7.3 the overall *Accuracy* rate is computed along with a 95% confidence interval, *Sensitivity*, also known as *Recall* is the number of positive predictions divided by the number of positive class values in the test data, and *PPV - Positive Predictive Value* is the number of positive predictions divided by the total number of positive class values predicted [Kuh08].

It is apparent that the model was not able to predict the "NO" answers in the range from 40% to 60% on the *earthquake* scenario, what was expected, once according to the bottom-left plot of Fig. 7.3, regardless of the number of used assets, the expected answer in this range was "YES". Nevertheless, these results suggest that the decision criterion $\phi(\cdot)$ can predict HO's preference with a (considered) good accuracy. In this sense, $\phi(\cdot)$ could indicate which framing should be presented by the system, i.e., a positive framing for an expected "YES" answer and a negative one, otherwise.

7.5 Discussion

Considering the prediction performance, some consideration could be highlighted. Firstly, this *random intercept model* assumes that whatever the fixed effect is, it is going to be the same for all subjects. However, this assumption cannot be totally valid, different people could respond differently in the same situation. Thus, the *perceived value* could be more a *personal perceived value* than a common one. Secondly, some of the participants did not make the experiment in their first language, so, they could misunderstand some information presented (as some of then reported at the end of the experiment), but it is important to notice that the GLMM analysis showed no significant correlation with that variable. By the way, this could reduce the accuracy of the model. And, finally, other participants reported that, at the begin, they not realized that there were different types of sentences and paid attention only in the probability value (*attentional tunneling*), leading to a incorrect situation awareness and, because of that, they took a "wrong" decision.

7.6 Conclusion

As far as we know, this work is the first study where a utility function based on the PT and a decisional model are proposed to approach HOs' utility function and predict human decisions in such operational context. Our model is based on the approach of multiple dimensions proposed by Kőszegi and Robin [KR06] in another context. But, contrary to them, any simplification assumption (as a linear utility for gains and losses and no probability weighting function) are here used. To consider a more general *gain-loss function*, we have considered a nonlinear probability weighting function $w(\cdot)$ that respects the mathematical conditions of PT (as strictly increasing function), and have identified different coefficients from collected data to approach a personal perceived value function. The contribution here presented, should allow to make the system chose, which framing could be presented to the operator in order to induce the required *HO decision* which should be aligned with the operational guidelines.

7.7 Summary

The aim of this work was to approach HOs' utility function and predict their decisions in a specific operational context, such as a cooperative human-robots mission.

The study in this chapter proposed: based on previous experimental collected data (see Chapter 6), (CH-8) the human operator's utility function approximation founded on the Prospect theory (PT), and as far as we know, (CR-9) the first decisional model based on the economics approach of multi-dimensional consumption bundle and PT without any simplifying assumption. The results here presented, in terms of utility function fit and prediction accuracy, are promising and shown that this kind of modeling and prediction should be taken into account when an intelligent cybernetic system drives human-robot interactions (HRI). The advantage in predicting the human's decision, in this operational context, is to anticipate, given the way a question is framed to the human operator, her decision. And so, in this sense, chose how to present the current information to the operator while expecting to align her non-deterministic decision with the operational guidelines of a given cooperative human-robots mission.

Finally, in the next chapter, we present our formal proposition of the whole system, where we close the loop, making use of everything presented until now. We also present the results of an experiment conducted to observe the system in action and the operational guidelines influence over the HO decisions.

CHAPTER 8

Closing the loop

Contents

Whether we are based on carbon or on silicon makes no fundamental difference; we should each be treated with appropriate respect.

Arthur C. Clarke

In this chapter we present our formal proposition of the whole system, where we close the loop, making use of a decentralized coordination game theoretical framework (Chapter 5), previous experimental data got in FE experiments (Chapter 6) and the proposed PT HO's decision prediction model (Chapter 7). This last one should allow us to decide how to present the information, expecting that the HO would decide in accordance with the mission guidelines. To evaluate the closed-loop system, we conducted an experiment with a large number of participants which allowed us to test the efficiency of our approach.

8.1 Motivation

To make our system efficient it is important to optimize each phase of the whole process. For the drones, they have to choose the best alternative available at the decision moment.

And, in order to improve the quality of decision-making, the expertise level of the DM should be improved, particularly in stressful or boring situations [KH08]. One way to boost expertise is by making novices repeat patterns used by experts. For example, we can see this type of learning system in flight lessons, in which a very detailed and logical explanation is not enough to a student has those skills mastered; in this case, the best practice is repeating standard patterns until the pilot student get used to them. This learning procedure reduces the cognitive charge [VMK12], transferring the mental effort from the analytical to the intuitive thinking. Thereby, using the *framing effect* we could try to transfer the patterns and strategies acquired by experts, instead of using analytical methods; and teach novices to see the world in the way experts do.

Note that, for our Experiment III, described later in Section 8.9, we used coefficients derived from the data collected in Experiments I and II (see sections 6.3 and 6.4) in order to infer the HO utility (as described in Chapter 7). Consequently, these coefficients are "biased" by those data, which created an "alignment" between the average preferences of the participants in that previous experiment and the framing selected by the system in Experiment III. Because of that, we considered those earlier participants as "experts" in order to persuade the new participants ("novices") to mimic them, the "experts".

8.2 System description

For this study, we defined a SAR mission in a bounded area (subdivided into small sectors) and assumed the following phases for this mission: (1) selection and moving to a destination sector, (2) selection and execution of a search pattern, and (3) interaction with the operator if a possible victim is found.

In this framework, each drone obtains its movement strategies and interacts with HO by using a game-theoretical approach. In this sense, they are self-centric agents trying to maximize their own payoffs, playing "against" each other, the environment and the operator. In the game among them, they have to coordinate their actions to avoid collisions, spread themselves along the area of interest and visit all predetermined points in a non-deterministic way. The interaction with the environment occurs when they have to "decide" how they will search for targets. With the operator, they adapt the human-robot interaction (HRI), via a graphical user interface (GUI), in order to improve the HO's decision-making process and then optimize the overall system utility. Fig. 8.1 shows the flowchart of a typical mission.

Finally, each payoff is influenced by the *guidelines* for the mission. These operational guidelines are statements and recommendations that determine a course of action in consonance with the decisions of the authority in charge of the mission. In this thesis, we will focus on what is more important in a specific mission: speed or accuracy. For instance, the sunset is coming (so, it is important to be fast) or not helped victims can freeze to death (then, be accurate).

8.3 Overall utility

The overall mission utility μ^t at timestep t is defined as an additive utility, i.e., the utility of a set of items is the sum of the utilities of each item separately (see Section 3.2.1), as shown in Eq. (8.1).

$$\mu^t = \sum_{\bar{a} \in \mathbb{A}} \mu_i^t(\cdot) \tag{8.1}$$

where i represents the index of a given drone in the team. So, we define the $Drone_i$'s utility as:

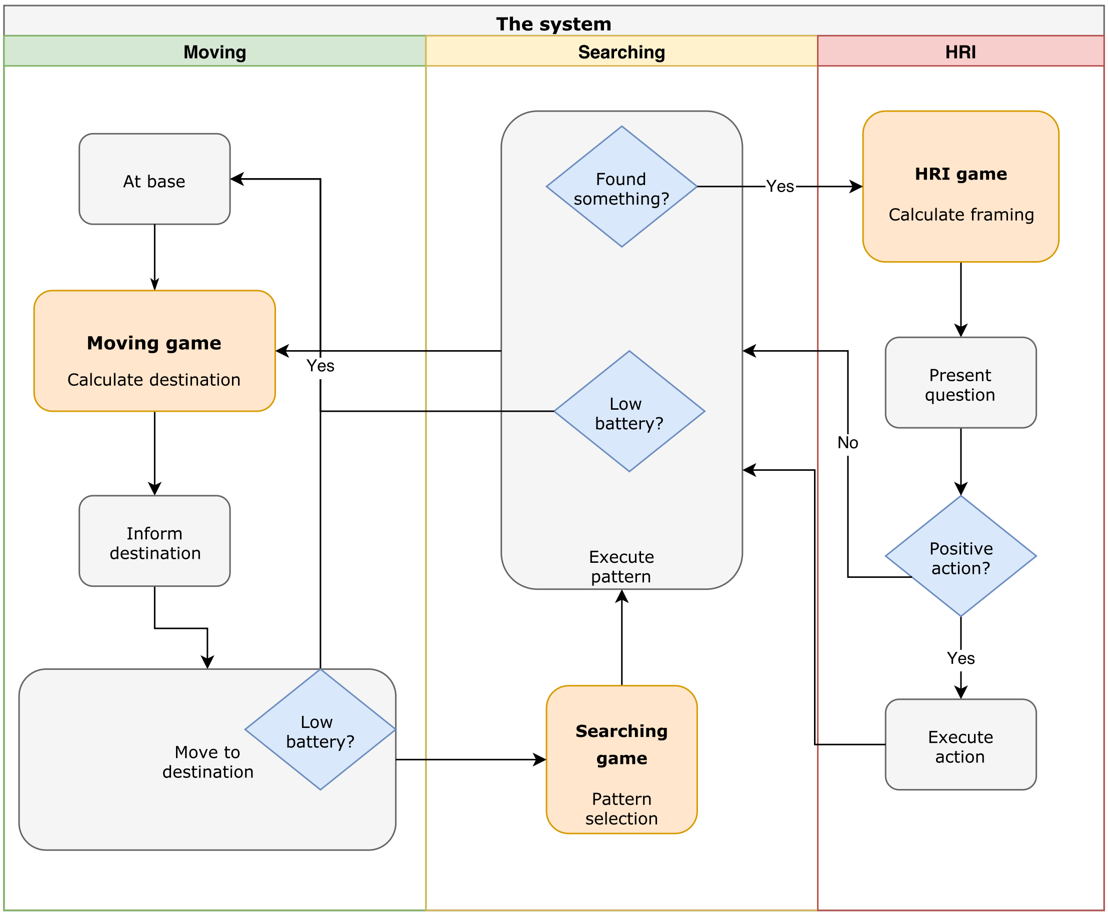


Figure 8.1: Flowchart of a typical mission.

$$\mu_i^t = \sigma_i^t(\cdot) + \tau_i^t(\cdot) + \phi_i^t(\cdot) \tag{8.2}$$

Where:

- t is the timestep.
- $\sigma_i^t(\cdot)$ is the reward function for moving to a given sector or point of interest (POI).
- $\tau_i^t(\cdot)$ is the payoff function for the search pattern.
- $\phi_i^t(\cdot)$ is the utility function for interaction with HO.

Each parcel of $\mu_i^t(\cdot)$ represents a different "game", i.e., $\sigma_i^t(\cdot)$ is a *anti-coordination game ACG* (see Section 4.2.1.2) among the robots, $\tau_i^t(\cdot)$ is a *Game against nature GAN* (Sec. 4.7) and

$\phi_i^t(\cdot)$ is a sequential *High-low game HLG* or a *team game* (Sec. 4.2.1.1) where one of the players (HO) is not "totally rational".

Remark
The three games are orthogonal to each other, thus, the result of a particular game have no influence in the other games.

The form of each function will be presented in the next sections. But before, we would like to explain how the guideline for a given mission is defined in terms of a weighting function.

8.4 Guideline

The guidelines of a given mission would suggest the tradeoff criteria for deciding during the execution time. In this study, we will focus on what is more important in a specific mission: speed or accuracy. For instance, in a SAR mission, the authorities could prefer to push the Human-robots team to be fast, in a case where the sunset is coming and no much more time rests to find possible victims. Or to be accurate in a case where not-helped victims can freeze to death.

We define two constants g and $G > 1$ and a function $\gamma(\cdot)$ which depends on these constants. g that can take two different values:

$$g = \begin{cases} 0 & fast \\ 1 & accurate \end{cases} \tag{8.3}$$

so, we can define $\gamma(\cdot)$ as:

$$\gamma(g, G) = G \cdot (1 - g) + g/G \tag{8.4}$$

Following, $\gamma(\cdot)$ will be used to adjust each utility (cf. eq. (8.2)) accordingly with the given guideline.

8.4.1 Moving game in a search mission

In a multi-robot SAR or sample-return mission, it is important to spread the drones out along the search area, taking into account the likelihood of the existence of a target in the destination POI. So, based on previous utility function, presented in Chap. 5, we propose the best strategy for $Drone_i$ ($\sigma_i^{t*}(\cdot)$) as

$$\sigma_i^{t*}(a_i, \bar{s}^t) = \max_{a_i \in \mathbb{A}} \left([-(\gamma \cdot \delta_i^t(a_i, s_i^t) + \theta_i^t(a_i, s_{-i}^{-t}))] \cdot \rho^t \right) \tag{8.5}$$

where,

- cost to move: $\delta_i^t(\cdot)$ is the distance for $Drone_i$ to move from its current position s_i^t to all its possible future locations $a_i^k \in A_i$, with $k \in \{1, \cdots, q\}$. Therefore, considering that $f^*(s_i^t, a_i^k)$ is the optimal distance cost that refers to the optimal (or sub-optimal, when the optimal cannot be calculated) path from node s_i^t to a_i^k, one gets:

$$\delta_i(a_i^k, s_i^t) = f^*(s_i^t, a_i^k) \tag{8.6}$$

  Here, $\gamma(\cdot)$ adjusts the value of $\delta(\cdot)$ in function of the selected guideline. When it is adjusted to "be fast" $\gamma(\cdot)$ increases the cost of moving, which ensures that the drones will not wander around the search zone. On the other hand, when the guideline says "be accurate", $\gamma(\cdot)$ reduces the cost of moving, making distant places more attractive.

  cost for not moving: infinity. The idea is to force $Drone_i$ to move to another place, then

$$\delta_i^t(s_i^t, s_i^t) = \infty$$

  .

- $\theta_i^t(\cdot)$ is the cost relative to the proximity of the other drones:

$$\theta_i^t(a_i, s_{-i}^{-t})) = \frac{\sum_j^{n-1}(\max(\delta_j^t) + \min(\delta_j^t) - \delta_j^t)}{n-1}, i \neq j \tag{8.7}$$

  $\theta_i^t(\cdot)$ is the weighted sum of all other drones "inverted distance", where *inverted distance* is defined as a value that is equal to the maximum distance for the nearest point and decreases with the distance. The idea here is to make the sectors more distant from the other drones more attractive for $Drone_i$.

- finally, different from Chap. 5, $\rho(\cdot)$ is a "common belief" that make use of Bayesian probabilities to infer about the "reward" to be collected when a sector is visited.

  In the case of a SAR mission, $\rho(\cdot)$ infers the existence of a victim in each sector before and after this sector has been visited. It works like an *attractor* to destinations not visited yet:

$$\rho^t = 1 - \begin{cases} \rho_{vis}^t = P(v|\neg a) & when\ visited \\ \rho_{\neg vis}^t = \frac{(1-\sum_{i=1}^k \rho_{vis}^{t,i})}{|\mathbb{S}|-k} & when\ not\ visited \end{cases} \tag{8.8}$$

in which

$$P(v|\neg a) = \frac{P(\neg a|v) \cdot P(v)}{P(\neg a)} \quad (8.9)$$

is the probability of existing a victim v, given that an action a (e.g. releasing a kit) was not taken; the cardinality $|\mathbb{S}|$ is the total number of POIs to be visited and k is the number of visited points; and $P(v)$ is the probability of existing a victim v (note that $P(v)$ is not updated after a kit be released, because it is not possible to the drones know if a victim was really helped).

In this way, the previous actions and observations of all drones produce the "common belief", which is part of the instantaneous payoffs of each *stage game* (the underlying "state" of this *repeated game* – see section 4.4).

Observe that, during the selection of the POI (at instant t), γ and ρ^t are constants for any drone, thus, the drones have an *additive utility* (see section 3.2.1), which, in this case, is the same as a *wonderful life utility – WLU* (where each action of each player contributes to the global objective – section 4.3.1), which in turn leads to a *potential game* (section 4.3); given that, for $\sigma_i(\cdot)$ the action choice for $Drone_i$ is independent of the action choices of the others drones and its payoff is aligned with the global utility function.

8.5 Search game

In our framework, the drones decide by themselves where to go using the *moving game* presented above. In a search mission, when one of them arrives at the destination POI, it starts searching for the target, using for that a *search pattern*.

In a real-life search and rescue mission (SAR) the selection of a search pattern depends on several factors (for instance: the search area size, terrain roughness, number of agents, available search time, position of the sun, cloud coverage, number and size of the targets), where some may be more important than others [NAT95].

In this work, three search patterns were defined, inspired on NATO search patterns [NAT95]:

- *Square* (SPQ) - Based on the "NATO Parallel Search", it is fast and produce a uniform coverage, very useful when the area is flat and/or the search targets are totally visible.

  It is important to note that we suppose an onboard camera field-of-view corresponding to a 3×3 grid.

- *Star* (SPT) - The "NATO sector search" is good to view the search area from many different angles, minimizing terrain and lighting issues. It is useful when a victim can be seen

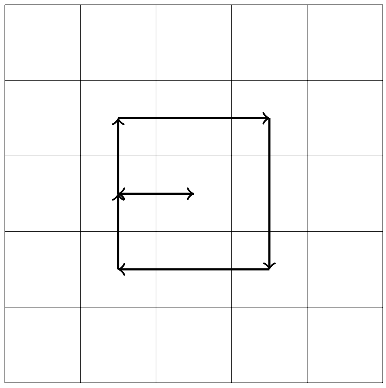


Figure 8.2: Square (SPQ) search pattern

only in some direction.

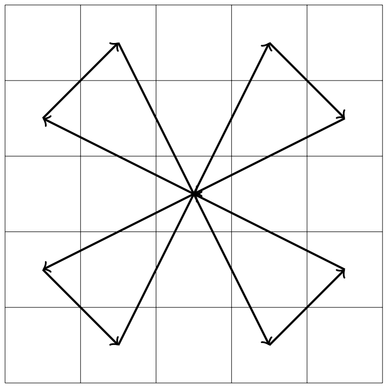


Figure 8.3: Star (SPT) search pattern

- *Snail* (SPN) - Very accurate and slow search pattern, based on the "NATO Expanding square". Useful when a victim is partially covered and can be identified only by a meticulous search.

In this way, each pattern has a tradeoff between velocity (vel) and accuracy (acc), which can be represented by

$$vel = \frac{b}{acc}, vel, acc, b \in \mathbb{R}^{+} \tag{8.10}$$

where b is a constant factor.

Based on this, we can derivate the second parcel (cf. eq. (8.2)) of our utility function (τ_i), using

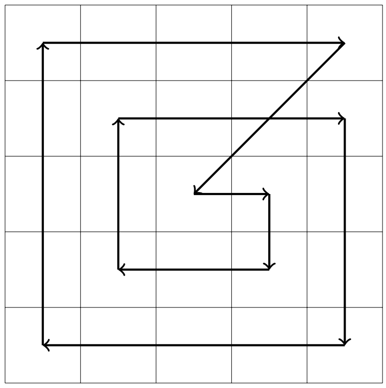


Figure 8.4: Snail (SPN) search pattern

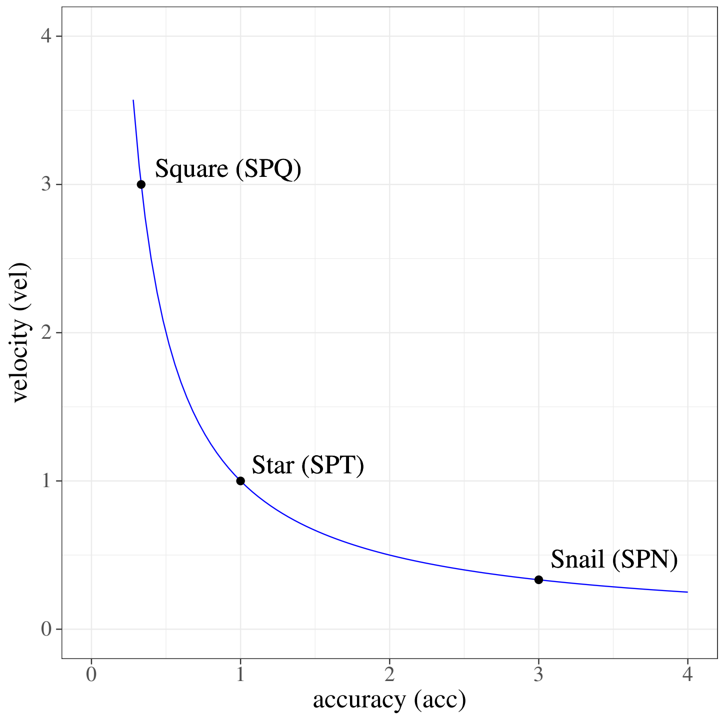


Figure 8.5: Indifference curve among the Search patterns with $b = 1$

$$\tau_i = ln(b) = ln(vel) + ln(acc) \tag{8.11}$$

Equation (8.11) generates the *indifference curve* plot in Fig. 8.5, which means that they have the same utility value and there is no preference among them.

As presented in Section 4.7, the decision-making process under uncertainty, where the problem is to make a choice between different alternatives, can be seen as a "lottery" or a "game against nature". In this case, certain events happen independently of the DM's decisions, i.e., it is a "one-player game", in which a single rational self-interested player must choose a strategy, and the outcome depends on both her chosen strategy and the "choice" made by a totally disinterested nature.

It is intuitive that if some information is known *a priori* like the terrain roughness and if the victims are totally visible or partially buried, it is easy to define the best pattern to use. However, in general, in cases of natural disasters, the "Murphy's Law" (the pessimistic philosophy that predicts that the worst will always occur) determines the behavior of nature [Bec08]. In other words, no matter which pattern you select, it will be the worst choice! Let's assume that the payoff matrix, shown in Table 8.1, represents this GAN[1]:

Table 8.1: Search pattern vs Nature

		Nature		
		VCV†	VVS‡	VVT§
Search pattern	SPQ	5	3	1
	SPT	2	5	2
	SPN	1	3	5

† Victim completely visible
‡ Victim visible only by one side
§ Victim visible only from the top

In this case, there is only one number in each cell because there is only one player, and nature is indifferent among outcomes and has no payoffs. Moreover, it is easy to observe that there is no pure strategy equilibrium. The reason is simply that if DM (a drone) knows what nature is doing, then it can win for sure, selecting the appropriate pattern.

Which is the best decision for a drone, given that it is engaged in a GAN? The solution is to randomize. And, based on the *principle of insufficient reason*, that states that if there are n possibilities with unknown probabilities, then each possibility should be assigned a probability equal to $1/n$, we assume that nature strategy is a triplet: (VCV, VVS, VVT).

Where,

$VCV \geq 0$, $VVS \geq 0$, $VVT \geq 0$ and $VCV + VVS + VVT = 1$

So, the mixed strategy for nature (the worst case scenario) could be:

$$(VCV^{*}, VVS^{*}, VVT^{*}) = (\frac{1}{3}, \frac{1}{3}, \frac{1}{3})$$

[1]Game against Nature

In this case, the expected payoff for DM from choosing SPQ is then:

$$\frac{1}{3}\cdot 5+\frac{1}{3}\cdot 3+\frac{1}{3}\cdot 1=3$$

If DM plays SPT we observe that the expected payoff is:

$$\frac{1}{3}\cdot 2+\frac{1}{3}\cdot 5+\frac{1}{3}\cdot 2=3$$

and if DM select SPN her payoff is:

$$\frac{1}{3}\cdot 1+\frac{1}{3}\cdot 3+\frac{1}{3}\cdot 5=3$$

We conclude that DM is indifferent to all available pure strategies. Hence, it is optimal to her pick *any probability distribution* over her pure strategies. In particular,

$$(SPQ^{*},SPT^{*},SPN^{*})=(\frac{1}{3},\frac{1}{3},\frac{1}{3})$$

becomes the best response for DM. Indeed, this is the only Nash equilibrium in the game.

8.5.1 Guideline adjustment

In order to make decisions aligned with the guideline (fast or accurate in a SAR mission, for instance), it is necessary to adjust the utility functions. And, as shown before, DM (a drone in this case) is indifferent to all available pure strategies, so it can pick any probability distribution over its pure strategies. Therefore, the payoff values could be biased by the guideline.

Then, the pattern utility adjusted by the guideline becomes:

$$\tau_i^{\gamma}=\begin{cases} ln(b)+\frac{g-\gamma}{\gamma} & for\ square\ (SPQ)\\ ln(b) & for\ star\ (SPT)\\ ln(b)-\frac{g-\gamma}{\gamma} & for\ snail\ (SPN)\end{cases} \tag{8.12}$$

Consequently, the payoff matrix, for a guideline where the time is important (*be fast* – $g=0,\gamma(\cdot)=2$, cf. Eq. (8.3) and (8.4)), becomes Table 8.2.

Now, *Square* (SPQ), the fastest pattern, becomes the favorite choice and the best response for DM is

$$(SPQ^{*},SPT^{*},SPN^{*})=(\frac{4}{9},\frac{3}{9},\frac{2}{9})$$

For the opposite guideline (*be accurate* – $g=1,\gamma(\cdot)=0.5$), consider Table 8.3.

Table 8.2: Search pattern vs Nature (Fast)

		Nature		
		VCV	VVS	VVT
Search pattern	SPQ	6	4	2
	SPT	2	5	2
	SPN	0	2	4

Table 8.3: Search pattern vs Nature (Accurate)

		Nature		
		VCV	VVS	VVT
Search pattern	SPQ	4	2	0
	SPT	2	5	2
	SPN	2	4	6

Then *Snail* (SPN) becomes more attractive than the others:

$$(SPQ^*, SPT^*, SPN^*) = (\frac{2}{9}, \frac{3}{9}, \frac{4}{9})$$

Following we present the last parcel of our overall utility.

8.6 HRI game

Now, the drones have to play against another mysterious (and not always rational) player: the human operator.

In this framework, HO has a very difficult task: to decide when to consume a valuable asset. For example, in a SAR mission, similar to the missions described in our previous experiments (see sections 6.3 and 6.4), the drone team has a limited quantity of first-aid kits. Then, it is imperative to maximize the usefulness of a kit. On the other hand, in our view, a human being should be the responsible agent (if she is available) to decide, when human lives are involved. Therefore, the drones have to ask HO if they can or cannot release a kit. To this end, they have to make a preliminary analysis with their onboard sensors in order to present an estimation to HO.

However, HO has a bounded rationality, i.e., her rationality is limited by the tractability of the problem, her cognitive limitations and the time available to make the decision (see Chapter 2). In this sense, HO cannot be modeled as a rational player (like a drone) neither as a non-deterministic one (as nature - which they have no idea what it will do), but as a probabilistic player, which, after some observations, some statistics could be gathered and her (presumed stationary) strategy could be derived. Thus, at each round, they can simulate the game ("fictitious play") and then best respond to the empirical frequency of play of their opponent.

In our game, a drone has to frame the information to share with HO in a way that maximizes the probability of HO to take a decision that optimizes its payoff.

Definition 8.1
Human interaction game

- *Framing options* $\phi \in \Phi$.
- *Estimated HO choice* $\psi \in \Psi$.
- *Payoff function* $L : \Phi \times \Psi \to \mathbb{R}^2$

Then, the payoff matrix is $|\Phi| \times |\Psi|$.

Assuming that $Drone_i$ have collected enough data in previous interactions to estimate $P(\psi)$, it may assume that HO will continue to choose in the same way as predicted by $P(\psi)$. In this case, an expected case analysis is used instead of a worst case analysis (as in a game against nature). This optimizes the average payoff to be gained over several trials [Ros16]. So, its best action is:

$$\phi_i^* = \underset{\phi \in \Phi}{\operatorname{argmax}} \{EU_\psi[L(\phi, \psi)]\}$$

Where, EU_ψ indicates that the expectations was taken according to $P(\psi)$. Then

$$EU_\psi[L(\phi, \psi)] = \sum_{\psi \in \Psi} L(\phi, \psi) \cdot P(\psi)$$

Note that, supposing that both players are rational, this is a *Coordination game* (COG), a class of games with multiple pure strategy Nash equilibria (from where players choose the corresponding strategies - see Section 4.2.1). Moreover, it is a *High-low game* (HLG), where rational players have the same interest and both prefer the same NE outcome that dominates the others. Observe the payoff matrix in Table 8.4.

Table 8.4: Drone vs Human - a team game

		HO	
		Yes (ψ^+)	No (ψ^-)
Drone framing	Positive (ϕ^+)	A	B
	Negative (ϕ^-)	C	D

where $A > C$ and $D > B$.

In this game, the strategy profiles (ϕ^+, ψ^+) and (ϕ^-, ψ^-) are pure Nash equilibria. And, for instance, if $A > D$, (ϕ^+, ψ^+) becomes the dominant profile. However, this formulation does not allow the drones to make use of any previous information before making a decision. They have to know which is the greatest A or D. But they have an onboard camera that can estimate how likely it is that a victim can be located below them. And only interact with the operator after something relevant is found. Hence, based on these data they can better predict the HO's decision.

So, let Ω be the set of all possible observations collected by the onboard camera (for simplicity suppose that Ω is discrete). Assuming that some constraints on ψ are known once $\omega \in \Omega$ is given and a conditional probability distribution $P(\psi|\omega)$ is specified. For instance, if $\omega = 0.99$ there is a very high probability that HO will choose ψ^+ (say "YES"). Thus, the best action becomes:

$$\phi^*(\omega) = \underset{\phi \in \Phi}{\operatorname{argmax}} \left(\sum_{\psi \in \Psi} L(\phi, \psi) \cdot P(\psi|\omega) \right) \tag{8.13}$$

Note that this game (Table 8.4) can be redesigned as a EFG[2], since $Drone_i$ presents its choice to HO before HO decides (Fig. 8.6).

Note that the strategy profiles (ϕ^+, ψ^+) and (ϕ^-, ψ^-) are still pure Nash equilibria. A rational opponent, after observes the choice of the drone, would choose in order to maximize her utility. However, HO is not a "rational" player, but someone that statistically has some preferences.

Remark
With this game, the idea is to approximate the HO's personal utility, leading her to act more "rationally". But, it is important to point out that, first, a "personal" utility is not always aligned to a "common" utility (used by the drones to infer her decision). And second, the drone can choose "wrong" too, if not, HO should be dismissed.

8.6.1 Guidelines alignment

In order to induce an HO's decision aligned to the operational guidelines, the drones have to skew their utility function $\phi(\cdot)$ by $\gamma(\cdot)$, according to:

$$\phi(h, p) = \arg \max_{neg,pos} \Big(\psi^-(h^-, pov, p)/\gamma, \psi^+(h^+, pov, p) \cdot \gamma \Big) \tag{8.14}$$

[2]Extensive-form game

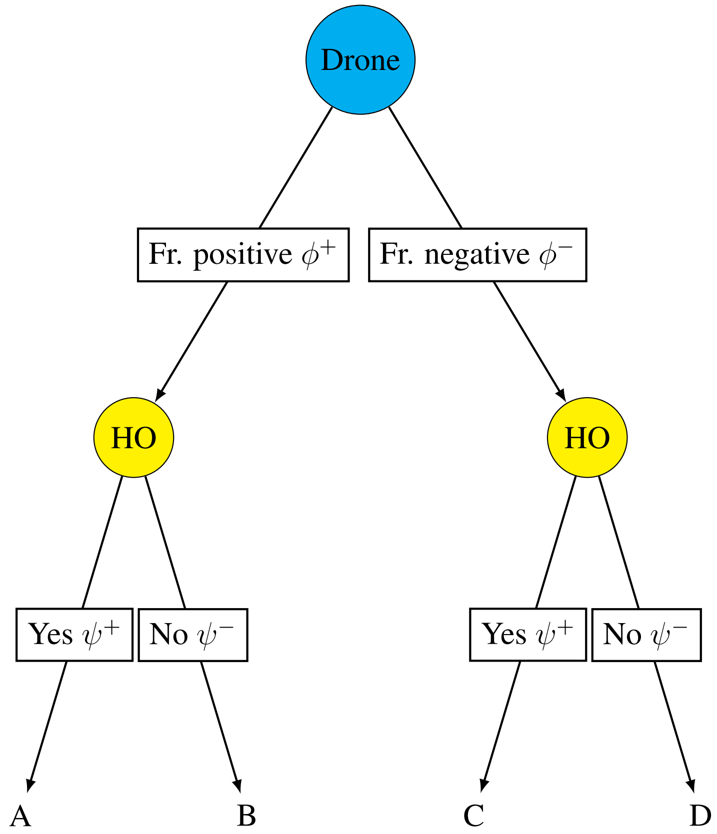


Figure 8.6: Sequential form for the *Drone vs HO game*, in which $A > C$ and $D > B$.

8.7 Evaluation

In order to evaluate our framework, we developed a computer simulation using Python 3.5 and MORSE[3] (Fig. 8.7), based on the *earthquake scenario* designed for the previous experiments. MORSE is an open-source 3D robot simulator designed to handle the simulation of several robots simultaneously. It can be used in several contexts for testing and verification of robotics systems as a whole, from a medium to a high level of abstraction [Ech+11].

MORSE is a known robotic simulator. The drawback is that it is a single-user application in the sense that it is not possible to run several simulations at the same time. Thus, it is good for collecting realistic data from the robots, but too costly for gathering information from the HOs.

Therefore, in order to optimize the drones' behavior, we collected all simulation data, without the interaction with the HO, from MORSE, and developed an *HTML5 Canvas* web-based experiment with a view to increasing the number of participants and, with that, boost the amount

[3]Modular open robots simulation engine

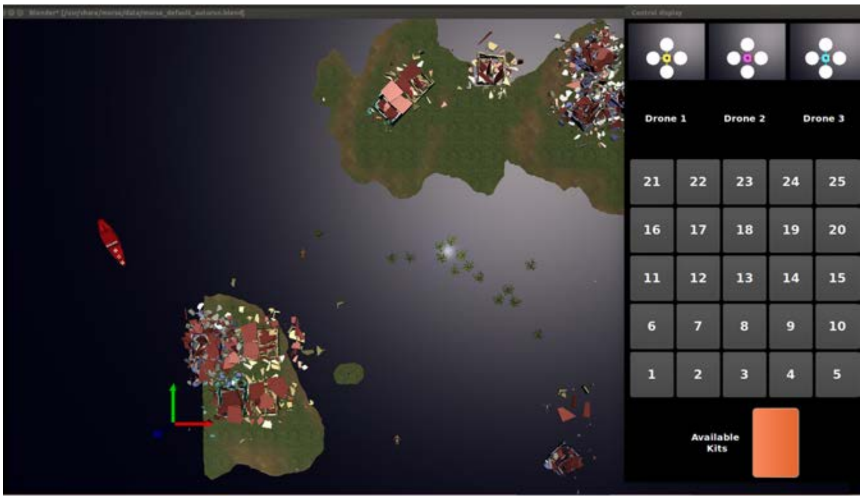


Figure 8.7: System developed in MORSE

of statistical data from the human resources.

8.8 Drone simulation

For the *moving game*, the topological model of the search area, homogeneously subdivided into 25 sectors (a 5×5 grid), was defined as a fully connected graph. Since the drones could fly from one sector to any other as the crow flies (i.e. in straight line). This graph had a special zeroth sector called “base” (the red boat in Fig. 8.7) used by the drones as the point of depart and reloading point.

For the *search game*, each sector was subdivided into another 5×5 grid and the onboard camera field-of-view was considered to be a 3×3 grid.

Each time a drone found something during the search, it had to stop, calculate the probability of a first-aid kit be useful, and request a decision to HO. With a “YES” answer, it should release the kit, return to base to get a new one and go back to the point where it stopped to resume the search. Otherwise (with a “No”), it should just continue the search.

When the battery level reached a critical level, they should return definitively to the base.

8.9 Experiment III

We created a website (available at http://phd.peus.pro.br) to host the experiment, collect anonymous general data from the participants and provide them with essential information about the experiment (Fig. 8.8).

Figure 8.8: Site developed for the experiment

In this experiment, we were interested in observing the HOs' behaviors in two different contexts, each with an operational guideline: "be fast" (BFG) or "be accurate" (BAG). During the experiment, they faced two different conditions in which the HRI was framed: "neutral" (NTC) and "in accordance" (IAC). Both initially framed accordingly with our *proposed personal utility (Ψ)* (see Section 7.2.3).

Here, as said before, we considered that the results of the study presented in Chapter 7 provided us with an image of the end-state for training. Then, we assumed those results as a training data gathered from "experts".

Thereby, we could attempt to lead the novice HOs (the participants of this study) to act as experts (with the NTC condition) and, moreover, adjusting the framing "in accordance" (IAC) with the selected operational guideline (Eq. (8.14)), we could try to persuade novices (and experts) to follow that guideline.

8.9.1 Objectives

With this experimental design, we expected that, firstly, the participants acted in accordance with the framing presented, making them mimic the participants from the previous experiments ("experts") behavior (NTC). Secondly, the operational guideline would modify this behavior (IAC).

In this way, the prime objectives of this experiment were: (1) to verify if the HRI, framed accordingly with the operational guidelines, could optimize the HOs' behaviors (*"in accordance" condition (IAC)*); and (2) to verify if just presenting the guideline, without adjusting the framing of the interaction might change their behaviors (*"neutral" condition (NTC)*).

8.9.2 Hypotheses

Our hypotheses were: for the first objective, ($H1$) the BFG guideline would produce a preference of saying "YES" greater than BAG, i.e., participants with the BFG guideline should accept to release a kit with lower probability levels, attempting to be faster; and for the second, ($H2$) NTC would have a smaller effect (but still significant) when compared with IAC. In other words, although NTC condition did not adjust the HRI in function of the guideline (but just presented this guideline to the HO), it was expected that the participants biased themselves to fit the guideline. However, with less efficiency than with IAC.

8.9.3 Participants

Participants were recruited by mailing lists in universities of France, Brazil, and Canada, and they were encouraged to invite their friends. One hundred and one anonymous volunteers (22.69% female, mean age: 28.9, sd: 8.78) from 13 different nationalities, participated in the experiment.

8.9.4 Design

The experiment followed a 2×2 mixed design, which manipulated the operational *Guideline* (a two-level between-subject factor: BFG and BAG), and the *Condition* used to present the text message to the HO (constructed with a two-level within-subject factor: NTC and IAC).

In this way, participants were, unknown to them, randomly sorted into one of two contexts with different operational guidelines (BFG or BAG), and within that context, they had to execute one training mission and four randomly presented valid missions (two repetitions of each condition – NTC and IAC). They were not rewarded for the participation.

8.9.5 Procedure

After necessarily pass through the tutorial page, participants could open the game link, where they were redirected to an informed consent page. In this page, they had to accept the terms of the study and declare that had been informed about the following conditions: (1) Participation was voluntary and they could freely abandon the study at any time, without being required to justify their decision; (2) The information collected was strictly for research purposes, and would be used anonymously. After the acceptance, a registration form appeared, in which a randomly generated "codename" was assigned to them, and their ages (obligatorily over 18 years old), sexes and nationality were collected.

The plot was about an earthquake and a flood that occurred in a residential area where there were 8 people. Figure 8.9 shows the "game" interface.

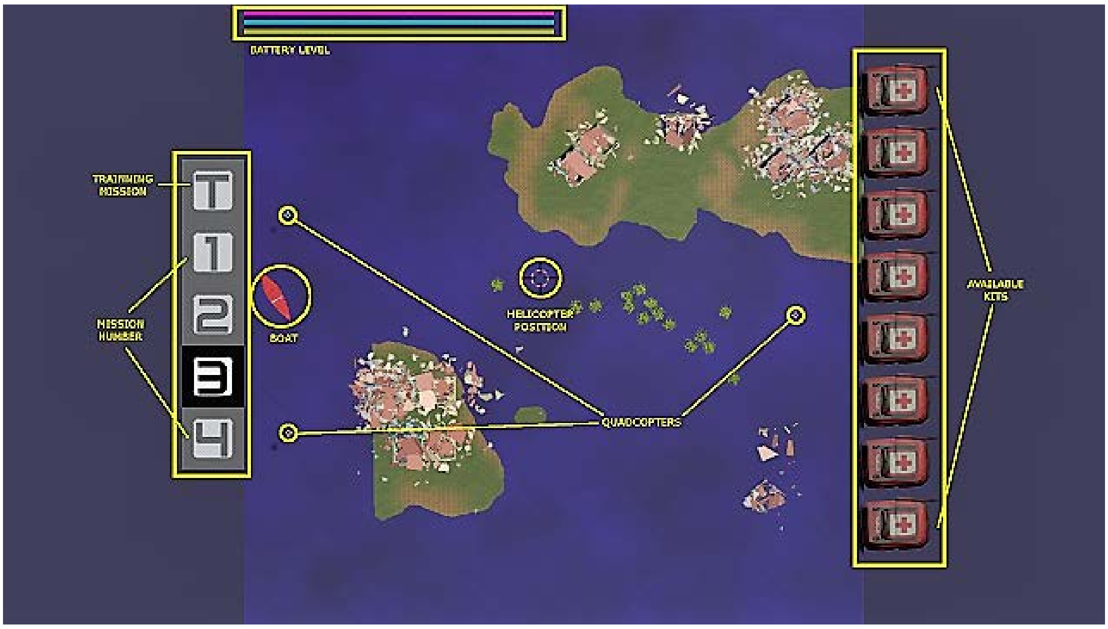


Figure 8.9: Experiment graphical interface

At the beginning of the "game", a briefing was presented to increase the understanding about their role in it (Fig. 8.10).

Then, at the beginning of each mission, the operational guideline was informed, as showed in Fig. 8.11a. At this moment, the system randomly generated the position of 8 "real" victims and 8 "fake" victims (for false positive purposes) and their respective probability values. Due to the (considered) good reliability of the system, the "real" victims had a range of probability

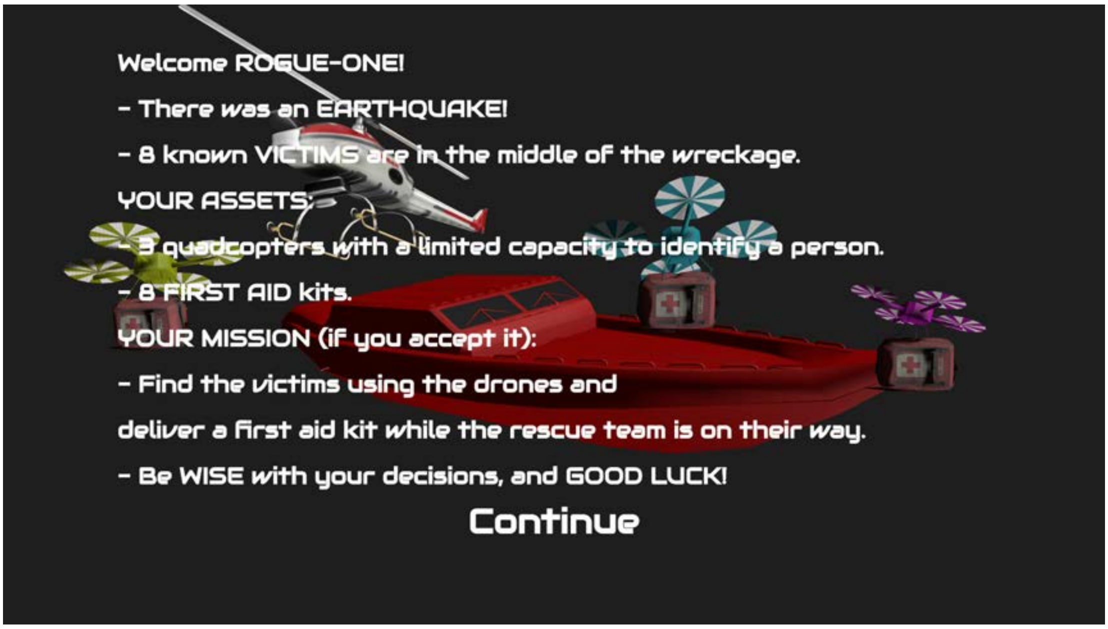


Figure 8.10: Briefing for the "game"

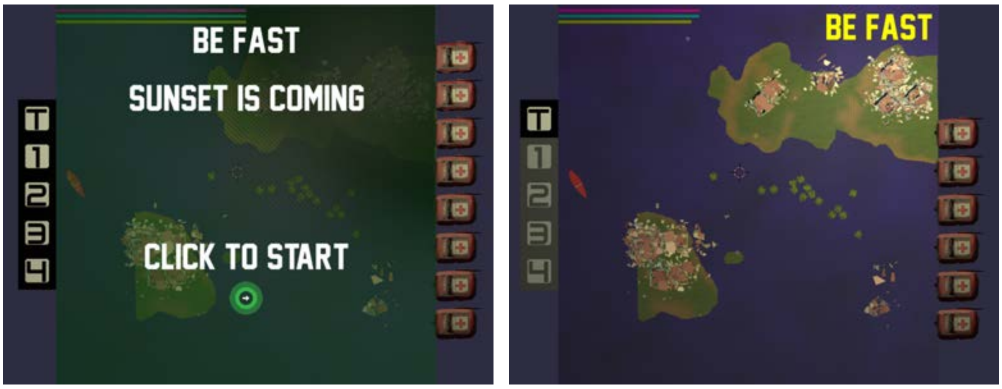
values between 40% and 80%, and the "fake" ones, from 15% to 55%. Here, we avoided the extreme probability values (respectively, greater than 80% and smaller than 15%), in which the *Attribute framing effect* (AFE) is less efficient and overlapped the values in the middle (40% to 55%), where the AFE is more effective [LSG98].

These ranges were selected based on the results of the calculation of the *probability weighting function ($w(\cdot)$)* presented in Section 7.4.1.1.

During a mission, a message with the respective guideline blinked in the top-right corner (Fig. 8.11b) every 30 seconds, reminding the HO of the guideline to follow.

Each mission had a duration of around three minutes. During the evolution of a given mission, when a drone found something, a sentence was presented in a pop-up window and the HO was requested to decide. This sentence was framed according to the guideline (BFG or BAG) and the current condition (NTC or IAC). Unknown to the participants, the border of the pop-up window was colored green or red accordingly to the framing presented, positive or negative, respectively (Fig. 8.12). This visual framing procedure aimed to increase the FE influence, as described and confirmed in Experiment II (see Sec. 6.4).

The participants had, then, 10 seconds to decide between say "YES", i.e, take a *positive action* and release a kid, or "NO". After this time period, without an answer, the drone who asked considered the HO's decision as a "NO". Thus, the HO unique task was to answer the questions made by the drones by clicking in YES or NO on the pop-up window.



(a) Guideline presented at the mission start (b) Guideline in the middle of a mission

Figure 8.11: Operational guideline example: *be fast!* (BFG).

The participants were informed about their performance at the end of each session (see Fig. 8.13). We decided to present those results just for an entertaining purpose, after the feedback of a group of beta-testers, in order to make the experiment more attractive to the participants.

Figure 8.12: Framed question.

In addition, we defined $G = 2$ in Eq. (8.4) in order to adjust the utilities accordingly with the guidelines. We also defined the $P(\neg a|v) = 0.15$ in Eq. (8.9), because some researches suggest

Figure 8.13: Total helped people at the end of a mission.

that the average people detection accuracy is around 0.85 [AS14]; [DT05]; [LWN08].

8.9.6 Results

We collected 5026 observations of 101 participants, from which 89% with completed data (3705 observations), so, 11.88% of the data were dropped.

Due to this incomplete data and the randomization procedure the experiment ended with an unbalanced sample as shown in Table 8.5.

Table 8.5: Sample distribution

	In_accordance (IAC)	Neutral (NTC)	Total
Accurate (BAG)	866	810	1676
Fast (BFG)	1022	1007	2029
Total	1888	1817	3705

One alternative might be to balance the data by under-sampling the dataset, randomly throwing away some from the larger classes. This could enhance the discriminatory power of the model, however, with the shortcoming that potentially important cases from the majority class of the sample could be discarded in the process. Moreover, [CF12] argues, in their empirical study of sample size and balancing, that for some methods of model construction, sample imbalance was not an issue at all. For logistic regression in particular (our case), there was absolutely no benefit in creating a balanced sample. What was far more important was use all the available data. Hence, we decided to maintain all the collected data.

Following, Fig. 8.14 shows the distribution of the probability values (randomly generated for the first-aid kits usefulness) by the type of victims (“real” or “fake”). As expected, the randomization generated an almost uniform distribution for each type of victims, then the values in the intersection (from 40% to 55%), where we had more interest (where the Attribute framing effect is more effective), had approximately the double of occurrences.

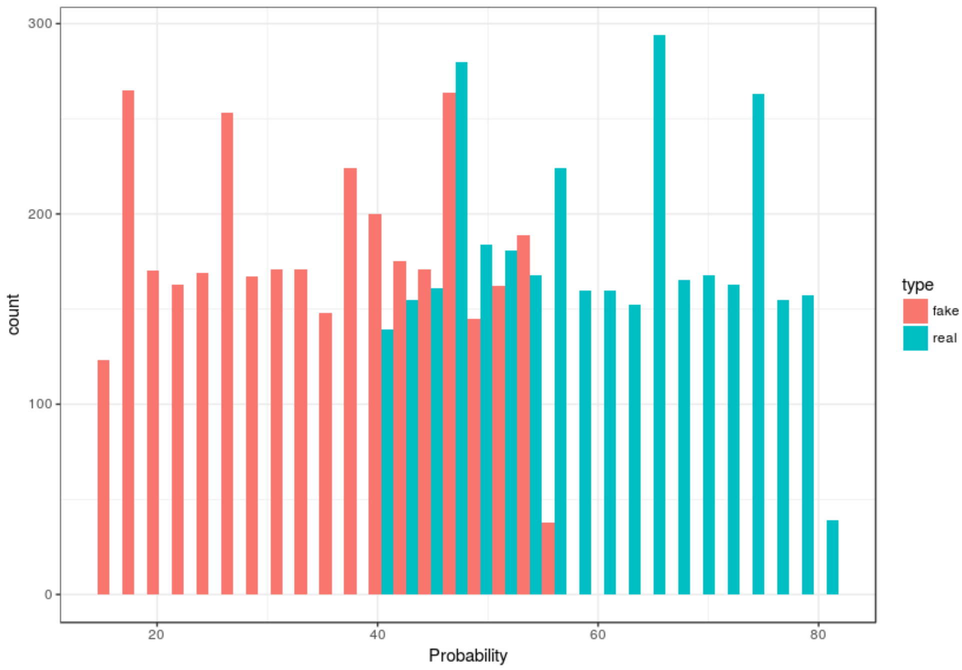


Figure 8.14: Distribution of first-aid kit usefulness probability values.

8.9.6.1 HO decisions analysis

Figure 8.15 shows the proportion of participants’ decisions as a function of the guidelines and the frame selection conditions. Boxes show the *standard error* with a confidence interval of 95% for the mean.

Once the interactions had probabilities uniformly distributed (Fig. 8.14) from 15% to 80%, a rational player should not perceive any difference among the sentences presented with different guidelines and conditions, thus, all their means should be around 47.5%. However, observing Fig. 8.15, it is easy to observe the “power” of the operational guidelines and the framing selection

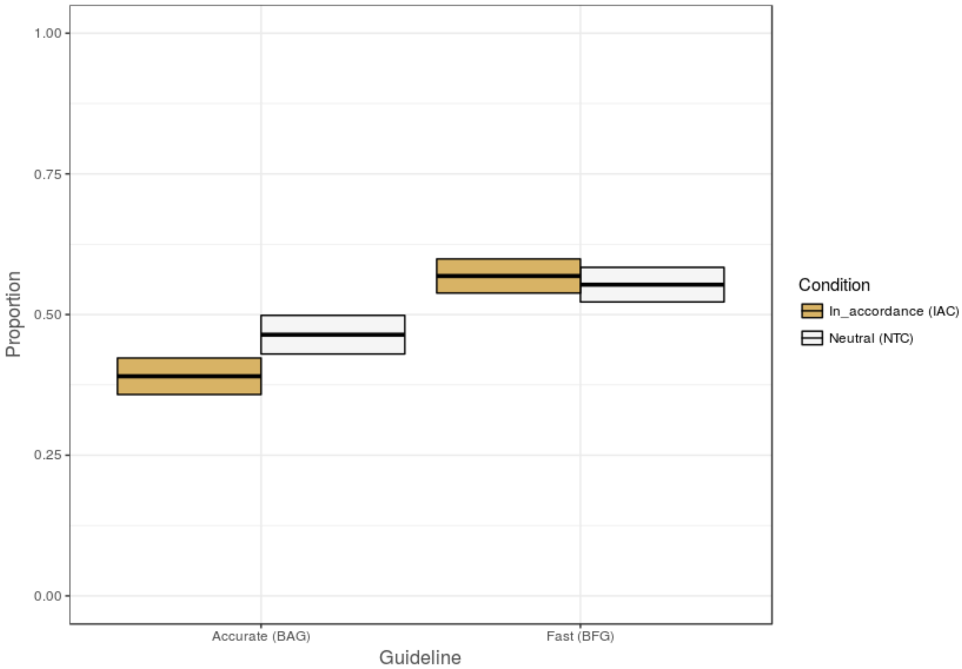


Figure 8.15: Proportion of kits released in function of the guidelines and frame selection conditions.

conditions.

We also can note that both hypotheses ($H1$ and $H2$) were confirmed. $H1$ stated that in the IAC condition, BFG would have more kits released (more "YES" answers) than BAG, and $H2$ affirmed that NTC would have a similar effect to IAC, but smaller. In fact, NTC presented means closer to the expected rational mean 47.5% than IAC.

In our statistical analysis of this study, we were interested in the relationship between HO's decision ($\boldsymbol{OD}$) and the main explanatory variables: Guideline ($\boldsymbol{G}$), Condition ($\boldsymbol{C}$), Framing ($\boldsymbol{F}$), Probability ($\boldsymbol{P}$) and number of available Kits ($\boldsymbol{K}$). As in the previous experiments, because we took several measures per participant, we used a Generalized Linear Mixed Model (GLMM) to analyze these data (Eq. (8.15)).

$$\boldsymbol{OD} \sim \boldsymbol{G} * \boldsymbol{C} + \boldsymbol{F} + \boldsymbol{P} + \boldsymbol{K} + (1|\boldsymbol{ID}) + \epsilon \tag{8.15}$$

Table 8.6 shows the estimated coefficients and errors of the GLMM. The value of an estimated coefficient denotes how the condition influences the HO preference in saying "YES".

Table 8.6: Experiment III - GLMM summary

	Dependent variable:
	answer
Guideline-Fast (BFG)	1.736^{***}
	(0.220)
Condition-Neutral (NTC)	0.912^{***}
	(0.150)
Framing	-0.817^{***}
	(0.140)
Probability	9.045^{***}
	(0.404)
Available Kits	-0.459^{***}
	(0.023)
Guideline-Fast (BFG):Condition-In accordance (IAC)	0.264^{*}
	(0.124)
Guideline-Accurate (BAG):Condition-Neutral (NTC)	-0.556^{**}
	(0.176)
Guideline-Accurate (BAG):Condition-In accordance (IAC)	-1.468^{***}
	(0.193)
Intercept	-2.570^{***}
	(0.200)
Note:	*p<0.05; **p<0.01; ***p<0.001

Hypothesis H1 Looking to the first line of Table 8.6 we can observe that, as expected, the participants tended to say more "Yes" with the guideline "be fast" (BFG) than with "be accurate" (BAG), confirming $H1$. The reason for that should be because, with the intention to be fast, they "sold" their kits cheap (with a low probability value), believing that they were still doing a good job with that decision.

Hypothesis H2 The second line shows that NTC condition (Estimate:0.912) is not as efficient as the IAC (Estimate:1.736) in influencing the HO's decisions, indicating that we should accept $H2$.

Another interesting (but also expected) result in this table is the negative value for the number of available kits, demonstrating that greater the number of kits, lower the willingness to giving up one of them (Endowment effect).

And finally, looking to the interaction between guidelines and conditions, after removing the random effects, we observe that they are different from each other, even with the guideline BFG there is a significant difference between the conditions (p-value = 0.049), confirming our findings of Fig. 8.15.

8.9.6.2 Mission time analysis

Figure 8.16 shows the effect of the guideline type (BFG vs BAG) and of the framing condition (IAC vs NTC) over the mission duration ($\boldsymbol{MT}$).

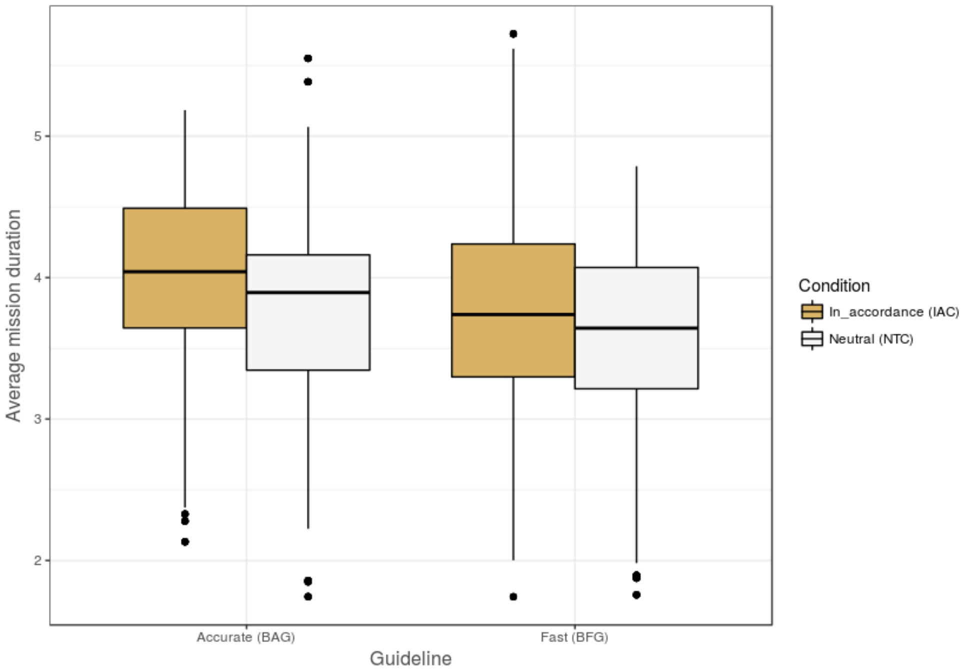


Figure 8.16: Average mission duration.

Looking to the results of a Linear mixed model (LMM)

$$MT \sim G * C + (1 \mid ID) + \epsilon$$

presented in Tab. 8.7, we can see how different the mission times are after removing random effects. The reference condition is the one not present in the table: *Guideline BFG:Condition NTC*.

Table 8.7: Experiment III - LMM summary of the interactions among guidelines and conditions and their effects in the mission duration

	Dependent variable:
	answer
Guideline-Fast (BFG):Condition-In accordance (IAC)	0.135^{***} (0.025)
Guideline-Accurate (BAG):Condition-Neutral (NTC)	0.186^{NS} (0.121)
Guideline-Accurate (BAG):Condition-In accordance (IAC)	0.405^{**} (0.121)
Intercept	3.552^{***} (0.077)
Note:	^{NS}p>0.1; **p<0.01; ***p<0.001

Looking at the second line of Tab. 8.7, we can see that there was no significant difference in the mission time between the two guidelines with the condition NTC, suggesting that participants from the two groups (BFG and BAG) had the same difficulty to decide in this condition. It is important to recall that in NTC the interactions were not framed in accordance with the guidelines, i.e., both groups faced the same situation.

On the other hand, once the framing selection condition (NTC and IAC) has no influence over the drones' velocity, apparently, people expended more time to decide in IAC, mainly in BAG.

8.9.7 Discussions

It is important to note that, in Experiment III, the number of saved victims was computed by an exogenous "god vision", and presented at the end of the experiment just for entertainment purposes. The drones could not know if a particular victim was real or not. Therefore, it was not possible for them to observe how many victims were helped and, hence, measure the effectiveness of the system.

Conversely, we can define a different measure of efficiency for our framework with the *overall utility* (Eq. (8.1)), the sum of all drones' utilities. Game-theoretical models, in which the players are self-centric (like ours), have a predictable degradation in their efficiency called *Price of anarchy (POA)* [KP09]. In a centralized system, a central authority tells each agent what to do in order to maximize the global utility. On the other hand, in a decentralized version, each agent chooses its own action, in accordance with some equilibrium with the opponents. In this sense, POA can be defined as the ratio between the optimal centralized solution and the "worst" equilibrium. Fortunately, in our framework the *moving game* is a *potential game* (see Sec. 4.3), in which the utilities of the players are aligned with the global utility, and the *search game* and *HRI game* involve respectively non-deterministic (nature) and stochastic (HO) opponents, thus, even a centralized system could not improve these utilities. Moreover, the utilities are orthogonal to each other (*additive utilities* – see Sec. 3.2.1). In other words, our system generates the same value for the global utility that a centralized system would produce ($POA = 1$).

Although we had not implemented a "control group", in order to define the "normal behavior" of the participants, our results suggest that they mimicked the participants from the previous experiments, since, they generally acted in accordance with the framing presented. Here, we may recall that the *neutral conditions (NTC)* of both groups (BFG and BAG) had the same coefficients to generate the framing, thus, without the guidelines influence they would be equal to each other and aligned to the behavior presented by the participants from the previous experiments (the "experts"). Our findings also suggest that the NTC should be enough to produce the expected average HO's conduct, although the *in accordance condition (IAC)* was more efficient and presented better results. However, as shown in Experiment I (Sec. 5.5), every person has some idiosyncratic factor that affects all decisions from the same subject, therefore, an average preference may not represent the preference of a particular HO.

We also believe that the blinking message at the top-right corner (Fig. 8.11b) enhanced the influence of the operational guidelines, reminding the participants how to proceed along the mission.

About the mission duration, the results showed that the participants expended more time to decide in IAC than in NTC. A possible explanation for this might be that the framing in accordance with the guidelines (IAC) was not always aligned with the personal preference of the participants. For instance, in a BFG situation, a positive frame could be presented with a so low probability value that was not easy to the participant to say "YES", making her or him expend more time to decide. This hypothesis can be supported by the non-significance between the results in NTC, in which the interactions were not framed in accordance with the operational guidelines.

To sum up, our findings suggest that it is possible to optimize the HO's decision-making process, framing the HRI in accordance with the operational guidelines and strategies collected from previous situations. In this sense, in a real-life context, it would be possible to lead novice operators to act as experts.

8.9.8 Limitations

While in a web-based experiment it is easier to recruit participants, in comparison to a laboratory-based experiment. They can participate at any time, from their homes or offices, or even on a bus, in any part of the world. It is hard to verify some experimental controls like for instance: comprehension of the experiment and the English language, attention and seriousness, network speed and reliability, browser type (the experiment was not designed for smartphones), and so on.

Due to the experimental manipulation it was necessary to reduce the number of variables, thus, this experiment was not a true MI-HRI, in the sense that only the drones had the initiative during the mission (adaptive autonomy). In a real scenario, the HO could also suggest a pattern or prioritize some sectors, according to her expertise and the drones could decide to release (or not) a kit if the HO was not available (or out of the communication range, for instance).

8.10 Considerations for a Real-World operation

Real-word operation of an air-robot requires several criteria that do not appear in abstract and theoretical situations (e.g., the operation of a Global Hawk high-altitude UAV or an armed Reaper medium-altitude UAV). In case of a team of them, the system must demonstrate inter-robot coordination, robustness to uncertainty and robustness to failures, computational feasibility and scalability [Dia+04]. This section discusses how the proposed framework could be able to meet these criteria.

8.10.1 Communication and coordination

In our model, the drones have a decentralized additive global utility and do not need a central coordination, neither have to select the best joint action for the team at each timestep, but rather play their lonely games and broadcast (in a limited range) their destination, and coordination rises.

Each can guest were the others are, based on the last information received. Moreover, they can not say if someone received their last report. In this sense, the range limitation make the drone team works like an ant colony, in which when they are close to each other, they "want to spread out" and explore the world, but if someone is too far, it "misses the others" and starts to include POIs in its path closer to them.

8.10.2 Robustness to uncertainty

Reasoning about uncertainty is intrinsic to GT. In our approach, the drones are able to select their action based on the available information at the moment. In this way, it is robust to incomplete information about teammates (HO included) and the environment.

Moreover, the framing effect approach can influence the novice operators and make them act as experts.

8.10.3 Robustness to failure

According to [Dia+04], there are three major types of failure in a robotic system: (1) communication failure, (2) a partial robot malfunction in which the robot is still operable but in a reduced capacity, and (3) complete robot failure in which the robot ceases to operate.

As shown in the Subsection 8.10.1, communication failure is not a big problem. If a drone loses its radio, it will work as if none else was in the mission.

One of the main advantages of providing the drones with the means for deciding their actions is the absence of a centralized coordinator, which would represent a critical point of failure. A distributed autonomous robotic system, enables redundancy, remaining functional if some of the agents fail. In the case of a complete failure of a drone, in function of the lack of information the *idleness* of the last point visited will start to increase, and the other teammates will consider paying a visit to that spot and eventually find the crashed drone. Note that, it is not in the scope of this work to define procedures to locate and rescue a team member.

In a partial malfunction, the mission efficiency is compromised, but nothing changes for the drones.

8.10.4 Computational feasibility

The size of the search/patrol area is not a limitation issue for our approach, because the POIs, distance costs, and all possible path are calculated offline (outside of the drones), before the mission, and a bank of optimal trajectories is registered in a lookup table inside the drones. Hence, the online process to select a path ($\delta_i^t(\cdot)$ – Eq. (5.1)) is $O(logPOI)$. Nevertheless, this calculation can be more or less complex according to the algorithm used, for instance, $O(POI^2)$ for a straight line among POIs and $O(POI \cdot ELogPOI)$ for a Dykstra Algorithm.

The communication process has a constant complexity $O(1)$, since the information is broadcast regardless the number of drones that is in range.

The most expensive online operation in our algorithm is $\sigma_i^t(\cdot)$ (see Eq. (5.1) and (5.2)) which has a linear complexity $O(n)$.

Finally, increasing the team size causes a linear increase in the computational time ($O(n)$).

8.10.5 Scalability

In a real-world mission, the maximum available number of agents must be considered, so the number of robots to be used is limited to the available robots. The proposed system have no big issues with increasing the size of the team ($O(n)$) and, thus, supports an arbitrary real-life team size, as explained before.

8.11 Summary

In this chapter, it is shown our dynamic and decentralized framework to handle a human-drones team by implementing game-theoretical models. In this way, a heuristic utility function, which considers three different games: (1) where to go, (2) how to search and (3) how to interact with HO, and the operational guidelines for the mission, was presented.

In the *moving game* (an anti-coordination potential game) not only the travel cost was considered, but also the current positions of the other team members as well as the likelihood of the existence of a target in a given POI (e.g., in a SAR mission). To improve the real-time performance, the game was played only in the destination POI of each drone (macro-actions).

In order to choose a *search pattern*, a GAN was designed taking into account the worst case scenario ("Murphy's law"), for which, we demonstrated that a mixed strategy might be the best response to play.

The *HRI game* (designed as a sequential team game) took into account the human cognitive biases (the framing and the endowment effects) to set the utility functions of the drones and to adapt dynamically HRIs, in order to increase the probability that HO selected the choice that maximizes the global utility.

Moreover, all games were adjusted by the operational guidelines of the mission (to be fast or accurate – in our context). These games were played inside each drone, wherein NE is applied to them in order to make their decisions.

In order to close the loop, we conducted an online experiment with a SAR context. Our findings denoted that participants could be led to mimic the behavior of the participants of our previous experiments, and the operational guidelines could influence the HO decision and in the drones utilities when the HRI is framed accordingly. The main contributions of this study were:

- CR-10 – the operational guidelines driving drones utilities.
- CR-11 – the decisional model proposed in CR-9 is explored to align HO decisions with the operational guidelines, allowing to close the loop in a "optimized" way.
- CH-12 – the FE leading HOs to decide in accordance with the operational guidelines.

Robust control of a drone team in the real world requires that a framework demonstrates inter-robot coordination, robustness to failures, computational feasibility and scalability. As discussed in this chapter our proposition should meet all these requirements.

Conclusion et perspectives

> *Good decisions come from experience. Experience comes from making bad decisions.*
>
> *Mark Twain*

Conclusion

Nowadays, research and design in HRI demand much greater attention from the Human Factors community. For instance, in a military context, should robots decide whether to kill someone? Or must humans always be in the decision loop [GTP+12]? And the current big question: what a self-driving car should do if a person falls onto the road in front of it, when it can either swerve into a barrier, potentially killing the passenger, or go straight, potentially killing the pedestrian [BSR16]?

There is no easy answer to those questions. Maybe the answer lies in the MI-HRI. Humans can respond to ethical questions using intuition, but it's not that simple for artificial intelligent systems, the robot decision may emerge from the interaction of several sensors in order to calculate the moral tradeoff, or it can have a preset collection of moral rules [Bel+14].On the other hand, the "fallible and emotional" human beings might improve their performances with a robotic helping hand.

With this in mind, this thesis was undertaken to design an MI-HRI framework made up of a HO and a team of drones, in which the HO and the drones have complementary skills and act synergistically as peers to improve the system overall performance. In this sense, this work fulfills a twofold objective: (1) taking care of the effectiveness of the human-robot team (*robotic perspective*), and (2) improving the human-decision process in such an operational context (*human perspective*).

Hence, we started the research with a literature review about dirty, dull and dangerous missions suitable for our framework, such as military, SAR, and space missions. Then, we studied the human decision-making process and some of its theories (e.g., Prospect theory). Meanwhile, in the *robotic perspective* we focused on decentralized decision processes such as the Game theory.

With those concepts, we designed our proposition step-by-step. Firstly, we developed a game-theoretical utility function to coordinate the drone team moves in an autonomous patrolling mission. Here, besides the path travel cost, we also considered the current position of all drones and the last time each point of interest (POI) was visited. With that information, we created an additive payoff function of an anti-coordination game (ACG), in which a pure NE solution aligns the self-centered objectives of the drones with a global objective.

Secondly, in order to observe if we could influence the HO's decisions under uncertainty, time pressure and imperfect information, we conducted two framing effect (FE) experiments, using a SAR and a Sample-return mission as back-stories. Our findings demonstrated the existence of the FE and the influence of the emotional commitment in such context, and that the use of colors as a complementary *visual framing* can enhance the influence of the *text framing*.

Thirdly, with the data collected in those experiments, we estimated a human utility function and proposed a decisional model for the robots frame the interaction with the operator (HO), in order to increase the probability of the HO choose an action that optimizes the global utility.

Thus, we close the loop, formalizing our dynamic decentralized game-theoretical proposition to drive the interactions of a human-drone team. For the interaction among the drones, we created an ACG[4], inspired in our patrolling mission approach. For the drone-environment interaction, when the drones had to select a search pattern, we designed a GAN and demonstrated that a *mixed strategy* might be the best response to play. For the HRI, we created a *sequential team game*, where the drones make use of a *fictitious play*, based in the estimated *HO's utility* to choose how to interact with the HO. And, then, we biased these three games to follow the operational guidelines (to be fast or accurate, in our last experiment). We also suggested that the *overall utility* may be used as an efficiency measure of the system.

At last, to evaluate our proposition, Experiment III was carried out. Our findings suggest that it is possible to lead the HO to act in accordance with the operational guidelines and the "experts" strategies, regardless their previous experience, framing the HRI accordingly.

Limitations

The current investigation was limited by the data collected in Experiments I and II, in which the numbers of participants were relatively small. And, moreover, despite those participants had executed ten missions each (in Experiment I), their data might not necessarily represent "experts' behaviors" as considered in Experiment III.

Another limitation is that Experiment III was not a true MI-HRI, in the sense that only the drones had the initiative during the mission (adaptive autonomy).

[4] Anti-coordination game

Finally, it is unfortunate that this study did not include a real manner set-up with real drones and human participants.

Contributions

This thesis provides authentic methods that can be replicated to evaluate the implementation of game-theoretical models and human-factors principles in an operational context. In this sense, this work brought together two different disciplines, engineering (robotics) and psychology (human factors). Hence, the main contributions are:

- CR-1 – the formulation of an original player's additive utility function composed by three parameters that are independent from the action choices of the others players;
- CR-2 – the demonstration that the game solution is a NE, and that this equilibrium can be obtained by optimizing separately and individually the single player's action choice;
- CR-3 – the proposal of a decentralized algorithm used to conduct a patrolling mission, which works considering minimum communication among agents.
- CH-4 – the observation of the FE in a operational context;
- CH-5 – the emotional commitment influence in the FE efficiency;
- CH-6 – the time-to-answer influence in the FE efficiency;
- CH-7 – the interference of the use of colors, as complementary visual framing, in the "power" of the FE;
- CH-8 – the HO's utility function approximation founded on PT;
- CR-9 – a decisional model based on the economics approach of multi-dimensional consumption bundle and Prospect theory;
- CR-10 – the operational guidelines driving drones utilities.
- CR-11 – the decisional model proposed in CR-9 was explored to align HO decisions with the operational guidelines, allowing to close the loop in a "optimized" way.
- CH-12 – the FE leading HOs to decide in accordance with the operational guidelines.

Future works

There is abundant room for further progress in this proposed framework. In the *robotic perspective*, future studies should consider uncertainties in the drone movements and in the HO availability, using online M/POMDP solvers. Offline solvers tend to be applicable only when dealing with small to mid-size domains, since the policy construction step takes significant time, because the algorithm returns a policy defining which action to execute in every possible belief state [Ros+08]. On the other hand, online solvers attempt to find a good local policy for the current belief state of the agent only, which is nothing else than an one-shot *stochastic game*. One advantage is that it only needs to consider belief states that are reachable from the current belief state. However, in order to enhance the local policy optimality, should be interesting to increase the horizon to a small number of timesteps (online planning), according to the onboard computational capacity (to avoid loss in performance). And, instead of re-planning at every step, make use of “macro-actions” (sets of atomic actions) to reduce the domain size.

Should be interesting as well to investigate an online reinforcement learning algorithm to tune the HRI on-the-fly, based on the previous decisions made by the current HO. This might adjust the system behavior in function of the HO performance.

In the *human perspective*, further research might explore tools from the *transfer learning* literature [PY10] to: (1) in a first step clustering people that have a similar *personal perceived value*; (2) applying in this case the appropriate *perceived value* function in accordance of this common behavior.

Future research should also take into account HO’s *cognitive states* as, for instance, the operator’s workload or stress level. In general, the HO has some level of situation awareness, that allow her to know the capacities of the artificial agent and its state. On the other side, when adaptive autonomy or mixed initiative are considered, the artificial agent should have a model of the HO’s “capacities” and her current “state” [TD12]; [Dur+15]; [Gat+16]; [Roy+16] (see also [SCD15] in Appendix A). This might enhance the artificial agent decision process in order to decide if it takeover the initiative or not.

And, finally, a natural progression of this work is a real MI-HRI system, with more drones and more HOs, in which all the agents can have the authority to control the initiative and, moreover, to opportunistically seize the initiative from the other when necessary.

APPENDIX A

MOMDP-based target search mission taking into account the human operator's cognitive state

This study discusses the application of sequential decision making under uncertainty and mixed observability in a mixed-initiative robotic target search application. In such a robotic mission, two agents, a ground robot and a human operator, must collaborate to reach a common goal using, each in turn, their recognized skills. The originality of the work relies in considering that the human operator is not a providential agent when the robot fails. Using the data from previous experiments, a Mixed Observability Markov Decision Process (MOMDP) model was designed, which allows to consider aleatory failure events and the partial observable human operator's state while planning for a long-term horizon. Results show that the collaborative system was in general able to successfully complete or terminate the mission, even when many simultaneous sensors, devices and operators failures happened. So, the mixed-initiative framework highlighted in this study shows the relevancy of taking into account the cognitive state of the operator, which permits to compute a policy for the sequential decision problem which prevents to re-planning when unexpected (but known) events occurs.

A.1 Introduction

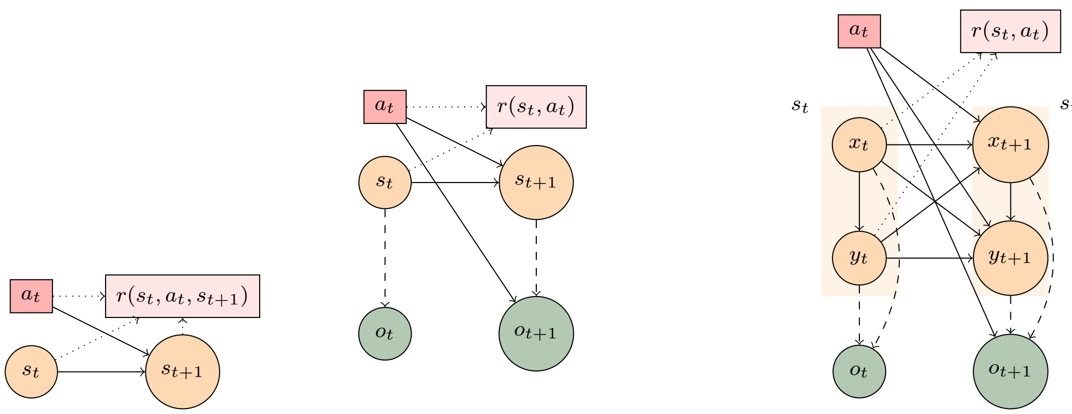
Unmanned Vehicles (UVs) are becoming increasingly present in a wide variety of operational contexts such as military operation, border security, inspection of contaminated area for prevent human from hazard exposure. Most of scientific and technical efforts have focused on the implementation of smart sensors, complex embedded systems and autonomy to enhance the efficiency of the UVs [Thr+04], especially when the human operator can not analyze or access visual data [Thr+04]; [SMT09]; [FO05]; [CM03]. However these developments were generally achieved without questioning the integration of the human operators *in the control loop* [SST03]: the human operator is considered as a providential agent that will be able to take over when sensors or automations fail [CM03]; [FO05]; [SMT09]. Yet, poor user interface design, complexity of automation and high operational pressure can leave the human operator ill-equipped when mental workload exceeds human capacity [Dur+14]. For instance, careless design of authority sharing can lead to human-automation conflicts when the human operator misunderstand the automation behavior [Deh+05]; [Deh+15]. The occurrence of such situation is critical as long as it may cause "mental confusion" (i.e. the human operator is unable to glance and process the relevant parameters) [Deh+15] or attentional tunneling (i.e. the human operator is excessively focused on a single display) [DCT11] yielding to irrational behavior [Deh+12]. Not surprisingly, a safety analysis report [Wil04] revealed that human factors issues were involved in 80% of accidents. This trend has led Cummings and Mitchell (2008) to state: "*Because of the increased number of sensors, the volume of information, and the operational demands that will naturally occur in a multiple-vehicle control environment, excessive cognitive demands will likely be placed on operators. As a result, efficiently allocating attention between a set of dynamic tasks will be critical to both human and system performance. - p. 451*".

A promising avenue to deal with these issues is to consider that robot and human abilities are complementary and are likely to provide better performance when joined efficiently than when used separately. This approach, known as mixed-initiative [AGH99]; [AC+04] defines the role of the human and artificial agents according to their recognized skills. It allows the human and the robot to set the appropriate level of autonomy of the robot [HG09]. An interesting mixed-initiative proposition, presented by [Sel+06], relies on a statistical approach to determine which entity (i.e human or UVs) is the most efficient for a given task. Interestingly enough, this approach paves the way for allocating roles and sharing authority between the human and artificial agents. In [FO05], a mixed-initiative planning approach is proposed to monitoring the system and to coordinate operator's interventions in a rescue scenario. In this work, the mixed-initiative planning continuously coordinates, integrates and monitors the operator's interventions and decisions. Another example can be found in [Gia+11], in which a robot and an human operator collaborate for an urban search and rescue mission in order to detect and report objects of interest.

A key issue to design a mixed-initiative system is to implement a decision system. This latter defines the role and the authority of human and artificial agents, while estimating capabilities of evolved human (intention, situation awareness, sensor's failure perception) and robotic agent (sensor's status, mission task, etc). Such decision-making system can be governed by a policy resulting from the resolution of a Partially Observable Markov Decision Process (POMDP), as proposed by [TMD11], which is able to adapt itself to the user's intention getting feedback from the user in terms of satisfaction. A different way to drive interaction using POMDPs is studied in [Hoe+07] for assisting persons with dementia during hand-washing. Note that, the state vector of the robot can be often considered as fully observable while the operator's cognitive state is, by definition, partial observable. Such decomposition can be addressed using a Mixed Observability Markov Decision Process (MOMDP) [Ong+10], which is a stochastic model derived from the POMDP [SS73]. The MOMDP is a formal framework that considers fully and partially observable state variables under probabilistic uncertainties while decreasing the computational cost required to produce a optimal policy [Ong+10]. In addition, these two types of agents may face unexpected random situations during the mission. It can be modeled as probabilistic effects of actions. Moreover, this kind of model allows the inclusion of the uncertainty in the observations of the agents' states (i.e the cognitive state of the human operator) and the environment. The MOMDP aim to achieve a policy that maps an optimal action for each belief state – composed by the observable state and the partially observable state estimation. Thus, it is expected that the resulting policy could help to implement a genuine adaptive interaction, because this formalism is perfectly suited to maintain a state estimation and to decide of the men-robot system dynamics based on data coming from sensors applied to the operator (e.g eye-tracker) and from sensors embedded in robots.

In this present study, we propose to test the MOMDP approach on an mission involving a human and a physical UV that cooperate to perform a target identification task. Data collected during previous experiments allowed us to set probabilities of UV failure as well as of human operators poor cognitive state. This paper is organized as follow: first we recall POMDP and MOMDP models. In the sequence we present the mission model treated. Afterwards we evaluate the results obtained for such modeling. And, finally we conclude and discuss future work.

A.2 Background



(a) MDP transition model.

(b) POMDP transition model.

(c) MOMDP transition model.

Figure A.1: Transition models of a POMDP and a MOMDP.

A.2.1 Markov Decision Process (MDP)

MDPs are a formalism long studied for decisions in stochastic domains [Put94]. In this model, it is possible at any time to observe the system state with certainty and the intelligent agent can choose an action from several, but the effects of actions can lead to several different states according to a probabilistic model of transition with respect to the starting state. Rewards or costs are associated with state-action pairs.

A MDP is a tuple (S, A, T, R, γ), where:

- S is a bounded set of states of the agent and its environment.
- A is a bounded set of actions.
- T is a transition function between states $T : S \times S \times A \to [0, 1]$, such that $p(s_{t+1}|s_t, a_t)$ is the probability of reaching the state s_{t+1} with respect to the state s_t and the action a_t.
- R is a reward function $R : S \times A \to \mathbb{R}$, such that $r(s_t, a_t)$ is the immediate reward associated to the execution of the action a_t in the state s_t.
- $\gamma \in [0, 1[$ is the discount factor.

A MDP is not one but several decision problems in sequence that an agent must solve, where every decision affects the current resolution of the following problem [Put94]. This sequence of decisions is typically found in probabilistic planning problems, which generalize the approaches of shortest path in a stochastic environment. The objective of solving a MDP is to find an optimal policy π^*, that associates an optimal action to each state. Solving a MDP can be saw as controlling an agent in order to perform a long term optimal behavior, that is equivalent to saying, as finding the policy that will maximize some cumulative function of the random rewards, typically the expected discounted sum over a potentially infinite horizon.

$$\pi^* \leftarrow \underset{\pi \in \Pi}{\operatorname{argmax}}\, E_\pi \left[\sum_{t=0}^{\infty} \gamma^t r(s_t, a_t, s_{t+1}) \middle| s_0 \right] \tag{A.1}$$

The solution is a policy or a strategy or a decision rule, which specifies the action to execute in each state, under the assumption that the agent has *a priori* perfect knowledge of its processes and status at any time. If the observation of the state of the process is incomplete, then the MDP model is insufficient.

A.2.2 POMDP overview

POMDPs model situations where the agent only has access to partial information about the state of the system. A POMDP is a Markov Decision Process where the agent does not have access to the state of the system: it has only a partial and imprecise observation [SS73]. In this context, the agent maintains a probability distribution over states, i.e. a belief state, which is updated after each action executed and observation perceived.

A POMDP is a tuple $(S, A, \Omega, T, O, R, b_0, \gamma)$ where:

- S is a bounded set of states;
- A is a bounded set of actions;
- Ω is a bounded set of observations;
- $T : S \times A \times S \to [0; 1]$ is a transition function such that $T(s_{t+1}, a, s_t) = p(s_{t+1} \mid a, s_t)$;
- $O : \Omega \times S \to [0; 1]$ is an observation function such that $O(o_t, s_t) = p(o_t|s_t)$;
- $R : S \times A \to \mathbb{R}$ is a reward function associated with a state-action pair, and;
- b_0 is the initial probability distribution over states.
- $\gamma \in [0, 1[$ is the discount factor

We note Δ the *belief state space*. At each time step t, the agent updates its *belief state* defined as an element $b_t \in \Delta$ using the Bayes' rule [SS73].

$$b_a^o(s') = \frac{p(o|s', a) \sum_s p(s'|s, a)b(s)}{\sum_{s'} p(o|s', a) \sum_s p(s'|s, a)b(s)} \tag{A.2}$$

Solving a POMDP consists in finding a policy function $\pi : \Delta \to \mathcal{A}$ that maps to each belief state an optimal action that maximizes a performance criterion. The expected discounted reward from any initial belief $V^\pi(b) = E_\pi \left[\sum_{t=0}^{\infty} \gamma^t r(b_t, \pi(b_t)) \mid b_0 = b\right]$ is usually optimized. The value of an optimal policy π^* is defined by the optimal value function V^* that satisfies the Bellman optimality equation:

$$V^*(b) = \max_{a \in A} \left[r(b, a) + \gamma \sum_{o \in \Omega} p(o|a, b) V^*(b_a^o) \right] \tag{A.3}$$

where, γ is the discount factor. When $r(b, a)$, can be computed as an average gain $r(b, a) = \sum_s r(s, a)b(s)$, the optimal value of belief states is proven to be piecewise linear and convex and solution of the Bellman's equation [SS73]. As it, at n^{th} optimization stage, the value function V_n can be parametrized as a set of hyperplanes over Δ known as α-*vectors*. An α-vector and the associated action $a(\alpha_n^i)$ define a region of the belief state space for which this vector maximizes V_n. Thus, the value of a belief b can be defined as: $V_n(b) = \max_{\alpha_n^i \in \Gamma_n} b \cdot \alpha_n^i$. The optimal policy at this step is then: $\pi_n(b) = a(\alpha_n^b)$.

Recent offline solving algorithms HSVI2 [SS05] or SARSOP [KHL08], for instance, approximate the value function with a bounded set of belief states $\mathcal{B}$, where $\mathcal{B} \subset \Delta$. These algorithms implement different heuristics to explore the belief state space using probabilistic trials reaching in this way only relevant belief states, and updating the value of V for them, instead of computing the value function for all the belief state space, which is a continuous space.

A.2.3 MOMDP

The Mixed Observability Markov Decision Process (MOMDP) is an extension recently proposed for the POMDP model [Ong+10], which explores the particular structure where certain state variables are fully observable. This factored model leads to a very significant time gain in policy computation, improving the efficiency of a point-based algorithms. According to [Ong+09] the completely observable state is represented by x and the partially observable state by y. In this way, the couple (x, y) specifies the complete state with $|S| = |\mathcal{X}| \times |\mathcal{Y}|$, where $\mathcal{X}$ represents the space with all the possible values of the variable x (resp. $\mathcal{Y}$ to y).

A MOMDP is a tuple $(\mathcal{X}, \mathcal{Y}, A, \Omega, T_{\mathcal{X}}, T_{\mathcal{Y}}, \Omega, R, b_0, \gamma)$, where:

- $\mathcal{X}$ is the bounded set of fully observable state variables;
- $\mathcal{Y}$ is the bounded set of partially observable state variables;
- A is a bounded set of actions;
- Ω is a bounded set of observations;
- $T_{\mathcal{X}} : \mathcal{X} \times A \times \mathcal{X} \times \mathcal{Y} \rightarrow [0; 1]$ is a transition function such that

$$T_{\mathcal{X}}(x, y, a, x') = p(x'|x, y, a)$$

- $T_{\mathcal{Y}} : \mathcal{Y} \times \mathcal{X} \times A \times \mathcal{X} \times \mathcal{Y} \rightarrow [0; 1]$ is a transition function such that

$$T_{\mathcal{Y}}(x, y, a, x', y') = p(y'|x, y, a, x')$$

- $O : \Omega \times \mathcal{Y} \rightarrow [0; 1]$ is an observation function such that $O(o, a, x', y') = p(o|x', y', a)$

- $R : \mathcal{X} \times \mathcal{Y} \times A \rightarrow \mathbb{R}$ is a reward function associated with a state-action pair; and:

- $b_0 = (x_0, b_{\mathcal{Y}_0})$ is the initial probability distribution over states.

- $\gamma \in [0, 1[$ is the discount factor.

Note that, as the probability distribution over states concerns only the $\mathcal{Y}$ set, the belief state update is redefined as:

$$b_{\mathcal{Y}}^{o,a,x'}(y') = \eta \sum_{y' \in \mathcal{Y}} p(o|y', x', a) p(y'|x, y, a, x') p(x'|x, y, a) b_{\mathcal{Y}}(y) \tag{A.4}$$

where, η is a normalization constant. The belief state b is now noted by the couple $(x, b_{\mathcal{Y}})$, and $\mathcal{B}_{\mathcal{Y}}$ is the belief state space y conditioned by x : $\mathcal{B}_{\mathcal{Y}}(x) = \{(x, b_{\mathcal{Y}}), b_{\mathcal{Y}} \in \mathcal{B}_{\mathcal{Y}}\}$. $\mathcal{B}_{\mathcal{Y}}(x)$ is a sub-space of $\mathcal{B}$, such that $\mathcal{B} = \bigcup_{x \in \mathcal{X}} \mathcal{B}_{\mathcal{Y}}(x)$.

Solving MOMDPs consists in finding *a set of policies* $\pi_x : \mathcal{B}_{\mathcal{Y}} \rightarrow A$, which maximize the criterion :

$$\pi_x^* \leftarrow \underset{\pi_x \in \Pi}{\operatorname{argmax}} \, E_{\pi_x} \left[\sum_{t=0}^{\infty} \gamma^t r((x_t, b_{\mathcal{Y}}^t), \pi((x_t, b_{\mathcal{Y}}^t))) \middle| b_0 = (x_0, b_{\mathcal{Y}_0}) \right] \tag{A.5}$$

As for the POMDP, the value function at a time step $n < \infty$ can be also represented by a set of α-vectors:

$$V_n(x, b_{\mathcal{Y}}) = \max_{\alpha \in \Gamma_{\mathcal{Y}}^n(x)} (\alpha \cdot b_{\mathcal{Y}}) \tag{A.6}$$

where α is the hyperplan over the space $\mathcal{B}_y(x)$. In this way, the value function over the complete state space is parametrized by the set $\Gamma_{\mathcal{Y}}(x)$, i.e. $\Gamma = \{\Gamma_{\mathcal{Y}}(x), x \in \mathcal{X}\}$. So, given a belief state $(x, b_{\mathcal{Y}})$ the optimal action is defined by the action associated with the α-vector that maximizes $\max_{\alpha \in \Gamma_{\mathcal{Y}}(x)} (\alpha \cdot b_{\mathcal{Y}})$. For more details about MOMDP algorithm resolution, please see [Ong+09]; [Ong+10].

Next, we present previous experiments which were used as base for statistical data in order to leaning the MOMDP model for the target search mission taking into account the operator's cognitive state.

A.3 Previous Experiments

A.3.1 Material

The experimental set-up was developed at ISAE-SUPAERO. It was composed of a robot and a ground station. The robot was equipped with different sensors such as a GPS for autonomous navigation, an Ultrasound sensor to detect and avoid obstacle, a video camera and an Xbee transmitter to communicate with the ground station. It had a 15 minutes autonomy thanks to electrical battery. The robot could be operated in *manual mode* or in *supervised mode*. In manual mode, the robot was operated with a joystick. In supervised mode, the robot performed waypoint navigation autonomously, but any action of the operator with the joystick let her/him take over until the joystick was released. The ground station was displayed on a 24-inch screen showing different kinds of information to control and supervise the robot such as a tactical map, a panoramic video scene screen; a mission synoptic ; an interactive panel sending the requests to the human operator; a status panel panel indicating the state of the GPS, the ultrasound sensor and the battery; and a guidance mode state (i.e. supervised or manual). Note that the operator could not see the robot and only gathered information through the screen. Fig. A.2 shows the interface of the ground station to operate the robot during the mission.

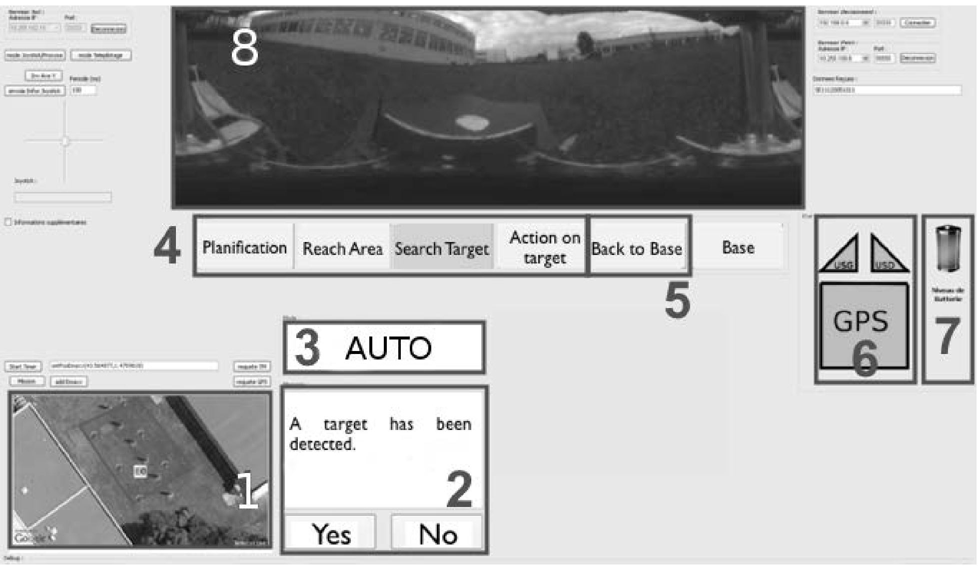


Figure A.2: Operator's interface and areas of interest [Rég+14].

A.3.2 Assessing probability of failures of the robot

A first experiment was conducted to assess the probability of failure of the different sensors and devices embedded in the robot. Thirty tests were run and consisted of a 10 minutes navigation task with the robot evolving among four waypoints in a field at ISAE-SUPAERO campus. The results are summarized on Table A.1, where **FP** design the failure probability.

Table A.1: Sensors statuses

Sensor	**Ok**	**Not Ok**	**FP**
Battery	battOK	battKO	$2/30$
GPS[1]	gpsOK	gpsKO	$3/30$
Ultrasound[1]	usOK	usKO	$3/30$
Camera[2]	camOK	camKO	$3/30$
Ground station[2]	stOK	stKO	$1/30$
Joystick[2]	jsOK	jsKO	$1/30$
Xbee[2]	xbOK	xbKO	$2/30$

[1] indicates the essential sensors for autonomous operation.
[2] indicates the essential devices for manual operation.

A.3.3 Assessing human's performance

Data collected from a previous experiment [Deh+12] were used to assessing the probability of the human operator to perceive robot failures. The scenario of this experiment consisted of a target localization and identification task involving a ground robot and a human operator. The target to be identified had two short messages written in white on each side (front side OK, back side KO). The mission had four main segments: S_1- *Reach the area*, S_2- *Scan for target*, S_3- *Identify target*, and S_4- *Battery-Failure*. At the beginning of the mission, the robot evolved in an autonomous *supervised mode* to reach the target area (S_1) and then start scanning the area to detect the target (S_2). When the robot was close to the target, the operator had to take over in manual mode and to identify the target S_3). While the operator was performing the identification task, a *low battery event* was triggered (S_4). In turn this event yield to a safety procedure that made the robot to go back to base autonomously. As this event occurred while the operator was excessively focused on his target identification task, it was expected that he would missed the alerts and thus persist in achieving the target detection task.

A.3.3.1 Assessing failure perception

12 subjects participated to the experiment and were equipped with an electrocardiogram (ECG) and a 25 Hz Pertech head mounted eye tracker. This latter device was used to collect participants' eye gaze on the user interface. More specifically we focused our eye tracking analysis on eight areas of interest (AOI) of the user interface: 1) tactical map, 2) message panel, 3) guidance mode (*supervised* vs *manual*), 4) synoptic, 5) "back to base" warning, 6) GPS and ultrasound status, 7) battery status, 8) panoramic video. The collected ocular data were used to set the probability of the operator to perceive the sensor's status (sensors statuses are summarized in Table A.1). This

sensor status perception probability is based on the normalized sum of the averaged fixation time ($\overline{\Delta T}$) on the related AOIs. For instance, when the GPS or the ultrasound are lost, the icons turns to red (area 6) and the robot is stopped (i.e it can be seen through the panoramic video - area 8). When the low-battery event occurs, three changes can be observed in the user interface: (i) the battery icon (area 7) turns to orange with the associated *low battery* message, (ii) the mode changes automatically from *manual* to *supervised*, and area 3 blinks twice and (iii) the segment status became *back to base* (area 5).

Thus we introduced the *spGpsUs* boolean state variable that can be used to model perception about a GPS or ultrasound status by the operator:

$$p(spGpsUs = Y \mid auto \;\&\&\; (gpsKO \mid\mid usKO)) = \frac{\overline{\Delta T}_{Area\ 6} + \overline{\Delta T}_{Area\ 8}}{\overline{\Delta T}_{all\ areas}} = 0.70$$

$$p(spGpsUs = Y \mid manual \;\&\&\; (gpsKO \mid\mid usKO)) \;= 0.86$$

With the same reasoning, for the *spBatt* (Battery status perception) boolean state variable, the transition probability was defined by the normalized sum of the averaged time that the participants expended looking to areas 3, 5 and 7 during the manual and autonomous operations:

$$p(spBatt = Y \mid manual \;\&\&\; battKO) = \frac{\overline{\Delta T}_{Area\ 3} + \overline{\Delta T}_{Area\ 5} + \overline{\Delta T}_{Area\ 7}}{\overline{\Delta T}_{all\ areas}} = 0.021$$

$$p(spBatt = Y \mid auto \;\&\&\; battKO) \;= 0.033$$

A.3.3.2 Assessing cognitive availability

the result of the experiment revealed that 8 participants out of 12 did not understand the robot behavior, though some of them glanced at the battery failure indicator. These 8 participant persevered to achieve the no-longer-relevant identification task [Deh+12]. This typical behavior is known as "attentional tunneling" and is defined as *"the allocation of attention to a particular channel of information, diagnostic hypothesis or task goal, for a duration that is longer than optimal, given the expected costs of neglecting events on other channels, failing to consider other hypotheses, or failing to perform other tasks"* [TW04]. Therefore, the inference of such impaired attentional state is of great importance to design a mixed initiative system. We implemented an Adaptive Neuro-Fuzzy Inference System (ANFIS) to detect attentional tunneling that is associated with higher cardiac activity, decreased saccadic activity and long concentrated eye fixations [Rég+14]. The ANFIS classifier had a probability of 91.1% to detect *Attention Tunneling* (please report to [Rég+14] for more details). This detection probability was used in this study to define the *observation function* of the *Cognitive Availability* state variable as shown further. *Cognitive Availability* is defined here as the capability of the human operator to be available and aware of the robot's status during all mission tasks.

Table A.2: Attention tunneling probability function

	available_N	**available_Y**
oAvailable_N	91.1	8.9
oAvailable_Y	0	100

A.3.3.3 Cognitive countermeasure to assist the human operator

many studies revealed that alarms are inefficient to warn human operator during high workload situations such as performing manual control and identifying target [Deh+14]. Rather than adding alarms during stressful situations, an optimal solution to warn the human operator consists of temporarily removing the information the human operator is focusing on, and replacing it by an explicit visual stimulus designed to change the attentional focus. The principle of this cognitive countermeasure was tested in second experiment with 11 participants facing the same scenario (i.e. target identification task and battery failure). The results revealed that these cognitive countermeasures helped 10 participants out of 11 to perceive the battery failure and to let the robot go back to base [DCT11].

A.4 Modeling the collaborative target identification mission

Using all those previous experimental data, a MOMDP model was defined in order to drive the adaptive interaction between the human operator and the UV. The choice for a *Mixed Observability* model comes from the nature of our problem: the robot and mission states can be considered as fully observable, while the operator's cognitive ability, here considered as *Cognitive Availability* is a partially observable state variable by definition.

The mission can be decomposed in six high level phases: *going to zone, searching the target, handling the target, returning to base, on base* and *failed*. The robot states can be defined by the cross product of the phases, the embedded sensors statuses, the statuses of the ground station, the on board camera, the Xbee and the joystick devices, and the *Cognitive Availability* as cognitive state of the operator. Next, we present the fully and partially observable state variables considered in the model.

Fully observable state variables ($\mathcal{X}$) The section A.3.3 and tables A.1 and A.3, present the fully observable state variables considered in the mission modeling. As discussed before, mission phases were classified according to the operation mode. The sensors statuses were discretized in two possibilities: OK and KO (not OK). It was also assumed that after a sensor failed, it switches to KO and remained KO until the end of the mission. The sensors' failure probabilities were shown in Table A.1.

Fig. A.3 summarizes the transition function for the mission phase state variable. A manual mode was associated with each autonomous mode (except the on base and failed mission phases). One can argue that, in a human operator's point of view, there is only one *manual mode*, but for modeling propose, the *manual mode* was factored in four phases (see Table A.3) to prevent the planner from selecting a *supervised mode* already held when returning to the autonomous operation mode.

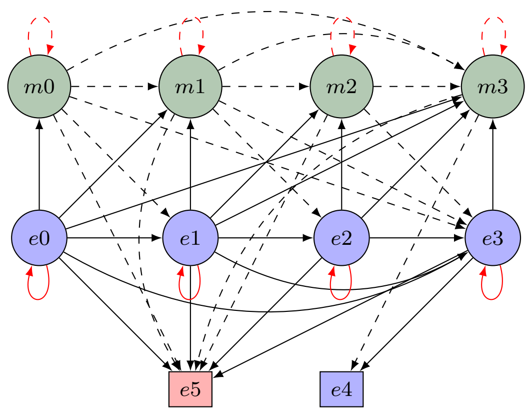


Figure A.3: Mission phases and summarized transitions. The loop transitions (red lines) indicate the transitions observed after *getAttention* or *cMeasure* actions.

Table A.3: Mission phases

mission phase	autonomous mode	manual mode
going to zone	e0	m0
target searching	e1	m1
target handling	e2	m2
returning to base	e3	m3
on base (final)	e4	-
failed (final)	e5	-

As show in previous experiments presented before, it is relevant to define two fully observable variables that model the operator's sensor's status perception (see section A.3.3). Note that, operator's perception about sensor's status (GPS/ultrasound and battery) state variables are assumed as fully observable, because it is not possible to observe if the human operator perceived (i.e. his cognitive process) only with the eye-tracker device. In this case, for example, if the operator looked to the areas (6 and 8) between two decision time steps, he should detect, with a probability of 0.70, for *supervised mode*, or 0.86, for *manual mode*, if there was a GPS or a ultrasound breakdown because the related icon turns to orange (see Fig. A.2 and Section A.3.3).

Partially observable state variable ($\mathcal{Y}$) The operator's *Cognitive Availability* is considered in this study as the opposite of *Attentional Tunneling* [DCT11]; [PDT11]; [Rég+14]. The measure of the allocation of attention if not a straightforward task [Rég+14]. Therefore, we consider the *Cognitive Availability* of the human operator as a partially observable variable. Hence: *available_Y* models that the human operator is cognitively available (resp. *available_N*, not cognitively available). Associated with this partially observable state variable we have two possible observations: *oAvailable_Y* meaning that the operator is observed as cognitively available and potentially aware of the situation and *oAvailable_N* modeling that he is observed as not cognitively available. Table A.2 summarizes the observation probability function for this observation variable.

Actions Discrete actions were defined as: *goToZone, tgtSearch, tgtHandle, retBase, onBase, getAttention* and *cMeasure*. Action result depends on the aleatory sensors behavior (cf. Table A.1). For instance, in a nominal case and based on previous works [DCT11]; [PDT11]; [Rég+14], the robot is able to autonomously navigate and avoid obstacles, but if the robot chosen *goToZone* and the ultrasound sensor fails, the mission phase turns to manual mode (*m0*) (see Fig. A.3) because the robot is no more able to avoid obstacles autonomously. If a low battery event arrives, the robot can return to the base automatically if it was in a *supervised mode*. When it was in a *manual mode*, it can switch to returning to base (with any action) automatically only if the human operator is aware of the failure, i.e. if he was observed as cognitively available being aware of the situation and by consequence leaving the joystick.

The *getAttention* is considered as a non deterministic action, since it should be used when the robot needed help and the operator's *Cognitive Availability* was estimated as "not available" (*oAvailable_N*). The same occurs with the action *cMeasure* (countermeasure), which should be executed when a *low battery* event arrives during a manual operation and the operator was considered as "not available" (e.g his attention was focused on handling the robot and he would not notice the alerts on the user interface). In such case, when a *cMeasure* action is launched the robot *wait* the human operator leaves the joystick (see Fig. A.3).

Rewards The reward function (R) was designed in order to payoff suitable actions, for instance, *goToZone* in the phase *e0* when the navigation sensors are *OK*, and to punish otherwise.

The same occurs with the *manual modes* and its essential devices (cf. Table A.1). Note that, we have chosen to associate a increasing reward with sequential phases, i.e. reward associated with the action *tgtSearch* in *e1* considering essential sensors are OK (R=15) is more important than the action *goToZone* in the *e0* phase (R=10). We have considered that processing the target in *manual mode* is more dependable than in *autonomous mode*, since the interpretation done by the human operator is more reliable. In this case, the reward for the choice of *tgtHandle* in *manual mode* (R=30) is more important than *tgtHandle* in *supervised mode* (R=20).

The action *getAttention* only has a positive payoff (R=30) if the operator's *Cognitive Availability* is estimated as "not available" (*oAvailable_N*) considering that at least one of the essential devices are *KO* and that the human operator did not see the alert, otherwise the reward is negative (-500). Similarly, the action *cMeasure* has a positive payoff (R=50) only if the operator is perceived as "not available" in a *manual mode* when a low battery event arrives.

A mission is considered as fully accomplished if the robot had passed through the phases *e2* or *m2* (resp. processed the target autonomously or manually) and arrived at base *e4*. When the robot returns to the base (autonomously or manually) before processing the target, the mission is considered as aborted and when the robot is unable to reach the base, the mission is considered as failed.

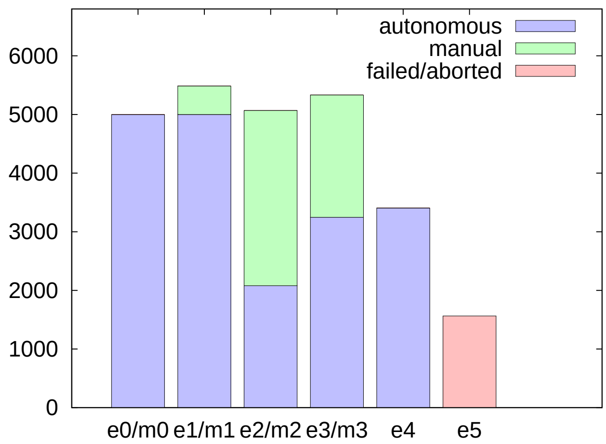
A.5 Simulation Results

The APPL_0.96win SARSOP[1] [Ong+09] was used as solver. The grammar of this solver has a special format that differs from the classical input POMDP file format[2]. Therefore, we have developed a script written in *Python 2.7.8* to produce the MOMDP input file. For the MOMDP resolution, we have set the precision ϵ to 0.01. We recall that this precision is related to the difference between the upper and lower bound of the value function for the initial belief state, which is considered as a stop optimization criterion.

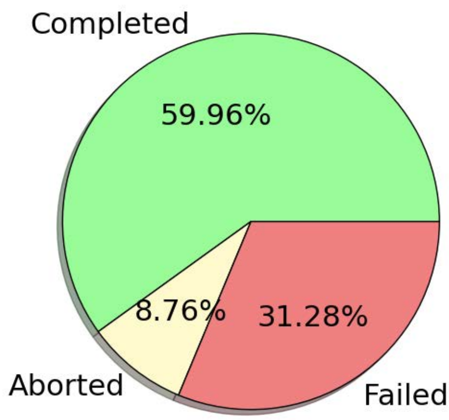
Statistical analysis was performed to process the results over 5000 policy simulations. Fig. A.4a provides an overview of how many times the robot passed by each mission phase. Note that, the robot passed through phase *e1* exactly 5000 times and never crossed the phase *m0*, this can be explained by the fact that the initial state, when all fully observable state variable values are known, caused a deterministic cycle in the first time stamp.

To sum up, the mission was fully accomplished 2998 times (59.96%) (cf. Fig. A.4b), meaning that the robot has passed through the phases *e2* or *m2*, respectively processing the target autonomously or manually, and arrived at base *e4*. In such cases, the target was handled in

[1] http://bigbird.comp.nus.edu.sg/pmwiki/farm/appl/
[2] http://www.pomdp.org/code/pomdp-file-spec.shtml



(a) Number of visits per mission phase.



(b) Percentages.

autonomous mode (*e2*) 1228 times, which represents 41% of successful missions, and it was handled in manual mode (*m2*) 1770 times (resp. 59% of successful missions). Fig. A.4b also shows that the robot returned to the base in 68.72% of times (including aborted missions). The mission completely failed, i.e. it reached *e5*, 1564 times (31.28%).

The Table A.4 presents an example of a *Fully accomplished mission* where the robot changed its mode to manual (*m2*) for the operator process the target (bigger reward), then the GPS failed. This was not a problem at that moment because the operator did not need the GPS to handle the target. Next, the robot remained in manual (*m3*) but the operator seemed not to be aware, so, the robot ask for his attention (action *getAttention*), and the operator led the robot to the base.

Table A.4: *Fully accomplished mission* example

	O	*X*										*Y*		
Step	oAvailable	Batt	GPS	US	Cam	Joystick	Station	Xbee	Phase	spBatt	spGpsUs	available	Action	Reward
1	-	OK	OK	OK	OK	OK	OK	OK	e0	Y	Y	N	goToZone	10
2	Y	OK	OK	OK	OK	OK	OK	OK	e1	N	N	Y	tgtSearch	15
3	Y	OK	KO	OK	OK	OK	OK	OK	m2	N	N	Y	tgtHandle	30
4	N	OK	KO	OK	OK	OK	OK	OK	m3	N	Y	N	getAttention	30
5	Y	OK	KO	OK	OK	OK	OK	OK	m3	N	Y	Y	retBase	35
6	N	OK	KO	OK	OK	OK	OK	OK	e4	N	Y	N	onBase	35

Finally, a *aborted mission* is shown in the table A.5. In this aborted mission a low battery event occurred while the operator was processing the target and the robot observed him or her as "not available" (not aware) of the failure. Consequently, the robot executed a countermeasure action (*cMeasure*) trying to show the situation to the operator. After, the robot changed its phase to *returning to base* (*e3*) and went home. Here, is interesting to observe that the operator never looked to the areas 3, 5 or 7 (cf. Fig. A.2), where the low battery event could be identified without the countermeasure.

Table A.5: *Aborted Mission* example

	O	X										Y		
Step	oAvailable	Batt	GPS	US	Cam	Joystick	Station	Xbee	Phase	spBatt	spGpsUs	available	Action	Reward
1	-	OK	OK	OK	OK	OK	OK	OK	e0	Y	Y	N	goToZone	10
2	Y	OK	OK	OK	OK	OK	OK	OK	e1	N	N	Y	tgtSearch	15
3	N	KO	OK	OK	OK	OK	OK	OK	m2	N	Y	N	cMeasure	50
4	Y	KO	OK	OK	OK	OK	OK	OK	m2	N	Y	Y	tgtHandle	0
5	N	KO	OK	OK	OK	OK	OK	OK	e3	N	Y	N	retBase	25
6	Y	KO	OK	OK	OK	OK	OK	OK	e4	N	Y	Y	onBase	35

A.6 Conclusions

This study has shown the effectiveness of the MOMDP model as basis for mixed-initiative actions planning. In such cases, agents must collaborate by bringing, according to their recognized skills, the relevant elements to reach together a shared goal. In our application case, the robot counts on the operator to process a target, since the operator's interpretation is considered more reliable that the robot's. Also, the robot may needs the intervention of a human operator in cases where an essential sensor for autonomous navigation breaks down. Our principal contribution in this mixed-initiative problem is that *we have considered that the human operator is not a providential agent*, i.e. he can be unaware of the situation. To model the problem, we have used data collected from previous experiments with an heterogeneous human-robot system. Based on it, the probability functions were assigned for the sensors failure, operator's perception about sensor's status and for the operator's cognitive availability. With the MOMDP model and a simulated environment, we checked that the collaborative system was in general able to successfully complete or terminate the mission, even when the simulated environment caused many simultaneous sensors/devices/operator failures.

Future work shall to take into account in the model more than one partially observable state variable. For the human factor community, the *estimation of the operator state* is obviously more complex and composed by more state variables than the one considered in this study (workload, stress, engagement, etc). In the future, we hope to take into account more *cognitive states* as, for instance, the operator's workload or stress level, and evaluating the policy in a real manner set-up with human operator participants.

Bibliography

[Abd+16] Mohammed Abdellaoui et al. "Measuring loss aversion under ambiguity: a method to make prospect theory completely observable". In: *Journal of Risk and Uncertainty* 52.1 (2016), pp. 1–20 (cit. on p. 37).

[ABG09] Francesco Amigoni, Nicola Basilico, and Nicola Gatti. "Finding the optimal strategies for robotic patrolling with adversaries in topologically-represented environments". In: *Robotics and Automation, 2009. ICRA'09. IEEE International Conference on*. IEEE. 2009, pp. 819–824 (cit. on p. 10).

[AC+04] Mitchell Ai-Chang et al. "Mapgen: mixed-initiative planning and scheduling for the mars exploration rover mission". In: *Intelligent Systems, IEEE* 19.1 (2004), pp. 8–12 (cit. on pp. 2, 146, 178).

[AGH99] JE Allen, Curry I Guinn, and E Horvtz. "Mixed-initiative interaction". In: *IEEE Transactions on Intelligent Systems and their Applications* 14.5 (1999), pp. 14–23 (cit. on pp. 2, 15, 146, 178).

[AK11] Alan Agresti and Maria Kateri. *Categorical data analysis*. Springer, 2011 (cit. on p. 86).

[AKK14] Christopher Amato, George D Konidaris, and Leslie P Kaelbling. "Planning with macro-actions in decentralized POMDPs". In: *Proceedings of the 2014 international conference on Autonomous agents and multi-agent systems*. International Foundation for Autonomous Agents and Multiagent Systems. 2014, pp. 1273–1280 (cit. on pp. 3, 179).

[Ama+13] Christopher Amato et al. "Decentralized control of partially observable Markov decision processes". In: *Decision and Control (CDC), 2013 IEEE 52nd Annual Conference on*. IEEE. 2013, pp. 2398–2405 (cit. on pp. 3, 179).

[Ama+14] Christopher Amato et al. "Decentralized Decision-Making Under Uncertainty for Multi-Robot Teams". In: *the Workshop on Future of Multiple Robot Research and its Multiple Identitie at IROS. IEEE*. 2014 (cit. on pp. 3, 179).

[Ami+10] Francesco Amigoni et al. "Moving game theoretical patrolling strategies from theory to practice: An usarsim simulation". In: *Robotics and Automation (ICRA), 2010 IEEE International Conference on*. IEEE. 2010, pp. 426–431 (cit. on p. 66).

[An+12] Bo An et al. "Security games with limited surveillance". In: *Ann Arbor* 1001 (2012), p. 48109 (cit. on pp. 66, 67).

[AS14] Fahed Awad and Rufaida Shamroukh. "Human Detection by Robotic Urban Search and Rescue Using Image Processing and Neural Networks". In: *International Journal of Intelligence Science* 4.02 (2014), p. 39 (cit. on p. 130).

[AT+15] Hend Al Tair et al. “Decentralized multi-agent POMDPs framework for humans-robots teamwork coordination in search and rescue”. In: *Information and Communication Technology Research (ICTRC), 2015 International Conference on*. IEEE. 2015, pp. 210–213 (cit. on p. 9).

[Bar02] Luiz Fernando Barrichelo. “Game Theory for Managers”. In: (2002) (cit. on pp. 40, 183).

[Bar07] J. Baron. *Thinking and Deciding*. Cambridge University Press, 2007 (cit. on pp. 20, 22, 25, 29, 30, 32).

[Bar13] Nicholas C Barberis. “Thirty years of prospect theory in economics: A review and assessment”. In: *The Journal of Economic Perspectives* 27.1 (2013), pp. 173–195 (cit. on p. 35).

[Bat+15] Douglas Bates et al. “Fitting Linear Mixed-Effects Models Using lme4”. In: *Journal of Statistical Software* 67.1 (2015), pp. 1–48 (cit. on p. 86).

[BCJ15] Michael J Barnes, Jessie YC Chen, and Florian Jentsch. “Designing for Mixed-Initiative Interactions between Human and Autonomous Systems in Complex Environments”. In: *Systems, Man, and Cybernetics (SMC), 2015 IEEE International Conference on*. IEEE. 2015, pp. 1386–1390 (cit. on p. 16).

[BE01] Brian H Bornstein and A Christine Emler. “Rationality in medical decision making: a review of the literature on doctors’ decision-making biases”. In: *Journal of evaluation in clinical practice* 7.2 (2001), pp. 97–107 (cit. on p. 23).

[Bec08] Martin Beckenkamp. “Playing strategically against nature? Decisions viewed from a game-theoretic frame”. In: (2008) (cit. on pp. 57, 58, 118).

[Bel+14] Aline Belloni et al. “Towards A Framework To Deal With Ethical Conflicts In Autonomous Agents And Multi-Agent Systems”. In: *CEPE 2014 Well-Being, Flourishing, and ICTs*. 2014, paper–8 (cit. on pp. 141, 192).

[Ber+02] Daniel S Bernstein et al. “The complexity of decentralized control of Markov decision processes”. In: *Mathematics of operations research* 27.4 (2002), pp. 819–840 (cit. on pp. 3, 179).

[Bev+15] Giuseppe Bevacqua et al. “Mixed-Initiative Planning and Execution for Multiple Drones in Search and Rescue Missions.” In: *ICAPS*. 2015, pp. 315–323 (cit. on p. 16).

[BGA09] Nicola Basilico, Nicola Gatti, and Francesco Amigoni. “Developing a deterministic patrolling strategy for security agents”. In: *Web Intelligence and Intelligent Agent Technologies, 2009. WI-IAT’09. IEEE/WIC/ACM International Joint Conferences on*. Vol. 2. IEEE. 2009, pp. 565–572 (cit. on p. 78).

[BJR08] G.E.P. Box, G.M. Jenkins, and G.C. Reinsel. *Time Series Analysis: Forecasting and Control*. Wiley Series in Probability and Statistics. Wiley, 2008 (cit. on p. 75).

[BM04] JL Burke and RR Murphy. "Human-robot interaction in USAR technical search: Two heads are better than one". In: *Robot and Human Interactive Communication, 2004. ROMAN 2004. 13th IEEE International Workshop on*. IEEE. 2004, pp. 307–312 (cit. on pp. 9, 11).

[BSR16] Jean-François Bonnefon, Azim Shariff, and Iyad Rahwan. "The social dilemma of autonomous vehicles". In: *Science* 352.6293 (2016), pp. 1573–1576 (cit. on pp. 141, 192).

[Bur+00] Wolfram Burgard et al. "Collaborative multi-robot exploration". In: *Robotics and Automation, 2000. Proceedings. ICRA'00. IEEE International Conference on*. Vol. 1. IEEE. 2000, pp. 476–481 (cit. on pp. 1, 10, 177).

[Bur+05] Wolfram Burgard et al. "Coordinated multi-robot exploration". In: *IEEE Transactions on robotics* 21.3 (2005), pp. 376–386 (cit. on pp. 1, 10, 177).

[Cal+16] Gloria L Calhoun et al. "Human-autonomy collaboration and coordination toward multi-RPA missions". In: *Remotely piloted aircraft systems: A human systems integration perspective* (2016), p. 109 (cit. on p. 13).

[Car70] Jaime R Carbonell. "AI in CAI: An artificial-intelligence approach to computer-assisted instruction". In: *IEEE transactions on man-machine systems* 11.4 (1970), pp. 190–202 (cit. on p. 15).

[CDL11] Christos G Cassandras, Xu Chu Ding, and Xuchao Lin. "An optimal control approach for the persistent monitoring problem". In: *Decision and Control and European Control Conference (CDC-ECC), 2011 50th IEEE Conference on*. IEEE. 2011, pp. 2907–2912 (cit. on p. 78).

[CF12] Sven F Crone and Steven Finlay. "Instance sampling in credit scoring: An empirical study of sample size and balancing". In: *International Journal of Forecasting* 28.1 (2012), pp. 224–238 (cit. on p. 130).

[Che+13] Ting Brendan Chen et al. "Management of heterogeneous UAVs through a capability framework of UAV's functional autonomy". In: (2013) (cit. on p. 11).

[Che04] Y. Chevaleyre. "Theoretical analysis of the multi-agent patrolling problem". In: *Intelligent Agent Technology, 2004. (IAT 2004). Proceedings. IEEE/WIC/ACM International Conference on*. 2004, pp. 302–308 (cit. on p. 66).

[Cho+13] Eun Kyoung Choe et al. "Nudging people away from privacy-invasive mobile apps through visual framing". In: *IFIP Conference on Human-Computer Interaction*. Springer. 2013, pp. 74–91 (cit. on p. 83).

[CM03] Jennifer Casper and Robin R. Murphy. "Human-robot interactions during the robot-assisted urban search and rescue response at the World Trade Center". In: *IEEE Transactions on Systems, Man, and Cybernetics, Part B: Cybernetics* 33.3 (2003), pp. 367–385 (cit. on pp. 1, 145, 146, 177).

[CM08] Mary L Cummings and Paul J Mitchell. "Predicting controller capacity in supervisory control of multiple UAVs". In: *Systems, Man and Cybernetics, Part A: Systems and Humans, IEEE Transactions on* 38.2 (2008), pp. 451–460 (cit. on pp. 2, 178).

[Col04] Frank Colucci. "Air Force refines training programs for UAV (unmanned aerial vehicle) operators". In: *National Defense* 88.606 (2004), pp. 36–39 (cit. on pp. 8, 11).

[DCT11] Frédéric Dehais, Mickaël Causse, and Sébastien Tremblay. "Mitigation of Conflicts with Automation Use of Cognitive Countermeasures". In: *Human Factors: The Journal of the Human Factors and Ergonomics Society* 53.5 (2011), pp. 448–460 (cit. on pp. 2, 25, 146, 155, 157, 178).

[Deh+05] Frédéric Dehais et al. "Towards an anticipatory agent to help pilots". In: *AAAI 2005 Fall Symposium" From Reactive to Anticipatory Cognitive Embodied Systems", Arlington, Virginia*. 2005 (cit. on pp. 2, 146, 178).

[Deh+12] Frédéric Dehais et al. "Cognitive conflict in human–automation interactions: a psychophysiological study". In: *Applied ergonomics* 43.3 (2012), pp. 588–595 (cit. on pp. 2, 146, 153, 154, 178).

[Deh+14] Frédéric Dehais et al. "Failure to Detect Critical Auditory Alerts in the Cockpit Evidence for Inattentional Deafness". In: *Human Factors: The Journal of the Human Factors and Ergonomics Society* 56.4 (2014), pp. 631–644 (cit. on p. 155).

[Deh+15] Frederic Dehais et al. "Automation Surprise in Aviation: Real-Time Solutions". In: *Proceedings of the 33rd Annual ACM Conference on Human Factors in Computing Systems*. ACM. 2015, pp. 2525–2534 (cit. on pp. 2, 146, 178).

[Dia+04] M Bernardine Dias et al. "Robust multirobot coordination in dynamic environments". In: *Robotics and Automation, 2004. Proceedings. ICRA'04. 2004 IEEE International Conference on*. Vol. 4. IEEE. 2004, pp. 3435–3442 (cit. on pp. 137, 138).

[DM+06] Benedetto De Martino et al. "Frames, biases, and rational decision-making in the human brain". In: *Science* 313.5787 (2006), pp. 684–687 (cit. on pp. 19, 25, 182).

[DS] Avinash Dixit and Susan Skeath. "Games of Strategy. 1999". In: *Duncan Luce &* () (cit. on pp. 40, 183).

[DT05] Navneet Dalal and Bill Triggs. "Histograms of oriented gradients for human detection". In: *Computer Vision and Pattern Recognition, 2005. CVPR 2005. IEEE Computer Society Conference on*. Vol. 1. IEEE. 2005, pp. 886–893 (cit. on p. 130).

[Dur+14] Gautier Durantin et al. "Using near infrared spectroscopy and heart rate variability to detect mental overload". In: *Behavioural brain research* 259 (2014), pp. 16–23 (cit. on pp. 1, 146, 178).

[Dur+15] Gautier Durantin et al. “Processing functional near infrared spectroscopy signal with a Kalman filter to assess working memory during simulated flight”. In: *Frontiers in human neuroscience* 9 (2015) (cit. on pp. 144, 196).

[EAS17] EASA. *unmanned aircraft systems uas and remotely piloted aircraft systems*. 2017. URL: https://www.easa.europa.eu/unmanned-aircraft-systems-uas-and-remotely-piloted-aircraft-systems-rpas#group-easa-downloads (cit. on pp. 8, 12).

[Ech+11] Gilberto Echeverria et al. “Modular open robots simulation engine: Morse”. In: *Robotics and Automation (ICRA), 2011 IEEE International Conference on*. IEEE. 2011, pp. 46–51 (cit. on pp. 123, 189).

[ESA16] ESA. *ESA - Robotic exploration of Mars: Mars sample return*. 2016. URL: http://exploration.esa.int/mars/44995-mars-sample-return/ (cit. on pp. 9, 10).

[FO05] Alberto Finzi and Andrea Orlandini. “A mixed-initiative approach to human-robot interaction in rescue scenarios”. In: *American Association for Artificial Intelligence (www. aaai. org)* (2005) (cit. on pp. 1, 145, 146, 177).

[Fon+05] Terrence Fong et al. “The peer-to-peer human-robot interaction project”. In: 2005 (cit. on p. 82).

[Gat+16] Thibault Gateau et al. “Considering human’s non-deterministic behavior and his availability state when designing a collaborative human-robots system”. In: *Intelligent Robots and Systems (IROS), 2016 IEEE/RSJ International Conference on*. IEEE. 2016, pp. 4391–4397 (cit. on pp. 144, 196).

[GGK02] Thomas Gilovich, Dale Griffin, and Daniel Kahneman. *Heuristics and biases: The psychology of intuitive judgment*. Cambridge university press, 2002 (cit. on p. 26).

[Gia+11] Mario Gianni et al. “Awareness in Mixed Initiative Planning.” In: *AAAI Fall Symposium: Robot-Human Teamwork in Dynamic Adverse Environment*. 2011 (cit. on p. 146).

[Gon+05] Cleotilde Gonzalez et al. “The framing effect and risky decisions: Examining cognitive functions with fMRI”. In: *Journal of economic psychology* 26.1 (2005), pp. 1–20 (cit. on p. 25).

[Gon07] Cristophe Gonzales. *A tutorial on additive utility functions*. 2007. URL: http://webia.lip6.fr/~gonzales/research/tutoriel_utilite.php (cit. on pp. 30, 31).

[GT99] Gerd Gigerenzer and Peter M Todd. “Fast and frugal heuristics: The adaptive toolbox”. In: *Simple heuristics that make us smart*. Oxford University Press, 1999, pp. 3–34 (cit. on p. 26).

[GTP+12] Florian Gros, Catherine Tessier, Thierry Pichevin, et al. "Ethics and authority sharing for autonomous armed robots". In: *Autonomous Agents (RDA2) 2012* 7 (2012) (cit. on pp. 141, 192).

[HCB+13] Erik Hernández, Jaime del Cerro, Antonio Barrientos, et al. "Game theory models for multi-robot patrolling of infrastructures". In: *International Journal of Advanced Robotic Systems* 10.181 (2013) (cit. on pp. 10, 66).

[Hea99] Marti A. Hearst. "Trends & Controversies: Mixed-initiative interaction." In: *IEEE Intelligent Systems* 14.5 (1999), pp. 14–23 (cit. on pp. 13, 82).

[HG09] Benjamin Hardin and Michael A Goodrich. "On using mixed-initiative control: a perspective for managing large-scale robotic teams". In: *Proceedings of the 4th ACM/IEEE international conference on Human robot interaction*. ACM. 2009, pp. 165–172 (cit. on pp. 15, 146).

[Hoe+07] Jesse Hoey et al. "Assisting persons with dementia during handwashing using a partially observable Markov decision process". In: *Proc. Int. Conf. on Vision Systems*. Vol. 65. 2007, p. 66 (cit. on p. 146).

[Hua+04] Hui-Min Huang et al. "Autonomy measures for robots". In: *Proceedings of the 2004 ASME International Mechanical Engineering Congress & Exposition, Anaheim, California*. 2004, pp. 1–7 (cit. on p. 14).

[Hua+05] Hui-Min Huang et al. "A framework for autonomy levels for unmanned systems (ALFUS)". In: *Proceedings of AUVSI Unmanned Systems 2005* (2005) (cit. on p. 13).

[Hua07] Hui-Min Huang. "Autonomy levels for unmanned systems (ALFUS) framework: safety and application issues". In: *Proceedings of the 2007 Workshop on Performance Metrics for Intelligent Systems*. ACM. 2007, pp. 48–53 (cit. on p. 13).

[IHC11] Volkan Isler, Geoffrey A Hollinger, and Timothy H Chung. "Search and Pursuit-Evasion in Mobile Robotics, A survey". In: (2011) (cit. on p. 78).

[JA15] Shu Jiang and Ronald C Arkin. "Mixed-Initiative Human-Robot Interaction: Definition, Taxonomy, and Survey". In: *Systems, Man, and Cybernetics (SMC), 2015 IEEE International Conference on*. IEEE. 2015, pp. 954–961 (cit. on pp. 8, 15, 16).

[Jea10] Abdel-Illah Mouaddib Shlomo Zilberstein Aurélie Beynier Laurent Jeanpierre. "A Decision-Theoretic Approach to Cooperative Control and Adjustable Autonomy". In: *European Conference on Artificial Intelligence (ECAI)*. 2010 (cit. on p. 15).

[JPL17] JPL. *Mars sample return*. June 2017. URL: `https://www.jpl.nasa.gov/missions/mars-sample-return-msr/` (cit. on pp. 8, 10, 11).

[Kah11] Daniel Kahneman. *Thinking, fast and slow*. Macmillan, 2011 (cit. on pp. 20–22, 24, 25, 82).

[KH08] Derek J Koehler and Nigel Harvey. *Blackwell handbook of judgment and decision making*. John Wiley & Sons, 2008 (cit. on p. 110).

[KH93] Gary A Klein and Robert R Hoffman. "Perceptual-cognitive aspects of expertise". In: *Cognitive science foundations of instruction* (1993), pp. 203–226 (cit. on p. 27).

[Kha07] Mohammad Emtiyaz Khan. *Game theory models for pursuit evasion games*. Tech. rep. Technical report, University of British Columbia, Vancouver, 2007 (cit. on p. 66).

[KHL08] H. Kurniawati, D. Hsu, and W.S. Lee. "SARSOP: Efficient point-based POMDP planning by approximating optimally reachable belief spaces". In: *Proc. RSS*. 2008 (cit. on p. 150).

[Kle89] Gary A Klein. *Strategies of decision making*. Tech. rep. KLEIN ASSOCIATES INC YELLOW SPRINGS OH, 1989 (cit. on p. 26).

[Kle97] Gary Klein. "Developing expertise in decision making". In: *Thinking & Reasoning* 3.4 (1997), pp. 337–352 (cit. on pp. 27, 82).

[Kle99] Gary A Klein. *Sources of power: How people make decisions*. MIT press, 1999 (cit. on pp. 4, 27, 180).

[Kni12] Frank H Knight. *Risk, uncertainty and profit*. Courier Corporation, 2012 (cit. on p. 34).

[KP09] Elias Koutsoupias and Christos Papadimitriou. "Worst-case equilibria". In: *Computer science review* 3.2 (2009), pp. 65–69 (cit. on p. 136).

[KR06] Botond Kőszegi and Matthew Rabin. "A model of reference-dependent preferences". In: *The Quarterly Journal of Economics* (2006), pp. 1133–1165 (cit. on pp. 35, 37, 38, 98, 101, 107).

[KT79] Daniel Kahneman and Amos Tversky. "Prospect theory: An analysis of decision under risk". In: *Econometrica: Journal of the econometric society* (1979), pp. 263–291 (cit. on pp. 4, 33, 35, 98, 180).

[Kuh08] Max Kuhn. "Building Predictive Models in R Using the caret Package". In: *Journal of Statistical Software, Articles* 28.5 (2008), pp. 1–26 (cit. on p. 106).

[LaV06] Steven M LaValle. *Planning algorithms*. Cambridge university press, 2006 (cit. on pp. 32, 33).

[LBS08] K. Leyton-Brown and Y. Shoham. *Essentials of Game Theory:A Concise Multidisciplinary Introduction*. Morgan and Claypool, 2008, p. 88 (cit. on pp. 40, 42–44, 47, 55, 183).

[Lev+02] Irwin P Levin et al. "A new look at framing effects: Distribution of effect sizes, individual differences, and independence of types of effects". In: *Organizational behavior and human decision processes* 88.1 (2002), pp. 411–429 (cit. on p. 26).

[LKS16] Subhash R. Lele, Jonah L. Keim, and Peter Solymos. *ResourceSelection: Resource Selection (Probability) Functions for Use-Availability Data*. R package version 0.2-6. 2016 (cit. on p. 87).

[LL13] Matthieu Lesnoff and Renaud Lancelot. *aods3: analysis of overdispersed data using S3 methods*. aods3 package version 0.4-1. 2013 (cit. on p. 87).

[LSG98] I. P. Levin, S. L. Schneider, and G. J. Gaeth. "All frames are not created equal: A typology and critical analysis of framing effects". In: *Organizational behavior and human decision processes* 76.2 (1998), pp. 149–188 (cit. on pp. 25, 26, 83, 128).

[LWN08] Yuan Li, Bo Wu, and Ram Nevatia. "Human detection by searching in 3D space using camera and scene knowledge". In: *Pattern Recognition, 2008. ICPR 2008. 19th International Conference on*. IEEE. 2008, pp. 1–5 (cit. on p. 130).

[MBJ15] Olivier Masson, Jean Baratgin, and Frank Jamet. "NAO robot and the "endowment effect"". In: *Advanced Robotics and its Social Impacts (ARSO), 2015 IEEE International Workshop on*. IEEE. 2015, pp. 1–6 (cit. on p. 24).

[MCB09] Katherine L Milkman, Dolly Chugh, and Max H Bazerman. "How can decision making be improved?" In: *Perspectives on psychological science* 4.4 (2009), pp. 379–383 (cit. on p. 26).

[Men08] Yan Meng. "Multi-robot searching using game-theory based approach". In: *International Journal of Advanced Robotic Systems* 5.4 (2008), pp. 341–350 (cit. on pp. 3, 10, 66, 67, 179).

[MG92] John McMillan and Strategies Games. *Managers: How Managers Can Use Game Theory to Make better Business Decisions*. 1992 (cit. on pp. 3, 179).

[MJM+12] Laëtitia Matignon, Laurent Jeanpierre, Abdel-Illah Mouaddib, et al. "Coordinated Multi-Robot Exploration Under Communication Constraints Using Decentralized Markov Decision Processes." In: *AAAI*. 2012 (cit. on p. 3).

[MJM12] Laëtitia Matignon, Laurent Jeanpierre, and Abdel-Illah Mouaddib. "Distributed value functions for multi-robot exploration: a position paper". In: *Multi-Agent Sequential Decision Making in Uncertain Multi-Agent Domain (MSDM)(workshop of AAMAS)*. 2012 (cit. on p. 10).

[MM11] Richard Mattingly and Lisa May. "Mars sample return as a campaign". In: *Aerospace Conference, 2011 IEEE*. IEEE. 2011, pp. 1–13 (cit. on p. 10).

[Mon12] D.C. Montgomery. *Design and Analysis of Experiments, 8th Edition*. John Wiley & Sons, Incorporated, 2012 (cit. on p. 86).

[Mor+09] Carey K Morewedge et al. "Bad riddance or good rubbish? Ownership and not loss aversion causes the endowment effect". In: *Journal of Experimental Social Psychology* 45.4 (2009), pp. 947–951 (cit. on p. 24).

[Mor+15] Carey K Morewedge et al. “Debiasing decisions: Improved decision making with a single training intervention”. In: *Policy Insights from the Behavioral and Brain Sciences* 2.1 (2015), pp. 129–140 (cit. on p. 26).

[MPR09] MPRNews. *Uav pilots*. 2009. URL: `https://www.mprnews.org/story/2009/09/14/uav-pilots-grandforks` (cit. on p. 13).

[MS96] Dov Monderer and Lloyd S. Shapley. “Potential Games”. In: *Games and Economic Behavior* 14.1 (1996), pp. 124 –143 (cit. on pp. 53, 54, 71).

[MSØ03] Maja J Matarić, Gaurav S Sukhatme, and Esben H Østergaard. “Multi-robot task allocation in uncertain environments”. In: *Autonomous Robots* 14.2-3 (2003), pp. 255–263 (cit. on p. 8).

[Mur+08] Robin R Murphy et al. “Search and rescue robotics”. In: *Springer Handbook of Robotics*. Springer, 2008, pp. 1151–1173 (cit. on pp. 10, 13).

[Nag+08] Amir M Naghsh et al. “Analysis and design of human-robot swarm interaction in firefighting”. In: *Robot and human interactive communication, 2008. RO-MAN 2008. the 17th IEEE international symposium on*. IEEE. 2008, pp. 255–260 (cit. on pp. 8, 13).

[NAT95] NATO. *ATP-10(D) Manual on Search and Rescue*. North Atlantic Treaty Organization. 1995 (cit. on p. 115).

[NBV16] V Sriram Siddhardh Nadendla, Swastik Brahma, and Pramod K Varshney. “Towards the design of prospect-theory based human decision rules for hypothesis testing”. In: *Communication, Control, and Computing (Allerton), 2016 54th Annual Allerton Conference on*. IEEE. 2016, pp. 766–773 (cit. on p. 36).

[NK08] Nikhil Nigam and Ilan Kroo. “Persistent surveillance using multiple unmanned air vehicles”. In: *Aerospace Conference, 2008 IEEE*. IEEE. 2008, pp. 1–14 (cit. on p. 78).

[Ong+09] Sylvie C.W. Ong et al. “POMDPs for Robotic Tasks with Mixed Observability”. In: *Proceedings of Robotics: Science and Systems (RSS)*. 2009 (cit. on pp. 150, 151, 158).

[Ong+10] Sylvie CW Ong et al. “Planning under uncertainty for robotic tasks with mixed observability”. In: *The International Journal of Robotics Research* 29.8 (2010), pp. 1053–1068 (cit. on pp. 146, 147, 150, 151).

[Ong14] Chee S Ong. *Logistics supply of the distributed air wing*. Tech. rep. NAVAL POSTGRADUATE SCHOOL MONTEREY CA, 2014 (cit. on pp. 14, 15).

[Par08] Lynne E Parker. “Distributed intelligence: Overview of the field and its application in multi-robot systems”. In: *Journal of Physical Agents* 2.1 (2008), pp. 5–14 (cit. on pp. 10, 11).

[PDT11] Sergio Pizziol, Frédéric Dehais, and Catherine Tessier. "Towards human operator state assessment". In: *Proceedings of the 1st International Conference on Application and Theory of Automation in Command and Control Systems*. IRIT Press. 2011, pp. 99–106 (cit. on p. 157).

[Pes+00] Leonid Peshkin et al. "Learning to cooperate via policy search". In: *Proceedings of the Sixteenth conference on Uncertainty in artificial intelligence*. Morgan Kaufmann Publishers Inc. 2000, pp. 489–496 (cit. on pp. 66, 67).

[PFB10] Fabio Pasqualetti, Antonio Franchi, and Francesco Bullo. "On optimal cooperative patrolling". In: *Decision and Control (CDC), 2010 49th IEEE Conference on*. IEEE. 2010, pp. 7153–7158 (cit. on p. 66).

[PGJS14] George Philip, Sidney N Givigi Jr, and Howard M Schwartz. "Cooperative navigation of unknown environments using potential games". In: *International Journal of Mechatronics and Automation* 4.3 (2014), pp. 173–187 (cit. on p. 71).

[PR11] David Portugal and Rui Rocha. "A survey on multi-robot patrolling algorithms". In: *Technological Innovation for Sustainability*. Springer, 2011, pp. 139–146 (cit. on pp. 3, 10, 66, 68, 179).

[PR13a] David Portugal and Rui P Rocha. "Distributed multi-robot patrol: A scalable and fault-tolerant framework". In: *Robotics and Autonomous Systems* 61.12 (2013), pp. 1572–1587 (cit. on p. 66).

[PR13b] David Portugal and Rui P Rocha. "Multi-robot patrolling algorithms: examining performance and scalability". In: (2013) (cit. on pp. 66, 75).

[Put94] M.L. Puterman. *Markov decision processes: discrete stochastic dynamic programming*. John Wiley & Sons, Inc. New York, NY, USA, 1994 (cit. on p. 148).

[PY10] Sinno Jialin Pan and Qiang Yang. "A survey on transfer learning". In: *IEEE Transactions on knowledge and data engineering* 22.10 (2010), pp. 1345–1359 (cit. on pp. 144, 195).

[RN09] Stuart Jonathan Russell and Peter Norvig. *Artificial intelligence: a modern approach (3rd edition)*. 2009 (cit. on p. 30).

[Ros+08] Stéphane Ross et al. "Online planning algorithms for POMDPs". In: *Journal of Artificial Intelligence Research* 32 (2008), pp. 663–704 (cit. on pp. 144, 195).

[Ros16] Don Ross. "Game Theory". In: *The Stanford Encyclopedia of Philosophy*. Ed. by Edward N. Zalta. Winter 2016. Metaphysics Research Lab, Stanford University, 2016 (cit. on p. 121).

[Roy+16] Raphaëlle N Roy et al. "Operator Engagement During Prolonged Simulated UAV Operation". In: *IFAC-PapersOnLine* 49.32 (2016), pp. 171–176 (cit. on pp. 144, 196).

[RXH16] Peijia Ren, Zeshui Xu, and Zhinan Hao. "Hesitant Fuzzy Thermodynamic Method for Emergency Decision Making Based on Prospect Theory". In: *IEEE Transactions on Cybernetics* (2016) (cit. on p. 36).

[Rég+14] Nicolas Régis et al. "Formal Detection of Attentional Tunneling in Human Operator–Automation Interactions". In: *IEEE Transactions on Human-Machine Systems* 44.3 (2014), pp. 326–336 (cit. on pp. 25, 152, 154, 157).

[Sca+14] Davide Scaramuzza et al. "Vision-controlled micro flying robots: from system design to autonomous navigation and mapping in GPS-denied environments". In: *Robotics & Automation Magazine, IEEE* 21.3 (2014), pp. 26–40 (cit. on p. 10).

[SCD15] Paulo Eduardo Ubaldino Souza, Caroline Ponzoni Carvalho Chanel, and Frédéric Dehais. "MOMDP-based target search mission taking into account the human operator's cognitive state". In: *Tools with Artificial Intelligence (ICTAI), 2015 IEEE 27th International Conference on*. IEEE. 2015, pp. 729–736 (cit. on pp. 15, 144, 196).

[Sch+04] Jean Scholtz et al. "Evaluation of human-robot interaction awareness in search and rescue". In: *Robotics and Automation, 2004. Proceedings. ICRA'04. 2004 IEEE International Conference on*. Vol. 3. IEEE. 2004, pp. 2327–2332 (cit. on pp. 9, 13).

[Sel+06] Brennan Sellner et al. "Coordinated multiagent teams and sliding autonomy for large-scale assembly". In: *Proceedings of the IEEE* 94.7 (2006), pp. 1425–1444 (cit. on p. 146).

[Sim55] Herbert A Simon. "A behavioral model of rational choice". In: *The quarterly journal of economics* 69.1 (1955), pp. 99–118 (cit. on p. 20).

[Sim57] HA Simon. "Models of man Wiley". In: *New York* (1957) (cit. on p. 20).

[SLB08] Yoav Shoham and Kevin Leyton-Brown. *Multiagent systems: Algorithmic, game-theoretic, and logical foundations*. Cambridge University Press, 2008 (cit. on pp. 3, 40, 43, 44, 46, 54, 180, 183, 184).

[SM11] Jesus Suarez and Robin Murphy. "A survey of animal foraging for directed, persistent search by rescue robotics". In: *Safety, Security, and Rescue Robotics (SSRR), 2011 IEEE International Symposium on*. IEEE. 2011, pp. 314–320 (cit. on pp. 10, 13).

[SMT09] Nathan Schurr, Janusz Marecki, and Milind Tambe. "Improving adjustable autonomy strategies for time-critical domains". In: *Proceedings of The 8th International Conference on Autonomous Agents and Multiagent Systems-Volume 1*. International Foundation for Autonomous Agents and Multiagent Systems. 2009, pp. 353–360 (cit. on pp. 1, 145, 146, 177).

[SS05] T. Smith and R.G. Simmons. "Point-Based POMDP Algorithms: Improved Analysis and Implementation". In: *Proc. UAI*. 2005 (cit. on p. 150).

[SS16] Katie Steele and H. Orri Stefánsson. “Decision Theory”. In: *The Stanford Encyclopedia of Philosophy*. Ed. by Edward N. Zalta. Winter 2016. Metaphysics Research Lab, Stanford University, 2016 (cit. on pp. 30, 31).

[SS73] R.D. Smallwood and E.J. Sondik. “The optimal control of partially observable Markov processes over a finite horizon”. In: *Operations Research* (1973), pp. 1071–1088 (cit. on pp. 147, 149, 150).

[SST03] Nathan Schurr, Paul Scerri, and Milind Tambe. “Impact of human advice on agent teams: A preliminary report”. In: *Workshop on Humans and Multi-Agent Systems at AAMAS*. 2003 (cit. on pp. 1, 145, 177).

[Suh07] Niko Suhonen. “Normative and descriptive theories of decision making under risk: A short review”. In: *Joensuu, Finland: University of Eastern Finland* (2007) (cit. on p. 20).

[Tal07] Nassim Nicholas Taleb. *The black swan: The impact of the highly improbable*. Vol. 2. Random house, 2007 (cit. on p. 58).

[TBF05] Sebastian Thrun, Wolfram Burgard, and Dieter Fox. *Probabilistic robotics*. MIT press, 2005 (cit. on p. 56).

[TD12] Catherine Tessier and Frédéric Dehais. “Authority Management and Conflict Solving in Human-Machine Systems.” In: *AerospaceLab* 4 (2012), p–1 (cit. on pp. 15, 144, 196).

[TG00] Peter M Todd and Gerd Gigerenzer. “Précis of simple heuristics that make us smart”. In: *Behavioral and brain sciences* 23.05 (2000), pp. 727–741 (cit. on pp. 20, 26).

[Thr+04] Sebastian Thrun et al. “Autonomous exploration and mapping of abandoned mines”. In: *Robotics & Automation Magazine, IEEE* 11.4 (2004), pp. 79–91 (cit. on pp. 1, 145, 177).

[TK75] Amos Tversky and Daniel Kahneman. “Judgment under uncertainty: Heuristics and biases”. In: *Utility, probability, and human decision making*. Springer, 1975, pp. 141–162 (cit. on pp. 22–24).

[TK81] Amos Tversky and Daniel Kahneman. “The framing of decisions and the psychology of choice”. In: *Science* 211.4481 (1981), pp. 453–458 (cit. on pp. 24, 25).

[TK86] Amos Tversky and Daniel Kahneman. “Rational choice and the framing of decisions”. In: *Journal of business* (1986), S251–S278 (cit. on p. 98).

[TK92] Amos Tversky and Daniel Kahneman. “Advances in prospect theory: Cumulative representation of uncertainty”. In: *Journal of Risk and uncertainty* 5.4 (1992), pp. 297–323 (cit. on pp. 4, 24, 35, 36, 98, 180).

[TL09] Stelios Timotheou and Georgios Loukas. “Autonomous networked robots for the establishment of wireless communication in uncertain emergency response scenarios”. In: *Proceedings of the 2009 ACM symposium on Applied Computing*. ACM. 2009, pp. 1171–1175 (cit. on p. 8).

[TMD11] Tarek Taha, Jaime Valls Miró, and Gamini Dissanayake. “A POMDP framework for modelling human interaction with assistive robots”. In: *Robotics and Automation (ICRA), 2011 IEEE International Conference on*. IEEE. 2011, pp. 544–549 (cit. on p. 146).

[Tsu+11] Akira Tsuchiyama et al. “Three-dimensional structure of Hayabusa samples: origin and evolution of Itokawa regolith”. In: *Science* 333.6046 (2011), pp. 1125–1128 (cit. on p. 9).

[TW04] Lisa C Thomas and Christopher D Wickens. “Eye-tracking and individual differences in off-normal event detection when flying with a synthetic vision system display”. In: *Proceedings of the Human Factors and Ergonomics Society Annual Meeting*. Vol. 48. 1. SAGE Publications. 2004, pp. 223–227 (cit. on p. 154).

[USA17] USAF. *MQ-9 reaper*. 2017. URL: `http://www.af.mil/About-Us/Fact-Sheets/Display/Article/104470/mq-9-reaper/` (cit. on pp. 12, 13).

[Van14] Frédéric Vanderhaegen. “Dissonance engineering: a new challenge to analyse risky knowledge when using a system”. In: *International Journal of Computers Communications & Control* 9.6 (2014), pp. 776–785 (cit. on pp. 2, 178).

[Vin+08] Regis Vincent et al. “Distributed multirobot exploration, mapping, and task allocation”. In: *Annals of Mathematics and Artificial Intelligence* 52.2 (2008), pp. 229–255 (cit. on pp. 1, 10, 177).

[VMK12] Jeroen JG Van Merriënboer and Paul A Kirschner. *Ten steps to complex learning: A systematic approach to four-component instructional design*. Routledge, 2012 (cit. on p. 110).

[VNM07] John Von Neumann and Oskar Morgenstern. *Theory of games and economic behavior*. Princeton university press, 2007 (cit. on pp. 32, 33, 40, 51, 183).

[WD96] Peter Wakker and Daniel Deneffe. “Eliciting von Neumann-Morgenstern utilities when probabilities are distorted or unknown”. In: *Management science* 42.8 (1996), pp. 1131–1150 (cit. on p. 37).

[Wil04] Kevin W Williams. *A summary of unmanned aircraft accident/incident data: Human factors implications*. Tech. rep. DTIC Document, 2004, p. 18 (cit. on pp. 2, 146, 178).

[Wol04] David Wolpert. “Theory of collective intelligence”. In: *Collectives and the design of complex systems*. Springer, 2004, pp. 43–106 (cit. on p. 54).

[WVO12] Marco Wiering and Martijn Van Otterlo. "Reinforcement learning". In: *Adaptation, Learning, and Optimization* 12 (2012) (cit. on pp. 3, 179).

[XZZ11] Songdong Xue, Jianchao Zeng, and Guoyou Zhang. "A review of autonomous robotic search". In: *Electrical and Control Engineering (ICECE), 2011 International Conference on*. IEEE. 2011, pp. 3792–3795 (cit. on pp. 10, 13).

[Zha16] Guofeng Zhang. "Comparison of Decision-Making Mechanism between Emotion Behavior Selection and Prospect Theory". In: *Intelligent Human-Machine Systems and Cybernetics (IHMSC), 2016 8th International Conference on*. Vol. 1. IEEE. 2016, pp. 538–540 (cit. on p. 36).

[ZK15] Muhong Zhang and Derek Kingston. "Time-space network based exact models for periodical monitoring routing problem". In: *American Control Conference (ACC), 2015*. IEEE. 2015, pp. 5264–5269 (cit. on p. 66).

[ZPV11] Stéphane Zieba, Philippe Polet, and Frédéric Vanderhaegen. "Using adjustable autonomy and human–machine cooperation to make a human–machine system resilient–Application to a ground robotic system". In: *Information Sciences* 181.3 (2011), pp. 379–397 (cit. on p. 15).

Résumé — L'interaction homme-robot est un domaine qui en est encore à ses balbutiements. Les développements se sont avant tout concentrés sur l'autonomie et l'intelligence artificielle et doter les robots de capacités avancées pour exécuter des tâches complexes. Dans un proche avenir, les robots développeront probablement la capacité de s'adapter et d'apprendre de leur environnement. Les robots ont confiance, ne s'ennuient pas et peuvent fonctionner dans des environnements hostiles et dynamiques - tous des attributs souhaités à l'exploration spatiale et aux situations d'urgence ou militaires. Ils réduisent également les coûts de mission, augmentent la flexibilité de conception et maximisent la production de données. Cependant, lorsqu'ils sont confrontés à de nouveaux scénarios et à des événements inattendus, les robots sont moins performants par rapport aux êtres humains intuitifs et créatifs (mais aussi faillibles et biaisés). L'avenir exigera que les concepteurs de mission équilibrent intelligemment la souplesse et l'ingéniosité des humains avec des systèmes robotiques robustes et sophistiqués. Ce travail de recherche propose un cadre formel, basé sur la théorie de jeux, pour une équipe de drones qui doit coordonner leurs actions entre eux et fournir à l'opérateur humain des données suffisantes pour prendre des décisions « difficiles » qui maximisent l'efficacité de la mission, selon certaines directives opérationnelles. Notre première contribution a consisté à présenter un cadre décentralisé et une fonction d'utilité pour une mission de patrouille avec une équipe de drones. Ensuite, nous avons considéré l'effet de cadrage, ou « framing effect » en anglais, dans le contexte de notre étude, afin de mieux comprendre et modéliser à terme certains processus décisionnels sous incertitude. Ainsi, nous avons réalisé deux expérimentations avec 20 et 12 participants respectivement. Nos résultats ont révélé que la façon dont le problème a été présenté (effet de cadrage positif ou négatif), l'engagement émotionnel et les couleurs du texte ont affecté statistiquement les choix des opérateurs humains. Les données expérimentales nous ont permis de développer un modèle d'utilité pour l'opérateur humain que nous cherchons à intégrer dans la boucle décisionnelle du système homme-robots. Enfin, nous formalisons et évaluons l'ensemble du cadre proposé où nous "fermons la boucle" à travers une expérimentation en ligne avec 101 participants. Nos résultats suggèrent que notre approche permet d'optimiser le système homme-robots dans un contexte où des décisions doivent être prises dans un environnement incertain.

Mots clés : Initiative mixe, Planification décentralisée, Système multi-robot, Théorie de jeux, Théorie des perspectives, Interaction homme-robot, Facteur humain, Effet de cadrage.

Abstract — Human-robot interaction is a field that is still in its infancy. Developments have focused on autonomy and artificial intelligence, and provide robots with advanced capabilities to perform complex tasks. In the near future, robots will likely develop the ability to adapt and learn from their surroundings. Robots have reliance, do not get bored and can operate in hostile and dynamics environments - all attributes well suited for space exploration, and emergency or military situations. They also reduce mission costs, increase design flexibility, and maximize data production. However, when coped with new scenarios and unexpected events, robots pale in comparison with intuitive and creative human beings. The future will require that mission designers balance intelligently the flexibility and ingenuity of humans with robust and sophisticated robotic systems. This research work proposes a game-theoretic framework for a drone team that must coordinate their actions among them and provide the human operator sufficient data to make "hard" decisions that maximize the mission efficiency, according with some operational guidelines. Our first contribution was to present a decentralized framework and utility function for a drone-team patrolling mission. Then, we considered the framing effect in the context of our study, in order to better understand and model certain human decision-making processes under uncertainty. Hence, two experiments were conducted with 20 and 12 participants respectively. Our findings revealed that the way the problem was presented (positive or negative framing), the emotional commitment and the text colors statistically affected the choices made by the human operators. The experimental data allowed us to develop a utility model for the human operator that we sought to integrate into the decision-making loop of the human-robot system. Finally, we formalized and evaluated the close-loop of the whole proposed framework with a last online experiment with 101 participants. Our results suggest that our approach allow us to optimize the human-robot system in a context where decisions must be made in an uncertain environment.

Keywords: Mixed initiative, decentralized planning, Human-robot interaction, Multi-robot system, Game theory, Prospect theory, Human factor, Framing effect.

Institut Supérieur de l'Aéronautique et de l'Espace,
Université de Toulouse,
Toulouse

Résumé en français

Introduction

Le champ de l'interaction humain-robot (HRI) est encore à ses débuts. Dans le passé récent, nous avons vu la transformation des robots en agents artificiels autonomes capables d'exécuter des tâches de plus en plus complexes. Dans le futur, les robots probablement développeront la capacité d'apprentissage et d'adaptation vis-à-vis de leur environnement.

Les robots peuvent réaliser des tâches dangereuses, ennuyeuses et/ou en environement contaniné. Ils sont fiables, ne s'ennuient pas et peuvent fonctionner dans des environnements hostiles et dynamiques - tous attributs souhaités et bien adaptés pour l'exploration spatiale et pour les situations d'urgence ou militaires. Ils permettent également de réduire les coûts de mission, d'accroître la flexibilité de conception, et de maximiser la production de données. En outre, les systèmes multi-robots (MRS) peuvent potentiellement offrir plusieurs avantages par rapport aux systèmes avec un seul robot, à savoir la vitesse, la précision et la robustesse [Bur+00]; [Bur+05]; [Vin+08].

D'autre part, face à des événements imprévus, les robots ne peuvent pas être comparés aux êtres humains qui sont intuitifs et créatifs. Par exemple, les commandants militaires et les premiers intervenants sont souvent tenus de prendre de décisions dans des conditions où les informations sont limitées, incomplètes ou ambiguës, et sous pression temporelle. Ces experts peuvent prendre en charge des situations qui menacent la vie d'autres humains et décider comment utiliser leurs équipages et actifs d'une manière très efficace. Toutefois, dans ces situations, ils doivent travailler dans des conditions très difficiles, et sont soumis à la fatigue cognitive et physique, qui peut conduire à une réduction de la conscience de la situation et de la qualité de leurs décisions. Ainsi, l'avenir requerra un équilibre intelligent entre la flexibilité et la créativité humaine, et les systèmes robotiques robustes et sophistiqués.

Néanmoins, en ce qui concerne l'interactions humain-robot, il n'est pas facile de concevoir un cadre robuste et efficace. Récemment, la plupart des efforts scientifiques et techniques ont mis l'accent sur la mise en œuvre des capteurs intelligents, sur les systèmes embarqués complexes et sur l'autonomie décisionnelle pour améliorer l'efficacité des robots [Thr+04], particulièrement lorsque l'opérateur humain ne peut pas analyser ou accéder les données visuelles [Thr+04]; [SMT09]; [FO05]; [CM03]. Cependant, ces développements ont été généralement concretisés sans remettre en question l'intégration des opérateurs humains dans la boucle de décision ou contrôle [SST03]: l'opérateur humain est considéré comme un agent providentiel qui sera en mesure de prendre en charge le système lorsque les capteurs ou les automatismes échouent [CM03]; [FO05]; [SMT09]. En outre, la mauvaise conception de l'interface utilisateur, la complexité de l'automatisme et l'haute pression de la tâche peuvent dégrader la performance de l'opérateur humain si la charge mentale dépasse sa capacité cognitive [Dur+14]. Par exemple, une conception négligente du partage du pouvoir décisionnel dans tels systèmes peut conduire à des conflits entre l'humain et l'automatisme lorsque l'opérateur humain ne comprends pas bien le comportement de l'automatisme [Deh+05]; [Deh+15]. L'apparition d'une telle situation est critique tant qu'elle peut provoquer: une dissonance cognitive (une information contradictoire peut produire un inconfort, causé par les cognitions ou connaissances conflictuelles qui contrôlent ou affectent les comportements et les attitudes) [Van14]; une « confusion mentale » (i.e. l'opérateur humain est incapable de localiser et de traiter les paramètres pertinents) [Deh+15]; ou encore, la « tunnelisation attentional » (i.e. l'opérateur humain est excessivement concentrée sur un seul écran) [DCT11] cédant aux comportements irrationnels [Deh+12]. Sans surprise, un rapport d'analyse de sécurité [Wil04] a révélé que des problèmes de facteurs humains ont été impliqués dans 80% des accidents. Cette tendance a conduit Cummings et Mitchell à déclarer: *à cause du croissant nombre de capteurs, du volume d'information et des exigences opérationnelles qui se produiront naturellement dans un environnement de contrôle des véhicules multiples, des demandes cognitives excessives seront probablement imposées aux opérateurs*. En conséquence, l'allocation efficace de l'attention entre un ensemble de tâches dynamiques sera essentielle, à la fois pour la performance humaine, et pour la performance du système [CM08].

Une voie prometteuse pour traiter ces questions est de considérer que les capacités des robots et la capacité des humains sont complémentaires, et sont susceptibles d'offrir une meilleure performance lorsqu'ils collaborent efficacement que lorsqu'ils sont utilisés séparément. Cette approche, connue sous le nom d'interaction à initiative mixte (MII) [AGH99]; [AC+04] est au cœur de cette thèse de doctorat. Précisément, nous allons concentrer notre intérêt sur la prise de décision pour les robots et pour les humains.

Description du problème

Cette thèse porte sur le problème de la proposition d'un cadre robuste pour une équipe de robots aériens (aussi connus comme drones) qui doivent coordonner leurs actions entre eux, et fournir des données suffisantes à l'opérateur humain (HO) qui devra prendre de décisions critiques. Ces décisions (robotique et/ou humaines) doivent maximiser l'efficacité de la mission, le tout en respectant les consignes opérationnelles (voir Fig. R.1).

.

A ce titre, cette thèse répond à un double objectif: prendre soin de l'efficacité de l'équipe humain-robot (nous l'appellerons *perspective robotique*), et améliorer le processus de décision humaine dans ce contexte opérationnel (*perspective humaine*).

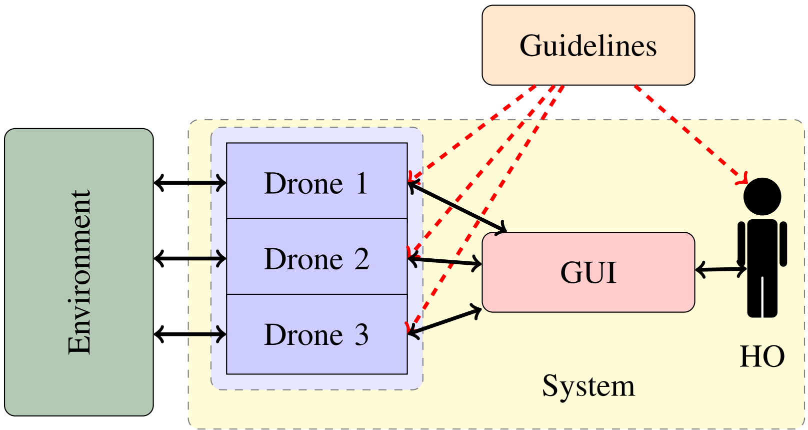


Figure R.1 : Architecture du cadre proposé.

Énoncé de la thèse

Dans cette thèse, nous considérons le problème de la conception de fonctions d'utilité des agents, un système multi-robots (MRS) et un opérateur humain (HO) (faillible et émotionnel), de sorte qu'ils travaillent de façon synergique pour maximiser une utilité global du système.

Ainsi, l'approche que nous avons considéré dans un premier temps a été d'utiliser le processus de décision markovien partiellement observable décentralisé (Dec-(PO)MDP), une extension du POMDP pour représenter des problèmes de coordination multi-agents. Les Dec-POMDPs ont été largement utilisés dans la communauté de l'intelligence artificielle (AI) comme un moyen d'aborder différences fondamentales dans la prise de décision décentralisée dans environnements incertains et partiellement observables [WVO12]; [Ama+13]. [Ama+14] déclare que tout problème où plusieurs robots partagent une seule récompense globale ou fonction de coût peut être formalisé comme Dec-POMDP. En ce sens, un solveur Dec-POMDP pourrait générer des stratégies pour les problèmes de contrôle décentralisés en présence de l'incertitude dans la position, dans les capteurs et dans des informations sur les coéquipiers. Malheureusement, cette généralité a un coût: les Dec-POMDP sont généralement dificiles à résoudre, sauf dans les cas où les problèmes considérés sont très petits [Ber+02]; [AKK14]. Cela signifie que la mise à jour de l'état de chaque agent à chaque étape de décision serait trop coûteuse en termes de calcul et mémoire et, donc, peu pratique dans les scénarios réalistes [Men08]; [PR11].

Comme [MG92] a déclaré: *les situations stratégiques de la vie réelle sont souvent extrêmement compliquées. La théorie des jeux fournit un modèle pour gérer cette complexité.* Nous avons donc décidé d'utiliser l'approche de la théorie des jeux, qui est une façon élégante de modéliser un processus de prise de décision d'un agent (un joueur) sur la base des décisions des autres agents, d'une manière décentralisée et distribuée. Un jeu implique multiples et parfois différents types de joueurs qui agissent dans l'incertitude fondée sur de vues partielles du monde. Dans un jeu, chaque joueur choisit une option (en parallèle ou séquentiellement) basée uniquement sur des informations observables au niveau local, ce qui résulte en un gain en temps de calcul immédiat [SLB08].

Dans la perspective robotique, afin d'améliorer la performance globale, d'abord nous avons conçu des jeux asynchrones, dans lesquels le jeu se produit lorsqu'un drone est disponible pour jouer, indépendamment de la situation des autres joueurs; ensuite, au lieu de jouer un jeu à chaque stade temporel, notre approche utilise des *macro-actions* (i.e. le jeu se produit lorsqu'un drone conclut sa tâche en cours), ce qui peut être considéré comme une modélisation simple et efficace pour les systèmes réels.

L'interaction entre les drones et l'HO est aussi un jeu, dans lequel la fonction de gain (ou d'utilité) de l'agent humain est estimée par les drones. Cependant, la nature de la prise de décision humaine est extrêmement complexe, donc, notre approche, dans la perspective humaine, est fondée sur la théorie des perspectives (PT) [KT79]; [TK92], et sur le cadre de la prise de décision Naturaliste (NDM[3]) [Kle99]. En ce sens, nous ne considérons pas l'HO comme un décideur (DM) sans faille et rationnel qui peut décider avec cohérence logique, quelle que soit la manière dont les options sont présentées. Toutefois, au lieu de tenter de *guérir* l'HO en lui permettant d'avoir une pensée logique et claire, ce qui consomme du temps et requiert des informations complètes (qui ne sont pas toujours disponibles), nous nous reposons sur la façon intuitive (et émotionnelle) humaine de penser, pour amener l'HO à agir en tant qu'expert et prendre la meilleure décision possible sous incertitude et sous la pression du temps.

Présentation de thèse

Cette thèse est divisée en deux parties. Dans la première partie, nous présentons une revue de la littérature pour modéliser notre système proposé: le chapitre 1 présente les théories sur l'interaction humain-robot, et certains cas réels où les robots fonctionnent en situations dangereuses, ennuyeuses ou en environement contaminés. Ensuite, dans le chapitre 2 nous présentons le processus de prise de décision humaine, en décrivant la théorie des heuristiques et biais, en particulier l'effet de cadrage, ainsi que le cadre décisionnel naturaliste. Le chapitre 3 est consacré à une révision générale, notamment à propos de la théorie de l'utilité et de la théorie des perspectives, ce qui aidera à comprendre et à corréler des concepts présentés plus loin dans ce manuscrit. Finalement, le chapitre 4 présente les définitions essentielles sur la théorie des jeux utilisées dans cette thèse.

La deuxième partie présente les contributions de cette thèse: au chapitre 5 nous présentons une fonction d'utilité décentralisée pour coordonner une équipe de drones; Dans le chapitre 6, nous présentons le rôle de l'opérateur humain dans l'équipe, et une expérience portant sur l'effet

[3]Naturalistic decision making

de cadrage dans le contexte de mission étudié; les données produites dans cette expérience sont utilisées pour estimer une function d'utilité de l'opérateur humain au chapitre 7; et enfin, dans le chapitre 8, nous mettons le tout ensemble (nous fermons la boucle), en formalisant et en évaluant le système complet.

PARTIE I - Etat de l'art

CHAPITRE 1 – Les robots « 3D »

La sécurité humaine est une des plus grandes préoccupations dans la société moderne, ainsi, les tâches ennuyeuses, dangereuses et celles réalisés en environment contaminé (3D[4]) ont été progressivement transférées aux robots. Ce chapitre a été consacré à décrire notre vision des robots « 3D » et à présenter certaines missions de MRS qui ont motivé nos expériences. Ceci illustre la proposition qui ressort de cette thèse.

D'abord, nous avons énoncé des recherches et des initiatives impliquant des robots en missions SAR et en missions de retour d'échantillons. Ensuite, nous avons introduit les MRS, les différents types d'interactions entre les coéquipiers robotiques et les défis pour changer le paradigme traditionnel des n opérateurs pour 1 robot à un nouveau paradigme de 1 opérateur (ou peu d'opérateurs) pour n robots. En ce sens, nous avons brièvement décrit l'opération du drone RPAS MQ-9 Reaper en cours à l'USAF[5]. Ensuite, nous avons présenté l' ALFUS, un cadre pour ajustements dynamiques des niveaux d'autonomie, et la catégorisation des modes d'initiative. Enfin, nous avons défini l'intéraction à initiative-mixte (MII[6]) et l'initiative-mixte pour l'interaction homme-robot (MI-HRI), cadres où les humains et les agents artificiels peuvent collaborer en tant que pairs dans une équipe efficace. Ces concepts ont été utilisés dans nos études comme des objectifs principaux à poursuivre. Dans la suite de ce document, nous aborderons les théories sur le processus de prise de décision humaine.

CHAPITRE 2 – Le facteur « H »

La prise de décision est une question cruciale pour la coopération entre humains et robots dits intelligents. D'une part, certaines théories de prise de décision affirment que nombreux biais cognitifs affectent les jugements humains, ce qui donne lieu à des décisions non optimales ou irrationnelles, et ont la tendance de mettre l'accent sur l'utilisation des processus analytiques

[4]Dirty, dull, or dangerous
[5]United States Air Force
[6]Mixed-initiative interaction

pour guider les décisions humaines. D'autre part, d'autres théories font valoir que les réponses intuitives et émotionnelles peuvent jouer un rôle décisif dans le processus de prise de décision humain dans les conditions d'information limitées et de contraintes de temps [DM+06].

Dans ce context, ce chapitre décrit comment le processus de prise de décision humaine est théorisé. Ensuite, nous nous sommes concentrés sur les théories descriptives, la théorie de double processus et la théorie des heuristiques et biais. Dans le cadre de cette dernière théorie, nous avons présenté deux biais cognitifs explorés dans notre étude: l'aversion à la dépossession et l'effet de cadrage. Enfin, nous avons décrit le cadre decisionel naturaliste (NDM) et ses hypothèses.

Dans cette thèse, au lieu de tenter d'enlever les biais naturels du comportement humain lors de décisions, notre approche explore l'effet de cadrage afin de permettre aux novices d'agir et de décider comme les experts, en conduisant les premiers à répéter les modèles et les stratégies utilisées par les derniers, grâce à la manipulation de la façon dont l'information est présentée.

Nous aborderons dans le chapitre 3 les modèles normatifs formels dans la théorie de décision, comme la théorie de l'utilité espérée (EUT), et à la fin, la théorie des perspectives (PT), un modèle descriptif proposant une alternative à l'EUT.

CHAPITRE 3 – Les décisions et les utilités

Dans cette thèse, nous avons considéré les situations où les robots et les humains doivent prendre des décisions critiques dans des conditions incertaines. Comme montrent les chapitres précédents, les robots peuvent ne pas s'adapter aux nouvelles situations (n'ayant pas été modélisées ou connues a priori) et les HO peuvent éprouver biais de décision. Nous avons donc identifié le besoin de définir un cadre formel pour optimiser la prise de décision de l'équipe humain-robot dans de telles circonstances. Le but de ce chapitre est de présenter le champ des théories de décision qui pourraient être appliquées à un tel problème.

Ainsi, ce chapitre décrit les situations où un décideur DM rationnel choisit parmi plusieurs options (théorie de décision – DT[7]) en fonction de leurs préférences (théorie de l'utilité), mettant en évidence l'utilité additive séparable. Ensuite, nous avons fourni les fondements de la théorie de l'utilité espérée (EUT), qui est adressée à l'analyse des choix en situations de risque. Après, nous avons parlé des décisions en situations d'incertitude (théorie de l'utilité subjective – SEU). Et, enfin, nous avons présenté la théorie des perspectives (PT), qui décrit comment les gens décident en situation d'incertitude dans la vie réelle. Ces théories ouvriront la voie aux chapitres suivants.

Dans la suite de ce document, nous nous concentrerons dans les problèmes qui impliquent

[7] Decision theory

plusieurs décideurs (DM), dans lesquels les décisions de chaque membre incident sur le résultat des décisions des autres, c'est-à-dire, la théorie des jeux.

CHAPITRE 4 – Je veux jouer à un jeu...

Ce chapitre décrit la théorie des jeux (GT), c'est-à-dire comment modéliser les problèmes qui impliquent plus qu'un décideur (DM), en se concentrant sur la prise d'une seule décision en présence d'autres décideurs qui influencent le résultat. L'objectif est de fournir, au lecteur non familiarisé, une base de connaissances sufficante sur la GT, afin que celui-ci puisse comprendre notre approche.

Il est important de préciser que ce chapitre ne vise pas à être un aperçu exhaustif de la GT. Il existe une énorme literature qui offre une excellente introduction à la GT (par exemple [SLB08]; [LBS08]; [VNM07]). En bref, la GT est une théorie mathématique conçue pour modéliser les phénomènes qui peuvent être observés lorsque deux ou plusieurs décideurs rationnels interagissent les uns avec les autres. Un DM est considéré comme rationnel s'il choisit ses actions afin de maximiser sa satisfaction, son bonheur, modélisées par une fonction d'utilité. La théorie des jeux est un outil intéressant pour comprendre comment les décisions affectent les joueurs [Bar02]. [DS] a déclaré trois types d'usage pour la GT:

- *Explication* - lorsque la situation implique l'interaction de décideurs ayant des objectifs différents, la GT fournit la clé pour comprendre la situation et explique pourquoi cela est arrivé.
- *Prévision* - quand on regarde des situations à l'avenir où plusieurs décideurs interagiront stratégiquement, il est possible d'utiliser la GT pour prévoir quelles sont les décisions qu'ils prendront et quels résultats seront obtenus.
- *conseils ou ordonnance* - la GT peut aider un participant d'une interaction future et lui indiquer quelles stratégies sont susceptibles de donner de bons résultats et quelles sont celles susceptibles de conduire à une catastrophe. Lors de sa création, la GT a attiré peu d'attention (documents anciens remontent au 18ème siècle). Cependant, le mathématicien John von Neumann a changé cette situation, et, en 1944, avec l'économiste Oscar Morgenstern, a publié le classique « La théorie des jeux et comportement économique » [VNM07]. Ainsi, la GT a envahi l'économie et les mathématiques appliquées.

Actuellement, la GT est utilisée pour étudier des sujets tels que les ventes aux enchères, l'équilibre du pouvoir, l'évolution génétique, la science politique, la psychologie, des études linguistiques, la sociologie, etc. [LBS08]; [Bar02]. Cependant, GT est étudiée principalement dans ses aspects mathématiques purs. Dans des applications, elle est utilisée comme un outil qui aide à la compréhension des systèmes plus complexes (par exemple, les systèmes multi-agents, la communication réseau) [SLB08].

Dans ce chapitre nous avons décrit quelques concepts clés de théorie des jeux (GT) que nous avons utilisé pour modéliser les interactions entre nos agents (joueurs) dans notre cadre d'application.

Dans le chapitre 5, l'interaction entre les drones est modélisée comme un jeu non-coordonné répété (ACG). Nous avons montré que le choix de modélisation nous permet de définir une utilité dite « wonderful life utility » (WLU[8]). Ceci, nous permet de traiter l'intéraction entre les drones en tant qu'un jeu potentiel.

Dans le chapitre 8 nous avons défini un jeu stochastique, dans lequel chaque jeu (chaque instant de décision) est considéré comme un jeu contre nature (GAN). Ceci est l'approche choisi pour la séléction d'un modèle (d'un pattern) de recherche; et pour l'interaction homm-drones nous avons utilisé un jeu fictif, basé sur la fontion d'utilité humaine proposée au chapitre 7, et apprise à partir de données colléctées dans l'étude présentée dans le chaptitre 6, pour concevoir un jeu séquentiel de type haut vers le bas « high-low » (HLG).

PARTIE II - Contributions

Dans la première partie de ce manuscrit, nous avons introduit les technologies de l'état de l'art en robotique pour des tâches « 3D » (ennuyeuses ou dangereuses, en environement contaminé), et nous avons présenté les concepts utilisés pour formuler notre approche. Ainsi, cette deuxième partie, est consacrée aux résultats de nos recherches et nos contributions.

CHAPITRE 5 – Le problème de la patrouille

Ce chapitre présente l'étude réalisée pour concevoir une fonction d'utilité heuristique utilisée par une équipe de drones dans une mission de patrouille. Les résultats de ce travail ont été présentés dans un papier de conférence intitulé (« *A Game Theoretical Formulation of a Decentralized Cooperative Multi-Agent Surveillance Mission* ») dans le *Workshop on Distributed and Multi-Agent Planning (DMAP) 2016*.

L'étude présentée s'agit de la coordination de plusieurs robots volants (drones) basée sur la théorie des jeux, pour effectuer une mission de surveillance dans un environnement bien structuré (Fig. R.2). Cette mission consistait à visiter périodiquement un ensemble de points d'intérêt tout en minimisant l'intervalle de temps entre les visites successives (oisiveté).

[8]Wonderful life utility

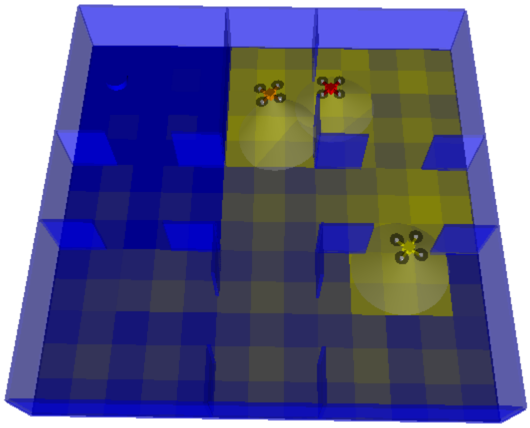


Figure R.2 : Modèle géométrique.

Les résultats ont démontré que l'approche proposée a optimisé la sélection des actions des agents basée sur un cadre N-joueur. Les contributions principales sont:

- CR-1 - la formulation originelle de la fonction d'utilité de chaque joueur, composé de trois paramètres indépendants des choix d'action d'autres joueurs;
- CR-2 - la démonstration que la solution du jeu est un *équilibre Nash* (NE), et que cet équilibre peut être obtenu en optimisant séparément et individuellement le choix de action des joueurs. Cet-à-dire que nous retrouvons la solution d'un *jeu potentiel*;
- CR-3 - la proposition d'un algorithme décentralisé utilisé pour réaliser la mission, qui prend en compte une communication minimale entre les joueurs.

Dans ce chapitre, une fonction d'utilité heuristique originale a été présenté, où non seulement le coût de déplacement a été considéré, mais aussi les positions actuelles des autres joueurs et la dernière fois depuis chaque point d'intérêt a été visité. Et, à partir de cette fonction d'utilité, un jeu anti-coordination (ACG) a été générée, où la solution NE guide le comportement du joueur vers le but de l'équipe.

Les simulations ont évalués les différentes politiques obtenues, qui ont été comparées utilisant comme indicateur l'*oisiveté moyenne* de tous les points d'intérêt (POI). Le cadre proposé a permis la diminution de l'oisiveté des POIs par rapport à sélection d'action aléatoire, tout en gardant une sorte de mouvement aléatoire (mesurée par un indicateur de *prévisibilité*). Cette qualité pourrait être souhaitable afin de limiter la possibilité de prédiction de la stratégie de surveillance de l'équipe par un intrus.

De cette façon, nous avons conclu cette étude sur le *jeu de mouvement* pour une mission de patrouille. Dans le chapitre suivant nous présentons la première étape pour mettre un opérateur humain dans l'équipe de drone. Nous avons observé comment les participants, d'une expérience menée dans notre laboratoire, ont réagi (ont décidé) en fonction de la façon dont le problème a été présenté, et en particulier, leur implication émotionnelle dans la situation qui a été décrite.

CHAPITRE 6 – L'effet de cadrage

Dans le Chapitre 5 nous avons présenté un algorithme décentralisé pour une équipe de drone de patrouille autonome. Cependant, il y a des missions qui, pour des raisons éthiques ou opérationnelles, il est obligatoire d'avoir un être humain dans la boucle, travaillant en équipe avec les robots.

Cependant, la prise de décision est une question cruciale pour les humains qui coopèrent avec les robots intelligents. En plus, il est bien admis que nombreux biais cognitifs affectent les jugements humains, conduisant à des décisions irrationnelles ou non optimales. L'effet de cadrage (FE[9]) est un biais cognitif typique qui amène les gens à réagir différemment en fonction du contexte, la probabilité des résultats et la façon dont le problème est présenté (perte ou gain) (ceci a été décrit plus en détail dans le Chapitre 2).

Dans ce chapitre nous présentons les résultats des expériences menées en laboratoire sur le effet de cadrage. Ces expériences ont été réalisées afin de mieux comprendre les effets de ce biais cognitif dans le contexte opérationnel étudié. Cette étape est essentielle pour optimiser les interactions humain-robot (HRI). Les résultats obtenus ont été présentés dans le papier de conférence *« Vers l'interaction homme-robot: une expérience d'effet de cadrage »* présenté à la *Conférence internationale IEEE sur Systèmes, Homme et Cybernétique (SMC 2016).*

Nous avons mené l'expérience sur l'effet de cadrage dans le contexte d'une mission de recherche et sauvetage (lors d'un tremblement terre) et dans le contexte d'une mission de retour des échantillons de Mars. L'interface graphique (voir Fig. R.3) été commune aux deux scénarios. Nous avons manipulé le cadrage (positif ou négatif), la probabilité des résultats dans une première expérience, et les couleurs de texte (cadrage visuel) dans une deuxième expérience.

Nous avons recueilli 1982 observations de 20 sujets dans la première expérience et 240 observations de 12 participants dans la deuxième expérience. Nos résultats ont révélé que la façon dont le problème a été présenté (positivement ou négativement encadré), l'engagement émotionnel (sauver des vies par rapport collecter le bon échantillon), et les couleurs de texte ont affecté statistiquement les choix effectués par les opérateurs humains.

Les principales contributions de cette étude étaient:

- CH-4 - l'observation de l'effet de cadrage dans ce contexte;

[9] Framing effect

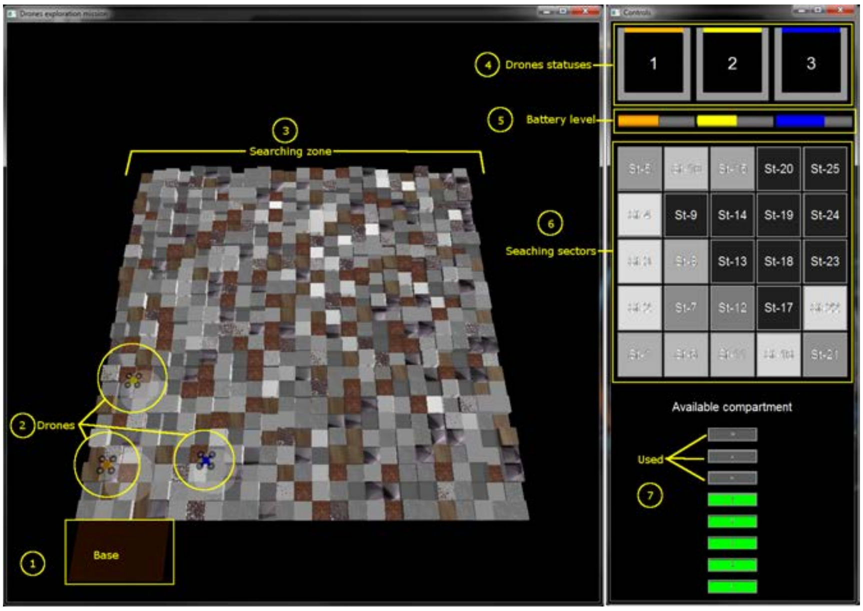


Figure R.3 : Interface graphique de l'opérateur.

- CH-5 - l'influence de l'engagement émotionnel sur l'efficacité de l'effet de cadrage;
- CH-6 - l'influence du temps à répondre sur l'efficacité de l'effet de cadrage;
- CH-7 - l'interférence de l'utilisation des couleurs, comme cadrage visuel complémentaire, sur la « puissance » du cadrage.

Dans les chapitres suivants nous avons pris en compte ces biais cognitifs, en utilisant la Théorie des perspectives (PT) comme facteur prédictif des décisions de l'opérateur humain (HO). Ceci, nous a permis de définir les fonctions d'utilité des drones et d'adapter dynamiquement l'HRI en choisissant automatiquement quel cadrage utiliser pour présenter l'information à l'HO. Le choix du cadrage permet de maximiser les chances que l'HO prenne une décision aligné (au sens d'un critère mathématique) avec les consignes opérationnelles lors l'exécution de la mission.

CHAPITRE 7 – La fonction d'utilité humaine

Dans ce chapitre, nous examinons les moyens d'inclure l'agent humain dans l'équipe de drones (interaction homme-robots). Dans notre approche, chaque drone doit calculer l'action optimale et le gain associé (à cet instant) en choisissant comment encadrer les informations à partager avec HO. Ce choix doit maximiser la probabilité que l'HO prenne une décision qui mène à un gain commun. Pour cela, il faut inférer une « fonction d'utilité humaine» pour l'utiliser lors du calcul de l'action optimale (voir Chap. 8).

Donc, le but de ce travail était d'aborder la fonction d'utilité des HO et de prédire leurs décisions dans un contexte opérationnel spécifique, comme une mission coopérative entre les robots et les humains.

L'étude de ce chapitre a proposé : sur la base des données expérimentales collectées précédemment (voir Chapitre 6), (CH-8) l'approximation de la fonction d'utilité de l'opérateur humain fondée sur la PT et, pour autant que nous le sachions, (CR-9) le premier modèle décisionnel basé sur l'approche économique de consommation multi-dimensionnel et la PT. Les résultats présentés, en ce qui concerne l'ajustement de la fonction d'utilité, et la précision de la prédiction, sont prometteurs et montrent que ce type de modélisation et de prédiction peuvent être pris en compte lorsqu'un système cybernétique intelligent dirige l'interaction homme-robot (HRI). L'avantage de prédire la décision de l'opérateur, dans ce contexte opérationnel, est d'anticiper sa décision, compte tenu de la façon dont une question est presentée (cadrage) à l'opérateur humain. Et ainsi, réaliser le choix de comment présenter l'information courante à l'opérateur, le tout en maximisant les chances d'aligner sa décision, par nature non-déterministe, avec les directives opérationnelles de la mission.

Enfin, le prochain chapitre, presente notre proposition formelle du système dans son ensemble, en utilisant tout ce qui a été présenté jusqu'ici. Nous présentons également les résultats d'une expérience menée pour observer le système en action et les lignes directrices opérationnelles qui ont été utiliser pour influencer les décisions de l'HO.

CHAPITRE 8 – Le système en boucle fermée

Dans ce chapitre, nous présentons notre proposition formelle du système, où nous fermons la boucle, en utilisant: (i) le cadre théorique du jeu de coordination décentralisé (Chapitre 5); (ii) le modèle de prédition de décision de l'opérateur humain proposé (Chapitre 7), basée sur les données expérimentales obtenues dans les expériences FE (Chapitre 6). Ce dernier devrait nous permettre de décider comment présenter l'information, en attendant que l'HO décide conformément aux lignes directrices de la mission. Enfin, pour évaluer le système en boucle fermée, nous menons une expérience avec un grand nombre de participants, ce qui nous a permis l'évaluer l'efficacité de notre approche.

Description du système

Pour cette étude, nous avons défini une mission SAR dans une zone délimitée (subdivisée en petits secteurs) et avons assumé les phases suivantes pour cette mission: (1) sélection et déplacement vers un secteur de destination, (2) sélection et exécution d'un type de recherche, et (3) l'interaction avec l'opérateur si une possible victime est trouvée.

Dans ce cadre, chaque drone calcule et choix ses stratégies de mouvement, de recherche et d'intéraction avec l'HO en utilisant une approche basée sur la théorie des jeux. En ce sens, ils sont des agents auto-centrés essayant de maximiser leurs propres gains, en jouant « contre » les autres, l'environnement et l'opérateur humain.

Dans le jeu entre eux, les drones doivent coordonner leurs actions pour éviter les collisions, se disperser dans les zones d'intérêt et visiter tous les points prédéterminés de manière non déterministe, ceci dépend des information qu'ils acuièrent au fur et à mesure de la mission. Dans ce *jeu non-coordonné (ACG)*, qui est aussi un *jeu potentiel*, non seulement le coût de déplacement a été considéré, mais aussi les positions courantes des autres membres de l'équipe, ainsi que la probabilité de l'existence d'une victime dans un POI donnée. Pour améliorer les performances de calcul en temps réel, ce jeu a été joué uniquement pour les POI de chaque drone (macro-actions).

L'interaction avec l'environnement se produit quand ils doivent choisir comment ils chercheront des cibles, c'est-à-dire, quel pattern de recherche ils utiliseront. Pour cela, un *jeu contre la nature GAN* a été conçu en tenant compte du pire scénario (« loi de Murphy »), pour lequel, nous avons démontré qu'une stratégie mixte pourrait être la meilleure alternative à mettre en oeuvre.

L'intéraction avec l'opérateur a été conçue comme un *jeu d'équipe séquentiel*, qui prends en compte les biais cognitifs humains tels que l'effet de cadrage, via une interface utilisateur graphique (GUI), afin d'améliorer le processus de prise de décision de l'HO et d'optimiser l'utilité globale du système. Ce jeu permet aux drones d'adapter l'interaction avec les opérateurs en fonction des ressources disponibles et de l'état courant de la recherche.

Ces jeux ont été joués à l'intérieur de chaque drone, où le NE est appliqué pour définier l'action optimale à réaliser à chaque étape. La Fig. R.4 montre l'organigramme d'une mission typique.

Enfin, chaque gain (chaque function d'utilité de differents jeux) est influencé par la *consigne directive* de la mission. Les consignes directives opérationnelles sont des déclarations et des recommandations qui déterminent une ligne de conduite en accord avec les décisions de l'autorité chargée de la mission. Dans cette thèse, nous nous concentrerons sur ce qui est plus important dans une mission spécifique : la vitesse ou l'exactitude. Par exemple, le coucher du soleil arrive (alors, il est important d'être rapide), ou les victimes qui n'obtient pas d'aide peuvent geler jusqu'à la mort (alors, soyez précis).

Évaluation

Afin d'évaluer notre cadre, nous avons développé une simulation par ordinateur en utilisant Python 3.5 et MORSE (Fig. R.5), basée sur un scénario d'un *tremblement de terre*, conçu pour les expériences précédentes. MORSE est un simulateur robotique *open source* conçu pour gérer la simulation de plusieurs robots simultanément. Il peut être utilisé dans plusieurs contextes pour le test et la vérification des systèmes robotiques dans leur ensemble, d'un niveau moyen à un haut niveau d'abstraction [Ech+11].

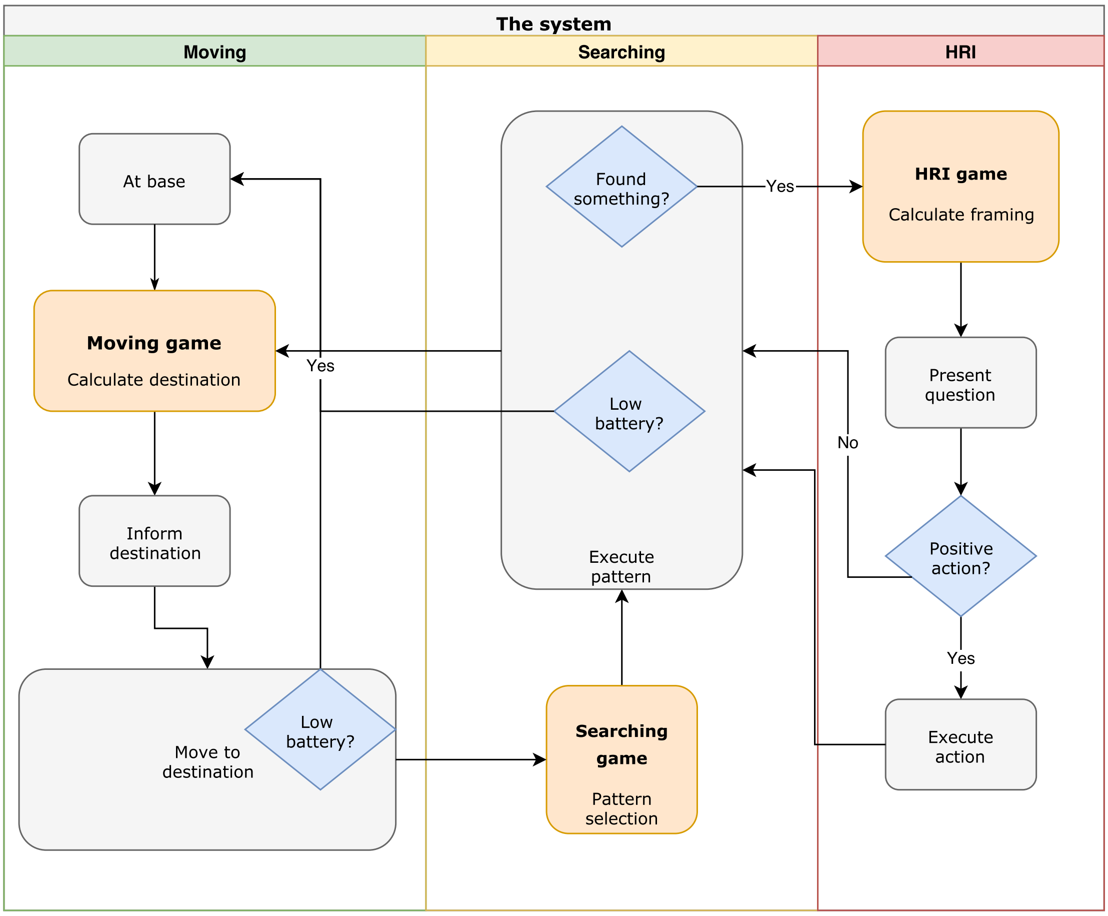


Figure R.4 : Diagramme d'une mission typique.

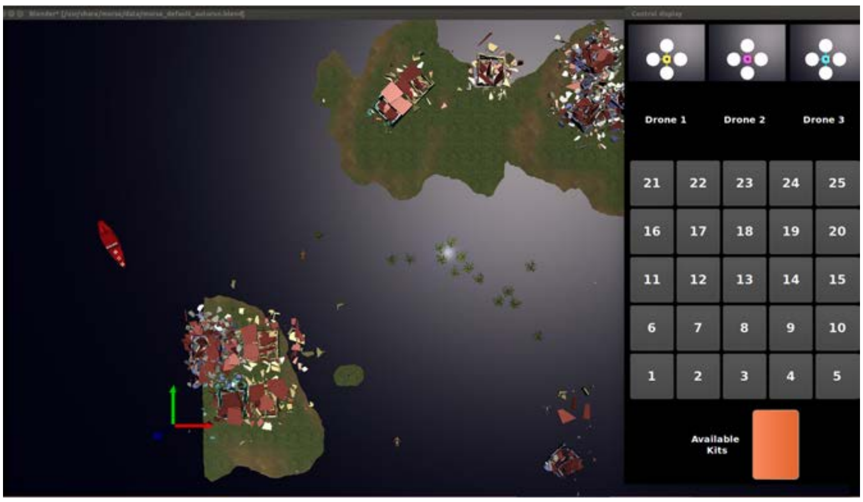


Figure R.5 : Système développé dans le MORSE.

Par conséquent, afin d'optimiser le comportement des drones, nous avons collecté toutes les données de simulation, sans l'interaction avec l'HO, dans MORSE, et développé une expérience en ligne (en utilisant le *HTML5 Canvas*) afin d'augmenter le nombre de participants et, donc, augmenter la quantité de données statistiques provenant des ressources humaines. Nous avons créé un site internet (disponible à http://phd.peus.pro.br) pour héberger l'expérience, recueillir des données générales des participants (de façon anonyme) et leur fournir des informations essentielles pour le bon déroulement de l'expérience (Fig. R.6).

Figure R.6 : Site développé pour l'expérience.

Dans cette expérience, nous nous sommes intéressés à observer le comportement des HOs dans deux contextes différents, chacun avec une ligne directive opérationnelle unique: «être rapide» (BFG) ou «être précis» (BAG). Au cours de l'expérience, ils ont fait face à deux conditions différentes: «neutre» (NTC) et «en conformité» (IAC), dans lesquelles l'HRI a été cadré (FE) en fonction de la fonction d'utilité humaine proposée (Psi) (voir la section 7.2.3).

Ici, nous avons considéré que les résultats de l'étude présentée dans le Chapitre 7 nous ont fourni une image de l'état final d'une hypothetique formation. Ensuite, nous avons supposé ces résultats en tant que données recueillies auprès de «experts».

Par conséquent, nous pourrions essayer de diriger les opérateurs novices (les participants de cette étude) pour agir en tant qu'experts (avec la condition neutre - NTC) et, en plus, en ajustant l'encadrement «en conformité» (IAC) avec la ligne directive opérationnelle sélectionnée (Eq. (8.14)), nous pourrions essayer de persuader les novices (et les experts) de suivre cette ligne directive.

Nous avons recueilli 5026 d'observations de 101 participants, dont 89% avec les données complètes (3705 observations), donc 11.88% des données ont été abandonnées.

Nos résultats indiquent que les participants pourraient être amenés à imiter le comportement des participants de nos expériences précédentes, et les lignes directives opérationnelles pourraient influencer la décision d'opérateur et l'utilité des drones, lorsque l'HRI est encadré en conséquence. Les principales contributions de cette étude étaient:

– CR-10 - les lignes directives opérationnelles définissent les utilités des drones.
– CR-11 - le modèle décisionnel proposé dans CR-9 a été exploité pour aligner les décisions d'opérateur avec les lignes directives opérationnelles, ce qui permet de fermer la boucle de manière « optimisée ».
– CH-12 - le effet de cadrage a conduit les opérateurs à décider conformément aux lignes directives opérationnelles.

Un contrôle rigoureux d'une équipe de drones dans le monde réel exige une coordination inter-robot robuste aux échecs, calculable, (faisabilité informatique) et évolutive. Comme indiqué dans ce chapitre, notre proposition devrait répondre à toutes ces exigences.

Conclusion

De nos jours, la recherche et la conception de l'HRI exigent une attention particulière des communautés des facteurs humains, d'éthique et de sociologie (entre autres). Par exemple, dans un contexte militaire, les robots devraient-ils décider de tuer quelqu'un? Ou, les humains doivent-ils toujours être dans la boucle de décision [GTP+12]? Et la grande question actuelle: qu'est-ce qu'une voiture autonome devrait faire si une personne tombe sur la route en face de celle-ci, quand elle peut soit se dévier vers une barrière et peut-être tuer le passager, soit aller tout-droit et potentiellement tuer le piéton [BSR16]?

Il n'y a pas des réponses faciles à ces questions. Peut-être que les réponses résident dans le MI-HRI. Les humains peuvent répondre à des questions éthiques sur de contranintes opérationnelles difficiles à l'aide de l'intuition, mais ce n'est pas simple pour les systèmes artificiels intelligents, la décision du robot peut émerger de l'interaction de plusieurs capteurs afin de calculer le compromis moral, ou peut-être une collection prédéterminée de règles morales [Bel+14].D'autre part, les êtres humains «faillibles et émotionnels» pourraient améliorer leurs performances avec l'aide du système robotique.

Dans cette optique, cette thèse s'est engagé à concevoir un cadre MI-HRI composé d'un opérateur humain (HO) et d'une équipe de drones, dans lequel l'HO et les drones ont des compétences complémentaires et agissent de manière synergique en tant que pairs pour améliorer la performance globale du système. Dans ce sens, ce travail remplit un double objectif: (1) prendre en charge l'efficacité de l'équipe humain-robot (*perspective robotique*), et (2) améliorer le processus décisionnel humain (*perspective humaine*) selon un contexte opérationnel .

Par conséquent, nous avons commencé la recherche avec une revue de la littérature sur les missions 3D adaptées à notre cadre, telles que les missions militaires, SAR et spatiales. Ensuite, nous avons étudié le processus décisionnel humain et certaines de ses théories (par exemple, la théorie des perspectives). Pendant ce temps, dans la *perspective robotique* nous nous sommes concentrés sur les processus de décision décentralisés tels que la *théorie des jeux*.

Avec ces concepts, nous avons conçu notre proposition étape par étape. Tout d'abord, nous avons développé une fonction d'utilité théorique pour coordonner l'équipe du drone dans une mission autonome de patrouille. Ici, en plus du coût du trajet, nous avons également considéré la position actuelle de tous les drones et la dernière fois que chaque point d'intérêt a été visité. Avec ces informations, nous avons créé une fonction de utilité additive d'un jeu anti-coordination (ACG), dans lequel une solution NE pure aligne les objectifs égocentriques des drones avec un objectif global.

Deuxièmement, afin d'observer si nous pouvions influencer les décisions de l'HO en raison de l'incertitude, de la pression temporelle et de l'information imparfaite, nous avons mené deux expériences sur l'effet de cadrage (FE), en utilisant une mission SAR et une mission de retourd'échantillon comme contextes. Nos résultats ont démontré l'existence du FE et la difference de l'engagement émotionnel dans des tels contextes, et que l'utilisation des couleurs *effet de cadrage visuel* peut améliorer l'influence du *effet de cadrage du texte*.

Troisièmement, avec les données recueillies dans ces expériences, nous avons estimé la fonction d'utilité de l'opérateur humain et proposé un modèle décisionnel pour que les robots choisissent le cadrage (présentation de l'information) lors de l'interaction avec l'opérateur, afin d'augmenter la probabilité que l'HO choisisse, lui, une action qui optimise l'utilité globale.

Ainsi, nous fermons la boucle, en formalisant notre proposition dynamique théorique décentralisée pour générer les interactions d'une équipe humain-drones. Pour l'interaction entre les drones, nous avons créé un ACG, inspiré de l'approche de mission de patrouille (cf. Chapitre 5). Pour l'interaction drone-environnement, lorsque les drones devaient sélectionner un modèle de recherche, nous avons conçu un GAN et nous avons démontré qu'une *stratégie mixte* pourrait être la meilleure réponse à ce jeux. Pour le HRI, nous avons créé un *jeu d'équipe séquentiel*, où les drones utilisent un *jeu fictif*, basé sur l'estimation de la fonction d'*utilité du opérateur* pour choisir comment interagir avec l'HO. Et, ensuite, nous avons biaisé ces trois jeux pour suivre les directives opérationnelles (pour être rapide ou précis, dans notre dernière expérience). Nous avons également suggéré que l'*utilité globale* soit utilisé comme mesure d'efficacité du système.

Enfin, pour évaluer notre proposition, l'expérience III a été réalisée. Nos résultats suggèrent qu'il est possible de conduire l'HO à agir conformément aux consignes directives opérationnelles et aux stratégies des «experts», quelque soit leur expérience antérieure, explorant l'effet de cadrage lors de l'interaction humain-robots.

Limitations

L'approche actuelle est limitée par les données recueillies dans les expériences I et II, dans lesquelles le nombre de participants était relativement faible. De plus, malgré que ces participants aient exécuté dix missions chacun (dans l'expérience I), leurs données pourraient ne pas représenter nécessairement le «comportement d'experts», ainsi considérés dans l'expérience III.

Une autre limitation est que l'expérience III n'était pas une vrai mission à initiative-mixte (MI-HRI). Seuls les drones avaient l'initiative pendant la mission (autonomie adaptative en ce qui concerne la décision prise par l'humain). Dans un scénario à initiative-mixte, en particulier dans le cadre de la mission SAR, le HO pourrait également suggérer un pattern de recherche ou donner la priorité à certains secteurs, selon son expertise, et les drones pourraient décider de libérer (ou pas) un kit si l'HO n'était pas disponible (ou hors du domaine de communication).

Contributions

Cette thèse fournit des méthodes authentiques qui peuvent être reproduites pour évaluer le mise en œuvre de modèles de la théorie des jeux et de principes de facteurs humains dans un contexte opérationnel. En ce sens, ce travail a réuni deux disciplines différentes, l'ingénierie (la robotique) et la psychologie (facteurs humains). Par conséquent, les principales contributions sont:

- CR-1 - la formulation originale d'une fonction d'utilité additive, pour un joueur (un drone de l'équipe), composée de trois paramètres indépendants des choix d'action des autres joueurs;
- CR-2 - la démonstration que la solution de ce jeu est un NE, et que cet équilibre peut être obtenu en optimisant séparément et individuellement le choix d'action d'un joueur unique;
- CR-3 - la proposition d'un algorithme décentralisé utilisé pour mener une mission de patrouille, ce qui implique une communication minimale entre les agents.
- CH-4 - l'observation de l'effet de cadrage (FE) dans un contexte opérationnel;
- CH-5 - l'influence de l'engagement émotionnel dans l'efficacité du FE;
- CH-6 - l'influence du temps de réponse dans l'efficacité du FE;
- CH-7 - l'interférence de l'utilisation des couleurs, en tant que cadrage visuel complémentaire, dans la «puissance» du FE;
- CH-8 - l'approximation de la fonction d'utilité de l'opérateur humain fondée sur la théorie des perspectives (PT);

- CR-9 - un modèle décisionnel basé sur l'approche économique de consommation multi-dimensionnelle et la PT;
- CR-10 - les consignes directives opérationnelles qui conduisaient les fonctions d'utilité des drones.
- CR-11 - le modèle décisionnel proposé dans CR-9 a été exploité pour aligner les décisions de l'HO avec les consignes directives opérationnelles, ce qui a permis de fermer la boucle de manière « optimisée ».
- CH-12 - les FE a mené les opérateurs à décider conformément aux directives opérationnelles.

Travaux futurs

Il y a plusieurs voies de progrès pour le travail proposé dans cette thèse.

Concernant la *perspective robotique*, les études futures devraient tenir compte des incertitudes dans le mouvement des drone et dans la disponibilité de l'HO, en utilisant les solveurs M/POMDP en ligne. Les solveurs hors ligne sont souvent appliqués dans de domaines de petite à moyenne taille, car la phase de construction de la politique prends un temps significatif pour que l'algorithme puisse approcher une politique (via une fonction de valeur), qui définit des actions à exécuter dans tous les états de croyance possibles [Ros+08]. D'autre part, les solveurs en ligne tentent de trouver une bonne politique locale pour seulement l'état de croyance actuel de l'agent, ce qui n'est rien d'autre qu'un *jeu stochastique*. Un avantage est qu'il faut seulement considérer les états de croyance qui sont accessibles à partir de l'état de croyance actuel. Cependant, afin d'améliorer l'optimisation de la politique locale, il pourrait être intéressant d'augmenter l'horizon à un petit nombre de d'étapes (planification en ligne), selon la capacité de calcul embarquée (pour éviter une perte de performance). Et, au lieu d'une re-planification à chaque étape, utiliser des « macro-actions » (ensembles d'actions atomiques) pour réduire la taille du domaine.

Il pourrait également être intéressant d'étudier un algorithme d'apprentissage par renforcement en ligne pour améliorer l'interaction humain-robots en fonction des décisions précédentes prises par le HO actuel. Cela pourrait ajuster le comportement du système en fonction de la performance de l'opérateur.

Concernant la *perspective humaine*, d'autres recherches pourraient explorer des outils du *transfert learning* [PY10] pour: (1) dans une première étape, pour regrouper des personnes ayant une *valeur perçue personnelle* semblable; (2) en appliquant, dans ce cas, la fonction de *valeur perçue* appropriée en fonction de ce comportement commun.

Les recherches futures devraient également prendre en compte les états cognitifs de l'opérateur humain, par exemple, la charge de travail ou le niveau de stress de l'opérateur. D'une part, l'opérateur a un certain niveau de conscience de la situation, ce qui lui permettrait de connaître les capacités de l'agent artificiel et de son état. De l'autre côté, lorsque l'autonomie adaptative ou l'initiative mixte sont considérées, l'agent artificiel devrait avoir un modèle de «capacités» de l'HO et son «état» actuel [TD12]; [Dur+15]; [Gat+16]; [Roy+16] (voir aussi [SCD15] dans l'Annexe A). Cela pourrait améliorer le processus de décision des agents artificiels afin de décider s'ils prennent ou non l'initiative.

Et, enfin, une progression naturelle de ce travail est un véritable système MI-HRI, avec, plus de drones et plus d'opérateurs, dans lequel, tous les agents peuvent avoir l'initiative (pouvoir de contrôler) et, en particulier, pouvoir saisir de façon opportuniste l'initiative de l'autre quand il s'avère nécessaire.