

Multi-Objective Heterogeneous Multi-Asset Collection Scheduling Optimization with High-Level Information Fusion

by

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Abstract

Surveillance of areas of interest through image acquisition is becoming increasingly essential for intelligence services. Several types of platforms equipped with sensors are used to collect good quality images of the areas to be monitored. The evolution of this field has different levels: some studies are only based on improving the quality of the images acquired through sensors, others on the efficiency of platforms such as satellites, aircraft and vessels which will navigate the areas of interest and yet others are based on the optimization of the trajectory of these platforms. Apart from these, intelligence organizations demonstrate an interest in carrying out such missions by sharing their resources. This thesis presents a framework whose main objective is to allow intelligence organizations to carry out their observation missions by pooling their platforms with other organizations having similar or geographically close targets. This framework will use Multi-Objective Optimization algorithms based on genetic algorithms to optimize such mission planning. Research on sensor fusion will be a key point to this thesis, researchers have proven that an image resulting from the fusion of two images from different sensors can provide more information compared to the original images. Given that the main goal for observation missions is to collect quality imagery, this work will also use High-Level Information Fusion to optimize mission planning based on image quality and fusion. The results of the experiments not only demonstrate the added value of this framework but also highlight its strengths (through performance metrics) as compared to other similar frameworks.

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Table of Contents

List of Tables	viii
List of Figures	ix
Acronyms	xi
1 Introduction	1
1.1 Motivation	1
1.2 Objectives and Contributions	3
1.3 Thesis Structure	5
2 Background and Related Work	6
2.1 Observation Missions	6
2.1.1 Earth Observation Missions	7
2.1.2 Intelligence, Surveillance and Reconnaissance	10
2.2 Mission Planning	14

2.2.1	Mission Planning in Risk Management Framework	18
2.2.2	Collection Scheduling Optimization	20
2.3	Image Quality in Mission Planning	22
2.3.1	Image Quality Assessment	22
2.3.2	Image Quality Prediction	23
2.4	Sensor Fusion	24
2.4.1	Background on Sensor Fusion	24
2.4.2	Image Fusion	25
2.5	High-Level Information Fusion	26
2.5.1	Joint Directors of Laboratories	26
2.5.2	Information Fusion Effectiveness	27
2.6	Artificial Intelligence	27
2.6.1	Evolutionary and Genetic Algorithms	27
2.6.2	Multi-Objective Optimization	28
2.6.3	Machine Learning	29
2.6.4	Correlation Coefficient	31
2.7	Chapter Summary	32
3	Multi-Objective Heterogeneous Multi-Asset Collection Scheduling Opti- mization with High-Level Information Fusion	34
3.1	Problem Definition	35

3.2	Methodology	35
3.3	Proposed Solution	37
3.3.1	Motivation behind Strategies in MOHMA-CSO-HLIF	38
3.3.2	Objectives Definition	41
3.4	Experiments and Results	46
3.4.1	Added Value of the QoO	47
3.4.2	MOHMA-CSO-HLIF Variants	50
3.4.3	Comparison of MOHMA-CSO-HLIF with MOHMA-CSO, DCSO and MO-GATHER	56
3.5	Chapter Summary	60
4	High-Level Information Fusion in a Mission Planning Context	61
4.1	Problem Definition	61
4.2	Methodology	62
4.3	Proposed Solutions	63
4.3.1	Expert-Driven Approach	63
4.3.2	Distributed Data Fusion-Based Approach	67
4.3.3	Neural Network - Based Approach	72
4.4	Experiments and Results	74
4.4.1	Expert-Driven Approach	74
4.4.2	DDF-Driven Approach	75

4.4.3	Neural Network - Based Approach	77
4.5	Chapter Summary	81
5	Future Work and Conclusion	82
5.1	Future Work	82
5.2	Conclusion	83
	APPENDIX	87

List of Tables

3.1	Comparison of Objective Values.	49
3.2	Scenario 2's Requests.	51
3.3	Scenario 2's Sub-planners' Assets.	52
3.4	Scenario 2's Results.	52
3.5	Scenario 2's Pareto Front Quality.	56
3.6	Scenario 3's Requests.	57
3.7	Scenario 3's Sub-planners' Assets.	58
3.8	Scenario 3's Results.	59
4.1	Mean Accuracies after 10 Experiments.	76
4.2	Platform, Time, Season, Sensor of the Synthesized Dataset.	79
4.3	Testing Mean Squarred Error.	79

List of Figures

3.1	A TR observed by three different COs. Opp1, Opp2 and Opp3 are COs using different types of sensors. Since Opp1 and Opp2 have some tiles in common, there will be a FCO, Fused Opp, covering their common tiles. . .	38
3.2	Impact of the Number of Platforms on QoO.	47
3.3	Snapshots of a scenario in Google Earth. In the top image, the three SPs deploy their platforms to observe six TRs. The bottom image shows the execution of the scenario several hours later.	49
3.4	PCCs of Objectives.	50
3.5	Snapshots of a TR and some platforms of Scenario 2.	53
3.6	3D Chart with the non-dominant solutions obtained by MOHMA-CSO-HLIF.	54
3.7	Snapshots of some TRs of Scenario 3.	57
4.1	Illustration of UAVs' Collection Opportunities (in white and pink).	62

4.2	An AOI was captured within the IR spectrum and the EO spectrum. Notice that in both of the top images some information is missing: the name of the store is clearly readable in the EO image while it is not in the IR; the pedestrians that can be seen in the IR image are hardly visible the EO image. The fused image contains almost all the features of the original images. . .	65
4.3	Different categories of datasets are used to train models to detect, recognize, classify or identify objects in EO and IR imagery.	69
4.4	Models are trained to detect, recognize, classify or identify using three fusion methods.	70
4.5	Prediction of DRCI ability given a CO.	71
4.6	Classifications of vessels done with the three levels of fusion.	73
4.7	Sample QoI Values of COs.	74
4.8	Images whose qualities and characteristics were used to experiment with some models. The images of the first line are those obtained with UAVs [72], those of the second line with ground vehicles [73], those of the third one with vessels [70] while those of the last one are obtained with satellites [74]. Except the last row, where all the images are obtained with EO sensors, the images of the first column are obtained with EO sensors, the second one with IR sensors and the last column contains their fusions.	78
4.9	Prediction values of models 1, 2 & 3 and the associated ground truth values.	80
1	Convolutional operation between a filter and an input image.	86
2	General architecture of a CNN.	86

Acronyms

AACM All-Asset Coverage Maximization.

AI Artificial Intelligence.

ANN Artificial Neural Network.

AOI Area of Interest.

CACM Cost-Aware Coverage Maximization.

cGAN conditional Generative Adversarial Network.

CNN Convolutional Neural Network.

CO Collection Opportunity.

CP Collection Plan.

CSO Collection Scheduling Optimization.

CSP Constraint Satisfaction Problem.

CV Collection Value.

DC Dollar Cost.

DCSO Distributed Collection Schedule Optimization.

DDF Distributed Data Fusion.

DL Deep Learning.

DRCI Detection, Recognition, Classification or Identification.

DS Demand Satisfaction.

EA Evolutionary Algorithm.

EO Electro-Optical.

ESA European Space Agency.

FCO Fused Collection Opportunity.

FP Fusion Possibility.

FPR Fusion Possibility and Revelance.

FR Fusion Revelance.

GA Genetic Algorithm.

GAN Generative Adversarial Network.

GIQE General Image-Quality Equation.

HLIF High-Level Information Fusion.

HV HyperVolume.

IB Information Benefit.

IC Information Confidence.

IFE Information Fusion Effectiveness.

IGD Inverted Generational Distance.

IR Infrared.

ISR Intelligence, Surveillance and Reconnaissance.

ISTAR Intelligence, Surveillance, Target Acquisition and Reconnaissance.

LC Local Conflict.

LTR Local Task Request.

MDP Markov Decision Process.

ML Machine Learning.

MO-GATHER Multi-Objective - Genetic Algorithm-based collecTion scHedulER.

MOEA Multi-Objective Evolutionary Algorithm.

MOHMA-CSO Multi-Objective Heterogeneous Multi-Asset Collection Scheduling Optimization.

MOHMA-CSO-HLIF Multi-Objective Heterogeneous Multi-Asset Collection Scheduling Optimization with High-Level Information Fusion.

MOO Multi-Objective Optimization.

NASA National Aeronautics and Space Administration.

NIIRS National Imagery Interpretability Rating Scale.

PCC Pearson Correlation Coefficient.

PIQE Perception based Image Quality Evaluator.

POI Point of Interest.

QoI Quantity of Information.

QoO Quality of Observation.

QoP Quality of Perception.

RC Resource Cost.

RL Reinforcement Learning.

RMF Risk Management Framework.

RSN Robotic Sensor Network.

SA-TL Tabu-List-based Simulated Annealing.

SACM Single-Asset Coverage Maximization.

SAR Synthetic Aperture Radar.

SP Sub-Planner.

STR System-level Task Request.

SVM Support Vector Machine.

TAP Task Assignment Plan.

TR Task Request.

UAV Unmanned Air Vehicle.

UGV Unmanned Ground Vehicle.

UUV Unmanned Underwater Vehicle.

Chapter 1

Introduction

This chapter introduces observation missions, the planning of observation missions and how High-Level Information Fusion (HLIF) can be used in observation missions. The first part will highlight the motivation of this work and its added value. Following the motivation, contributions of this work will be listed. The structure of the thesis ends this chapter.

1.1 Motivation

Observation missions to collect images of Areas of Interest (AOIs) are of great importance. The need for situational awareness, border surveillance and environmental analysis pushes intelligence organizations to deploy aircraft, satellites, vessels and ground vehicles to collect imagery of AOIs. The costs of carrying out large-scale observation missions that would require the use of platforms such as Unmanned Air Vehicles (UAVs), Unmanned Ground Vehicles (UGVs), Unmanned Underwater Vehicles (UUVs), vessels, satellites, and others are enormous. Due to their high costs, mission planning software are often used to evaluate

the usefulness of missions and optimize them.

Many of these mission planning software use Multi-Objective Optimization (MOO) algorithms in order to realistically and satisfactorily achieve observation missions [1–5]. The goal of these algorithms is to propose solutions maximizing and/or minimizing a certain number of fixed objectives while respecting constraints. Obtaining satisfactory results when using MOO algorithms requires the clear definition of both objectives and constraints. This is very important because objectives and constraints allow the system to compare typically non-dominant solutions. They also assess whether the functioning of the system meets the expectations. Most often, the objectives are ascribed to the variables to be maximized or minimized while the constraints are restrictions to the objectives.

Like MOO algorithms, Genetic Algorithms (GAs) are part of Artificial Intelligence (AI) and are a key solution to optimize observation missions. One of the main advantages of GAs is that they are inspired by genetic evolution to make it possible to create new solutions using populations of existing solutions. Instead of generating all possible alternative solutions to a problem, GAs also have this capability to assimilate search spaces in order to find the best solutions. This will be very useful in the optimization process of observation missions since the system may go from spending several hours to a few minutes searching for the most optimal solutions.

The costs of observation missions have the consequence of also pushing intelligence services to carry out their observation missions by pooling their resources, especially their platforms [6, 7]. UAVs, UGVs, vessels, satellites, etc. are used to carry out missions that could benefit several organizations at the same time. So on one hand, there are organizations with task requests (these organizations are called agencies) to perform and on the other hand there are other organizations that may have their own Task Requests (TRs) but also make their platforms available in order to reduce the individual cost of

carrying out their missions. These organizations are called Sub-Planners (SPs).

Research in the sensor fusion field has proven that an image resulting from the fusion of two images from different sensors can provide more information than individual images [8]. This is well illustrated in the fusion of images obtained within the Electro-Optical (EO) and the Infrared (IR) spectrum. The IR spectrum allows to better detect objects during the night while the EO spectrum is more effective during daytime operations [9]. The complementary aspect of these spectra often leads to obtaining images in each of the spectra in order to carry out an analysis by having either the two separate images or by fusing them. This is also the case for images obtained with Synthetic Aperture Radars (SARs) and those obtained with IR sensors. IR sensors provide images with good resolution but their capacities are reduced in bad weather conditions while SAR, despite their average resolution, offer acceptable capacities even in bad weather conditions [10].

Hence, this thesis highlights a mission planning framework optimizing the management of platforms by allowing SPs to carry out their TRs while also carrying out some TRs of the agencies. On the other hand, an emphasis will also be placed on the use of HLIF to assign TRs to SPs by taking into account the quality of acquired images, including fused ones.

1.2 Objectives and Contributions

This thesis has three main objectives. (1) Propose an optimizer of observation or surveillance missions allowing organizations to perform missions by pooling their resources considering different strategies. (2) Enable the optimizer to use HLIF to assign TRs to SPs by taking into account the quality of acquired images and the eventuality of fusing some of the acquired images. (3) Explore and propose methods to estimate the quality of future

images given a mission plan. These methods must consider the benefit of sensor fusion by predicting the quality of subsequent fused images given the mission plan.

To fulfill these objectives, this thesis uses and enhances an existing optimizer by adding the following contributions:

- The implementation of an algorithm allowing the system to optimize surveillance missions by reducing the number of platforms to only reach a minimum coverage percentage of AOIs. This work was presented at [11] and published at [12].
- The design and implementation of algorithms computing the quality of future images given a mission plan. Three algorithms were designed to consider three different strategies of mission planning optimization. The goal was to consider the quality of future images as one of the objectives of the optimization. This work was presented at [11] and published at [12].
- The use of the General Image-Quality Equation (GIQE) [13] and the Information Fusion Effectiveness (IFE) metric [14] to design and implement an algorithm to predict the quantity of information in future fused images. This algorithm was designed to take into account the complementary aspect of sensors.
- The proposition of a method that considers the ability of detection, recognition, classification and identification of objects in future images (including fused images) as an objective in the surveillance mission optimization process.
- The design of a method that computes the perception quality of future images (including fused images) given a mission plan.

1.3 Thesis Structure

This thesis is structured as follows. This section ends the first chapter. Chapter 2 presents a deep review of different studies pertinent for this thesis. Chapter 3 describes the proposed framework allowing the optimization of surveillance missions using some designed objectives. Analysis and comparisons of experimental results of the framework is done at the end of the chapter. Chapter 4 proposes and experiments with metrics to predict the quality of future images, including eventual fused images. The proposition of those metrics will consider the mission planning context and the sensor fusion benefit. Chapter 5 concludes this thesis and looks at future prospects.

Chapter 2

Background and Related Work

This chapter will present and analyze previous works that are essential to understand the contributions of this thesis. On one hand, there will be works giving some contexts on the importance of the thesis and on the other hand some technical concepts. The first sections of the chapter will focus on observation missions, surveillance missions and mission planning. The following sections will analyze the different methods to optimize observation missions. Among these methods, MOO will be the central theme. Then, the rest of the sections will show the importance of image quality on surveillance and observation missions before putting the emphasis on image fusion algorithms as well as determining image quality.

2.1 Observation Missions

During the last decades, certain fields of science and technology have known major advances. These areas include: forecasting weather, tracking biodiversity, wildlife trends,

measuring land-use change, monitoring and responding to disasters, military surveillance¹. In the military domain, the protection of a territory no longer requires as many troops at its borders as before. Indeed, the best protected countries are those which have the best means of surveillance and communication. Likewise in meteorology, although some challenges persist, science and technology make it possible to push back several limits. Thanks to meteorological predictions, today's tsunamis can be predicted several days or weeks in advance.

Several advances in the aforementioned fields are particularly due to recent and current capacities to carry out observation and surveillance missions. More public and private organizations are using satellites, UAVs, UUVs, UGVs and vessels equipped with sensors in order to collect information on target areas.

The following subsections will carry out analysis to better understand the usefulness and the advances acquired thanks to observation and surveillance missions. The analysis will mainly focus on Earth observation and military surveillance missions.

2.1.1 Earth Observation Missions

Improving the quality of images is an important task for image analysts. Images from observation missions need a lot of preprocessing to be put to good use. The authors of [15] confirm this fact and focus on improving the resolution of images collected during observation missions. They propose the use of a Generative Adversarial Network (GAN) to improve the resolution of images. Their model is trained using pairs of images: on one hand, images with low resolution and, on the other hand, images with better resolution. The goal is to train the GAN to improve the resolution of images by using images with better

¹https://www.earthobservations.org/g_faq.html

resolutions as targets. Their method highlights the usefulness of observation missions in image resolution enhancement.

Almost similarly, [16] proposes the use of GANs, more precisely conditional Generative Adversarial Networks (cGANs), to remove clouds from images. Their cGAN uses EO images as inputs and uses images obtained from SAR as targets to remove clouds from the images. Indeed, SARs are recognized to have this ability to perceive objects beyond clouds. As with the previous GAN, this method requires training images obtained from observation missions to provide descent results.

The analysis of ground deformations is of great importance in the field of geology. It makes it possible to prevent phenomena such as volcanic eruptions. Therefore, it is important to continuously study the soil in order to detect its deformations. [17] proposes the use of time series to carry out a continuous and semi-automatic analysis of the ground to alert as soon as there is a risk. The authors of [17] succeed in proving the effectiveness of their method by using data from the Sentinel-1 Earth observation mission in their experiments. This study is therefore proving to be an eventual milestone in the disaster prevention pipeline thanks to observation missions.

Data from the Sentinel-2 Earth observation mission are also used to study climate change, or rather how visible the impacts of climate change are. At a time when the debate on climate change is central, measuring and proving its impact is more than essential. Phenology is the study of repetitive phenomena in living beings (including plants). It is often used to show the impact of climate change. [18] reviews various phenological studies done using data from Sentinel-2. This review not only shows the importance of different studies but also points to new aspects that would be important to analyze.

Environmental dangers do not only come from climate change, some living organisms

are also dangerous for nature and other living beings. This is the case with algae which are species or organisms living in an aquatic environment. Their proliferation is often a danger because they often absorb polluting content that poses a danger to the health of humans and other living beings. [19] presents the danger of their proliferation not only on the health plan but also on the tourism and commercial plans. There is therefore a need to first detect areas of algae proliferation and then a way to make these areas of new proliferation frequentable. The study by [19] begins by presenting traditional methods based on collecting soil and performing laboratory analysis. These methods turn out to be extremely expensive and laborious. Instead, [19] proposes a method based on the analysis of water images obtained with EO sensors combined with others from in situ data. Experiments on this method, with images from Sentinel-2 mission, produce better results than traditional ones.

The analysis of the snow level during the winter seasons in the world is not only of great importance for measuring the effects of climate change but it also allows for analysis of energy, water and carbon cycles as mentioned in [20]. The authors of [20] go further by also indicating that the economy can therefore be impacted by the slightest changes in the quantities of snow. They therefore propose an approach based on the simultaneous use of two Sentinel satellites in order to study the quantities of snow in the globe and to have a snow map making it possible to predict sudden changes in the quantities of snow.

Data from observation missions are also used to carry out analysis of urban areas. These are important because they allow to prevent various dangers that may arise as a result of bad constructions in the city. The outbreak of erosion near residential areas is a perfect illustration of the dangers that can arise in urban areas. Another importance of the analysis of urban areas could be the detection of anarchic constructions, i.e. ones that do not respect urban regulations. The use of data from observation missions intervenes

to counter the examination on a case-by-case basis of urban areas and move it to a semi-automated or even fully automated analysis. The authors of [21] propose a method to classify different urban areas using data from Sentinel missions. The data used in their studies come from the cities of Stockholm and Beijing. They also manage to prove that the combined use of data from EO and SAR sensors in the classification of urban areas lead to better results than data from these sensors used individually. Another almost similar way to make sure that urban constructions follow the rules is to detect any new construction or changes in an urban area. If a zone with constructions initially followed the rules, there are only changes or new constructions that can cause the rules to be broken. The authors of [22] propose a system for detecting changes in urban areas. Their method uses three sub-methods, two of which are based on neural networks and the third is a multiband optical filter. The main method uses a fusion based on a proportionate average of the results of the sub-methods to give final results. They thus manage to prove, like the authors of [21], that data fusion produces better results in detecting changes in urban areas.

2.1.2 Intelligence, Surveillance and Reconnaissance

The need for information gathering is a necessity in several areas. Military and security fields are no exception to the rule. In fact, the ability to gather information in these areas is vital. However, collecting information is only the first step in the process called Intelligence, Surveillance and Reconnaissance (ISR) in which target acquisition is often included to morph into Intelligence, Surveillance, Target Acquisition and Reconnaissance (ISTAR). Surveillance, target acquisition and reconnaissance are often carried out through the deployment of different devices in surveillance missions with the objective of collecting as much information or data about a target or subject of interest as possible. The intelligence

step comes after that to make rational use of this information or to give it more value. As the remainder of the subsection will show, the scopes of surveillance and ISTAR missions are multiple.

National armies are not only used in times of war or when it comes to ensuring the territorial integrity of countries. They are also useful for helping populations before, during or after disasters. High-tech equipment, their speed of action or their deployment capacity in at-risk and difficult to access areas justify their presence during disasters. The corona virus crisis is a recent example of the need for the armed forces in urgent situations. Some vaccination centers in the United States of America have been assisted by the military to facilitate vaccination campaigns ². [23] confirms the need for ISR operations during emergencies caused by natural or health disasters. They explain this need in particular by the ability of intelligence services to quickly collect information. They bring great precision to the collection of information. In the context of ISR, the collection of information is often defined as the data collected after deployment of UAVs, satellites and other types of vehicles. The authors of [23] add that the notion of collecting information from the ISR process can also take into account information collected from newspapers or all types of information gathered online. While this information may require filtering, it is nonetheless important. They also suggest fusing data or information received from various sources in order to get a better idea of emergency situations. [23] illustrates the use of ISR during the 2010 earthquake in Haiti. The authors detail that the deployment of American aid was made possible thanks to the images and videos of their platforms in order to serve as a precursors and make it possible to know which places are the most affected and what would be the best way to come to the populations in relief.

²<https://www.defense.gov/Newsroom/Releases/Release/Article/2440556/dod-announces-covid-19-vaccine-distribution-plan/>

One of the keys to surveillance missions is the management of information in the ISR process. In addition to highlighting important factors thanks to the data collected, information management must also be used to better distribute the tasks to the various platforms available, considering the information collected about these tasks. This aspect of information management is quite similar to mission planning which will be discussed in depth in the next section. [24] studies the use of information collection management during the ISR process. The authors propose to assign tasks to platforms using AI. The first step of the proposed solution consists of representing the problem in a state-space representation, followed by a search for the best solution using graph search algorithms. The authors nevertheless point out a drawback to this type of solution: finding the best solution can be time consuming if the graph is large. As an alternative, they offer to choose in this case the best solution found within a reasonable amount of time even if it is not the best solution of the graph.

Although the use of ISR missions is common in the military fields of many countries, problems, and space for improvement of ISR missions abound. [25] makes an analysis of several factors which can have a negative impact during ISR missions before proposing solutions for some of these problems. To gain insight into the typical problems that arise when performing surveillance missions, the authors interview 14 US military personnel with proven experience in carrying out surveillance missions. Here are two examples of problems listed by [25] that emerged from these interviews: "It is extremely rare to find useful intelligence without prior information (i.e., formalized as information requirements)", "Unofficial ISR requests (Soldiers call these 'drug deals')". Notice that these problems are of various orders, they affect safety, comfort, better administration or even organization and many other aspects. For each category of problem, the authors of [25] suggest solutions that can improve the execution of missions. Generally speaking, [25] suggests using technologies to

solve or reduce the gap caused by most of these problems.

Among the ISR missions, several aim to detect certain objects in areas of interest. Without the use of AI, object detection in areas of interest would require human intervention for every object in sight. This may be acceptable in situations where there are a limited number of objects to be processed. Unfortunately, during ISR missions, the number of objects to be detected or exploited can turn out to be enormous. So to avoid continually multiplying the number of human operators in order to keep the ratio of objects to be processed per human acceptable, AI is often used to overcome this problem in order to replace or reduce the number of operators thanks to computer systems performing the detection task. [26] offers a similar system. The added value of the system proposed by [26] consists of making the system aware of the geographical context of the place where the object to be identified is found in order to increase the precision of the system.

While the trend to automate surveillance missions is growing, human intervention remains important. Indeed, UAVs, satellites, UUVs and other devices often need remote human intervention in order to either fully guide them or at least provide reassurance that everything is going as planned and be ready to intervene otherwise. It is with this in mind that the authors of [27] propose a decision-making system that will play the role of the human operator in an ISR mission. Ideally, the proposed system will have two roles: knowing when to act and acting by making the best decision. Since the study done in [27] is intended to be a basis for this field, the authors propose the creation of an operator in a simplified environment with several variables not taken into account. The simplified problem takes a system where the operator has a binary decision to make at each step. The methodology used first consists of letting the operator make quasi-random decisions and then giving rewards in relation to the decisions taken. The goal is to push the operator to have more rewards and therefore make better decisions. After obtaining a significant

number of rewards, the operator's decisions will be used to setup a policy on which the other operators will base themselves.

2.2 Mission Planning

Mission planning is an important step in the realization of surveillance missions. It is through this step that mission planners will be able to assess how achievable mission objectives are and how to deploy platforms to achieve those objectives. Thus, after having planned an observation or surveillance mission, the mission's planners can have an idea of its cost, the time needed to carry out the mission, the number of operators required as well as other indicators or variables. Nowadays, mission planning systems go further, they also have the role of providing machines or their remote-control systems with intelligence in order to be able to react to various unforeseen events that may arise during missions. The research on mission planning covers several aspects of surveillance missions. Some researchers rely exclusively on how to plan observation missions by better allocating the tasks to the platforms. In the latter context, the allocation of tasks to the platforms takes into account the capacities of the different platforms in order to spend a minimum cost and still achieve the objectives. Other researchers analyze observation missions within a Risk Management Framework (RMF). In RMF, the main objective of mission planning is to optimize the use of platforms at the slightest alert given by the RMF. There are also studies on Collection Scheduling Optimization (CSO) with the aim of optimizing the collection of images on the platforms' planned trajectories. In this subsection, a broader review of RMFs, CSO and different mission planning systems will be done in order to fully understand their utility and their operations.

[28] conducts a survey on the state of research in mission planning. The purpose of its

study is first of all to take stock of the advances that have taken place in the deployment of satellites and spacecraft during observation missions. Then, a comparison is made between two alternatives: Markov Decision Process (MDP) and model-based approaches. The National Aeronautics and Space Administration (NASA) and the European Space Agency (ESA) are among the organizations with enough significant resources to carry out observation missions with satellites and spacecraft. The observation missions undertaken by these two organizations with autonomous satellites and spacecraft are proof of recent advances in the field. In 1999, the NASA used the Remote Agent software on the Deep Space 1 spacecraft to perform one of its most important missions as it was later used as a base in carrying out missions with satellites and autonomous spacecraft ³. The Aurora Programme mission launched in 2001 by the ESA aimed to explore the solar system in order to examine the existence of life outside Earth ⁴.

In order to better explain autonomous systems, [28] establishes 4 different levels of autonomy. First, there are autonomous systems with intelligent sensing. This level of autonomy consists of determining a platform's state by using its sensors' information. The second level of autonomy is defined by [28] as the level of planning and execution of the mission. This level of autonomy uses the strategy often called "divide and conquer," mission objectives are broken down into partial objectives each with limited resources. After satisfactory planning, it will be a question of carrying out the mission. In most definitions of autonomous systems, one still wants to have a human presence in order to intervene in case of unforeseen circumstances. One of the qualities of some autonomous systems is that they have the capacity to deal with the unforeseen themselves, thereby

³<https://ti.arc.nasa.gov/tech/asr/groups/planning-and-scheduling/remote-agent/>

⁴https://www.esa.int/Science_Exploration/Human_and_Robotic_Exploration/Exploration/The_European_Space_Exploration_Programme_Aurora

reducing human intervention even further. These systems which take into account or are able to manage the unforeseen quasi-independently are part of the third level of autonomy established by [28]. Finally, the last level of autonomy presented by [28] corresponds to distributed decision making. The particularity of this level of autonomy is that it enables the cooperation of several autonomous agents in order to achieve certain objectives.

In the rest of their work, the authors of [28] return to the comparison of systems using MDP and model-based approaches. MDPs can be defined as problems in which we have an agent located in an environment. The agent located in the environment is always in a precise state. He can take actions that can cause him to change state and receive a reward if the action was good or a reward whose value is proportional to the distance remaining to his goal. At the end, policies are established when the agent has learned well from the system. The main disadvantage that the authors point out with autonomous spacecraft systems using MDPs is the lack of data to be able to have good agent policies. Model-based approaches can also be compared to agents being in an environment. Unlike MDPs, these agents have a certain knowledge of the environment which enables them, when in any situation or state, to decide to take actions given their knowledge of the environment. Here, the disadvantage pointed out by [28] is that as in most model-based approaches, one can easily reach an unmanageable number of states for a spacecraft system. The comparison of two types of systems also leads the authors to state that despite their advantages and disadvantages, recent articles on these two approaches tend to overcome the obstacles that exist in the planning of observation missions and the use of autonomous spacecraft.

UUVs are an important type of unmanned vehicles. Their particularity is, as their name suggests, that they are the only types of unmanned vehicles capable of effectively exploring the waters. Nevertheless, some communication problems were noted during the missions with UUVs [29]. These communication concerns are due to delays caused by

the water. Despite these concerns, the most technologically up-to-date countries cannot do without them given their particularity. The authors of [30] analyze the progress of research in the field of mission planning with deployment of UUVs. Unlike the authors of [28], those of [30] are based not only on mission planning but also on mission management and their different architectures. They consider that mission management differs from mission planning since mission management includes all the techniques used to manage the mission from its inception to its end; whereas mission planning is a series of steps to achieve a goal [28,30]. They also noted that several articles on mission planning and mission management use architectures that are specific to their problems and often difficult to reuse. Thus, [30] lists categories of features considered as important for mission planning and management architectures. Then, they propose some architectures using these key features in order to present the differences between them and possibly their fields of application. The authors emphasize that even if the majority of articles cited and analyzed by [30] are based on UUVs, their proposals can be applied to missions taking into account other types of vehicles.

The first important feature to define for a mission planning and management architecture according to [30] is the specification of the mission plan. This feature is also defined in [30] as a set of actions in order to achieve a goal. Thus, they propose the use of AI techniques to achieve the generation of a mission plan. This leads to listing different types of mission plan specifications divided according to two characteristics. First, there are deterministic and non-deterministic planners. Then there are multi-agent planners, with temporary constraints and/or with hierarchization of tasks. The second feature is the specification of a contingency management system. For this, they focus on an architecture called Monitor, Analyze, Plan, Execute - Knowledge. This architecture receives data input from sensors and at output, it executes an action. Between the perception provided by

the sensors and the action, the data is successively monitored, analyzed, used to plan and then execute, according to a certain knowledge which is updated. The third feature is the specification of UUV heterogeneity management. To overcome the problems that may arise due to the differences between UUVs used, [30] suggests the use of a certain level of abstraction in order to take into account the commonalities between the UUVs used. Finally, the last feature is the specification of how to dispatch and execute the mission plan to UUVs. According to this feature, the authors divide the mission planning and management architectures into several groups depending on whether the mission plan is entrusted or not to the vehicles before the mission or whether the mission plan is assigned through a task-by-task manner to vehicles.

2.2.1 Mission Planning in Risk Management Framework

As mentioned above, mission planning plays a key role in RMFs. There are places that require high security and in which the slightest security breach could cause diplomatic, economic, or other types of incidents. It is within this context that studies on RMFs have the role of designing systems establishing frameworks to adequately protect these places. Two ways in which mission planning are used in RMFs will attract attention in this subsection. First the use of platforms to ensure adequate surveillance of these places. Then there are systems where the use of platforms is only required when a security breach is detected.

One of the solutions for the protection of critical infrastructures is the use of Robotic Sensor Networks (RSNs). An RSN is a type of Wireless Sensor Network, where a node can be a simple sensor or a complex robot [31]. The efficiency of an RSN is directly linked to the management of the allocation of tasks to the different robots. Indeed, a good allocation

of tasks to robots will reduce the use of available resources and therefore, in some cases, allow to perform more tasks. The authors of [32] propose algorithms based on auction protocols for an efficient allocation of tasks to robots. Three variants of auction protocols are proposed by [32]. In the First-Price Sealed Bid Protocol, at the announcement of a new task, each robot will send a bid based on its battery level, its distance to the task, and other characteristics. The system will then select a specific number of top bidders depending on the task. As for the Dutch-Japanese Protocol, it is a protocol in which the emphasis is placed on the number of robots to take part in carrying out the tasks. For each task, an interval in which the number of robots must be found is established by the auctioneer. Thus, in order to respect this constraint, the bid threshold will be continuously modified until an acceptable number of robots can be able to respond to it. The English Protocol suggests fixing the bid threshold to 0 at the beginning and the coalition (the set of selected robots) will then be formed by robots that bid. The bid threshold will be continuously increased until no new bids are received. Then the coalition will be formed by the robots of the last round. Still in the protection of critical infrastructure using RSNs, [33] studies two types of alternatives for selecting robots through auctions. First, the pre-optimization auctioning scheme. In this type of solution, when a risk is detected, the system selects the robots able to accomplish the task. Then, an optimization process starts to select the best ones given the task and the task's location. Then, there is the post-optimization auctioning scheme where the auctioneer starts with the optimization which consists of finding the best locations for the robots. Then, based on those results, it lets the robots bid. After experimenting with the two methods, [33] conclude by indicating that each of these methods has a particular context in which it is preferable over the other. Thus, the pre-optimization method is preferable when the distances to be covered are short while the post-optimization is preferable in the opposite situations.

Maritime traffic is part of the most important traffic on Earth, especially involving trade [34]. RMFs are important in the maritime domain given the need for countries to ensure near-permanent surveillance in waters since the number of pirate attacks are still increasing⁵. Like several articles mentioned earlier, [33, 35] are based on continuous monitoring of maritime areas to detect suspect events and intervene if needed. [35]’s solution consists of using UAVs to monitor selected areas. Each area will be divided into genes to allow a better coverage of UAVs. Soft-data is assimilated to data coming from humans (data on the internet, in social networks, etc.) while hard-data is often assimilated to data from sensors [33]. Unlike several existing surveillance methods, [33] proposes the use of soft-data combined with hard-data in order to get an idea of the level of security of different maritime areas. This method saves resources like UAVs, vessels, helicopters and others to only intervene when there is a risk signaled by the system.

2.2.2 Collection Scheduling Optimization

The scheduling optimization problem can be defined as one in which each task given to an individual at a precise moment contributes to maximize one or more objective(s), and this, while respecting certain constraints⁶. This type of problem can also be assimilated to Constraint Satisfaction Problems (CSPs) which are problems of finding valid values to be attributed to a set of variables each having a domain and possibly constraints [36]. Unlike the scheduling optimization problems, the main objective of CSPs is to meet constraints and not to optimize objectives.

[37] presents the use of CSO algorithms as a solution to a two-stakeholder problem.

⁵<https://www.statista.com/statistics/266292/number-of-pirate-attacks-worldwide-since-2006/>

⁶<https://optimoroute.com/schedule-optimization/>

On one hand, there are organizations that want to carry out surveillance missions but do not have satellites. On the other hand, there are organizations that not only have their own missions to carry out but also possess satellites for this purpose. Organizations with platforms capable of performing observation missions often market the use of their platforms. This is very often made possible when in the initial trajectories of platforms to collect images for their organizations, there is also the possibility of collecting images for other organizations. The CSO algorithms are used to formalize the objectives of the mission in order to make the deployment of platforms profitable for all stakeholders. Although [37] studies this problem only from the perspective that the platforms are satellites, the study of this problem can be extended to UAVs, UUVs, vessels, etc.

The several articles in this research area can be grouped into three. Centralized architectures are architectures in which the optimization of the image collection to satisfy different stakeholders is done regardless of the organizations to which the platforms belong [2, 3]. Distributed architectures are architectures in which the optimization process is done on each platform considered as an individual agent. [6] proposes a distributed CSO architecture in which each agent optimizes its collection of images but can also at some point during the mission, affiliate with another agent to form a fixed-term cohort. There are also decentralized coordinated architectures where tasks are only assigned to organizations with platforms so that they perform them independently. [7] solves this type of problem and compares two types of algorithms: Highest-Weight-First-Allocated algorithm, and the second is a Tabu-List-based Simulated Annealing (SA-TL) algorithm. The authors came to the conclusion that SA-TL performs better.

2.3 Image Quality in Mission Planning

The quality of the images obtained from observation missions is an important factor in determining the success of a mission. The images obtained during observation missions are used in various ways as mentioned in the previous sections. Some applications in GANs improve the quality of certain images by using others of better quality [38]. If the images used as targets have a poor quality, this kind of application will not provide satisfactory results. Soil moisture is a very important variable in determining climate change and even preventing natural disasters [39]. The authors of [39] propose the use of images obtained from observation missions to analyze soil moisture. The success of this method depends on obtaining good resolution images as mentioned by the authors.

2.3.1 Image Quality Assessment

There are several methods to determine the quality of an image. These methods can be divided into two groups: no-reference image quality assessment and full-reference image quality assessment. In full-reference image quality assessment, the image quality is the result of a comparison between an input image and a reference image. The comparison is done based on metrics like mean-squared error, peak signal to noise ratio and others. No-reference image quality assessment methods use statistical metrics to evaluate the quality of the image. Some of them compute the quality based on the level of distortion of the input image.

Some image quality assessment methods are classified as no-reference although they use machine learning and therefore images during training to determine the quality of the images. The Blind/Referenceless Image Spatial Quality Evaluator and the Natural Image Quality Evaluator are part of these methods [41, 42]. Their main objective is to

examine the quality of the image taking into account its distortions. Another objective of these methods is to correlate this quality value with human perception. Unlike these two methods, the Perception based Image Quality Evaluator (PIQE) [43] does not use trained models to determine the quality of an image, instead this method is based on the use of distortion as one of the factors influencing the quality of an image.

2.3.2 Image Quality Prediction

As for mission planning, using the image quality assessment methods described in the previous subsection has limitations. When planning observation missions, mission planners do not yet have images and therefore cannot use these methods. These methods could be useful if one uses previously acquired images to predict the quality of future images. In order to predict the quality of images given a mission plan, several authors suggest the use of the GIQE [13, 44–46]. The GIQE is in fact a linear regression model whose features are the ground-sampled distance, the system modulation transfer function and the signal-to-noise ratio.

The goal of the first release of the GIQE was to predict the image quality based on sensors' characteristics. The quality was expressed in terms of the National Imagery Interpretability Rating Scale (NIIRS) that describes the quality of an aerial image based on 10 rating levels ⁷. Each of the 10 levels describes what information can be drawn from the image to be acquired. The rating level 0 describes the future image as an image where "Interpretability of the imagery is precluded by obscuration, degradation, or very poor resolution" while one of the descriptions of the rating level 9 is: "Identify vehicle registration numbers (VRN) on trucks."

⁷<https://fas.org/irp/imint/niirs.htm>

The authors of [44] performed an analysis of the quality of imagery to be acquired with an EO sensor from two specific UAVs: Global Hawk and Predator. The quality was obtained using the GIQE and expressed in terms of NIIRS. These analytical works demonstrate how the NIIRS is influenced by the flight altitude, the focal length of the sensor and the angle of view from the sensor to the target. Similarly, Defence Research and Development Canada [45] analyzed the performance of the GIQE with EO and IR sensors. Still in the aim of analyzing and facilitating the use of the GIQE, the Air Force Research Laboratory built a Python package, pyBSM [46], that uses environmental conditions and EO and IR sensors' information as inputs to predict the NIIRS based on the GIQE.

2.4 Sensor Fusion

2.4.1 Background on Sensor Fusion

Several articles analyzed in the previous sections highlight the use and amalgamation of data from different sensors to obtain a better image or a better perception of the environment. This fusion process is called sensor fusion [47]. [48] studies the performance of three classifiers that detect, from images, the land use. They compare the performance of Support Vector Machines (SVMs), Random Forests and k-Nearest Neighbor. The authors test each classifier with three types of data: data obtained from SARs, others obtained in the visible near-infrared spectrum as well as a combination of both. Their experiments show that the SVM obtains much better results than the other classifiers. On top of that, the accuracies, for each classifier, obtained from the fused data are superior than the others. On the other hand, [49] carries out a study to measure the growth of agricultural production. The authors of [49] propose a method called Phenological Sequence Pattern

to automatically count the number of agricultural areas in different images. They analyze the performance of their classifier, compare it with a Random Forest classifier and show that their classifier gives better accuracy. In their experiments, the authors test the efficacy on data from Sentinel 1 (SAR), Sentinel 2 (EO/IR) and then a combination of both. Although the different accuracies of Random Forest shows that the fused data achieves better accuracy, for their new classifier, it is the data from Sentinel 1 that gives better results. This proves that the efficiency of the fusion methods is not always automatic, several analyses are often necessary in order to take advantage of the efficiency of the data fusion.

2.4.2 Image Fusion

As for fusing images from multiple sensors, there are three main groups of image fusion methods: pixel-level fusion, feature-level fusion and decision-level fusion. With pixel-level fusion, images are fused pixel by pixel, this process requires having pairs of images almost completely aligned. Feature-level fusion consists of extracting features of pairs of images then obtain fused images based on those pairs of features. Decision-level fusion considers hypotheses drawn from pairs of images to make a final one. Several authors including those of [50] demonstrate that deep learning methods have reached state-of-the-art results in sensor fusion.

[51] proposes a pixel-level fusion method of visible and infrared images called hybrid-multi scale decomposition. Multi-scale decomposition is a method generally used for pixel level fusion. [51] finds that this method has issues concerning the level of perceptuality of the fused image. The main purpose of the method proposed by [51] is to use the knowledge gained from multi-scale decomposition and add new features to it in order to give better

results from a human perception point of view. The results of the experiments of [51] show that the images fused with their method have a better perception.

Still concerning the fusion of visible and IR images, the authors of [52] propose a feature-layer fusion method. [52] proposes the use of deep learning to merge the features of pairs of images at several levels before reconstructing them and obtaining the fused images.

Image fusion is also used in applications such as object classification. It then consists of fusing the images to better predict the types of objects. [40] suggests the use of decision-level fusion to perform this type of task. The method proposed is based on a training step of two Convolutional Neural Networks (CNNs) with SAR or IR images. After this step (i.e. the training mode), the models can be used (i.e. the testing mode), and their predictions fused.

2.5 High-Level Information Fusion

2.5.1 Joint Directors of Laboratories

For a better identification of different levels of fusion, the Joint Directors of Laboratories carries out a work which consists in describing and distinguishing between levels of fusion [53]. Their work was then modified by [54] to obtain five levels of fusion: sub-object assessment, object assessment, situation assessment, impact assessment and process refinement. As for the sub-object and object assessment, it consists of fusing data to predict the states of signals, objects and entities. Situation assessment predicts the entity states considering some links between them. Impact assessment aims to predict the impact that some actions can have in the environment. Finally, process refinement uses fused information to predict the best actions to take.

2.5.2 Information Fusion Effectiveness

In order to better protect maritime traffic, [14] suggests the use of a method based on the combination of soft- and hard-data. To this end, the authors propose a metric to measure the added value of data fusion. This metric is based in particular on the sensors used and the dates in order to estimate the added value of an eventual fusion. The impact of the time on the fusion value is measured through the use of fuzzy logic.

2.6 Artificial Intelligence

Many articles on mission planning opt for the use of AI to achieve improvement in one or more aspects of observation missions. For example, [55] analyses how AI can be used to reduce operator load on the ground during UAV missions. This section will provide a technical background on some AI topics used in mission planning.

2.6.1 Evolutionary and Genetic Algorithms

AI is often defined as a set of methods that allow machines to perform tasks that normally require human intelligence. Several AI algorithms are inspired by natural phenomena. This is particularly the case with Evolutionary Algorithms (EAs) which are inspired from natural evolutionary mechanisms in order to find the best solutions to problems. There are two prerequisites in order to apply EAs to a problem. First, it requires to define in a computer program what a solution to the problem can be. Then, it will be necessary to define a fitness function which is an evaluation function of the solutions of the problem. Multi-Objective Evolutionary Algorithms (MOEAs) are EAs used to solve problems where

solutions are evaluated based on several criteria. The different steps when looking for solutions to a problem by EAs are:

- Generation of an initial population of solutions
- The evaluation of each solution that is part of this population
- Generation of a new batch of solutions from the previous batch of solutions. This new batch of solutions will replace the bad solutions from the old batch.
- Repeat the last two steps until you reach a defined stop condition.

It is in the generation of new batches of solutions that imitations of natural evolutionary phenomena happens, through the use of operations like crossover, and mutation in the generation of new solutions. GAs are a part of EAs but differ from others in that their solutions are encoded in strings.

2.6.2 Multi-Objective Optimization

MOO problems are problems which consist of seeking the best solutions while taking into account more than one objective or criterion. Often, the search for solutions to these problems must consider certain constraints. Objectives are variables to be maximized or minimized while constraints are restrictions to the objectives.

The objectives of MOO problems often conflict: the maximization of one can cause the minimization of another. This is often the case in surveillance missions where the most frequent objectives are: the maximization of areas monitored and the minimization of the cost; monitoring areas increases the cost of the mission. MOO algorithms must take into account trade-offs in order to find the best solutions given the conflicts.

In cases where objectives conflict, it is very rare for MOO algorithms to find only one solution. The best solutions to the problem are rendered in a Pareto Front to eventually allow end-users to choose the most suitable one. There is domination of a solution A over a solution B if and only if the objective values of solution A are better compared to all the objective values of solution B. If only some of the objective values of solution A are better than those of solution B, solutions A and B are non-dominated [56].

2.6.3 Machine Learning

Machine Learning (ML) is a part of AI that unlike others uses data to "learn" to perform a task. The importance that ML has acquired in recent years even leads some people to bluntly confuse AI with ML ⁸. Three main branches of ML are often distinguished, these are: supervised ML, unsupervised ML and Reinforcement Learning (RL).

In supervised ML, the data used to train the system to perform a task is made up of inputs and outputs. The inputs are the data from which the system should learn to predict the outputs. There is a training phase where the system uses inputs and outputs to learn, an evaluation phase which consists of using only the inputs and evaluating the predictions of the system. Artificial Neural Networks (ANNs) are an ML method used to train a model to predict output values from a set of features. They are composed of several layers having a number of well-defined neurons through which the input values are transformed to obtain predictions. Depending on the complexity of the task, different architectures of ANNs can be adopted. They are often defined according to the number of neurons on each layer of the ANN [57]. If there are no intermediate layers between the inputs and the outputs, the

⁸<https://pub.towardsai.net/differences-between-ai-and-machine-learning-and-why-it-matters-1255b182fc6>

ANN becomes a logistic or linear regression model depending on whether the value(s) to be predicted are categorical or continuous values, respectively. CNNs are also an ML method, more specifically a Deep Learning (DL) one, used to analyze images (among other types of data). They are composed of a feature extraction phase and a fully connected network phase whose architecture is similar to those of ANNs [58].

In supervised ML, K-Fold Cross Validation is often used to obtain a generalized model when faced with limited amount of data. K-Fold Cross Validation is a process used to train and evaluate models by alternating training and evaluation data. If K equals 10, the dataset will be divided in 10 sets and the model will be successively trained using nine of the 10 sets and evaluated using one of them. In this case, 10 epochs will be necessary to train and evaluate the model with the different sets.

The mean squared error is a metric often used with supervised ML methods predicting continuous output values. Equation 2.1 describes how to compute the mean squared error. For supervised ML methods with discrete output values, the metric generally used is the accuracy. The latter is the ratio of correctly predicted values.

$$mse = \sum_{k=1}^K (y_k^2 - \bar{y}_k^2) / K \quad (2.1)$$

where:

- mse is the mean squared error.
- y represents ground truth values.
- \bar{y} represents predicted values.
- K is the size of the dataset.

Unlike supervised ML, unsupervised ML receives data containing only a set of inputs. The goal of unsupervised ML is to get the model to detect relationships between certain entries in order to group them into different categories.

Since these ML methods often require enough data to achieve satisfactory results and in some cases this data is scarce or difficult to collect, transfer learning techniques can be used to impart knowledge from one solved problem to a similar yet unsolved one.

There are several well-defined architectures of CNNs proposed by researchers, among which are ResNet [59], MobileNet [60], MobileNetV2 [61] and others. Most of these CNN architectures can also be used for transfer learning purposes since pre-trained versions of them exist. In this case, the feature extraction stage, the pre-trained stage, is only used to output the inputs of the fully connected layers during training, evaluation and testing.

In RL, the objective is to teach an agent, in an environment, to perform a task by pushing the agent to choose the best actions for the different states of the environment in which it may find itself. During the learning phase, the agent is driven to make the best decisions through the use of rewards. The reward value given for an action in a specific state will be proportional to the effectiveness of the action. Thus, at the end of the training, the agent will have a policy which it can use to carry out this task.

2.6.4 Correlation Coefficient

In AI, it is often important to measure the dependence between pairs of variables. One of the most used metrics to measure the dependence of two variables is the Pearson Correlation Coefficient (PCC), it allows to measure the linear correlation between two variables. If PCC between two variables X and Y is 1, there is a perfect linear correlation, they can be both written as an increasing affine function of the other. If PCC is -1, the linear cor-

relation is also perfect but the affine function is decreasing. There is no linear correlation if PCC is 0. The closer PCC gets to 1 or -1, the greater the linear correlation between the variables. On the other hand, the closer PCC gets to 0, the least the linear correlation between the variables. Equation 2.2 describes how to compute the PCC of two variables.

$$pcc = \frac{\sum(x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum(x_i - \bar{x})^2 \sum(y_i - \bar{y})^2}} \quad (2.2)$$

where:

- \bar{x} is the mean value of the variable X .
- \bar{y} is the mean value of the variable Y .

2.7 Chapter Summary

This chapter had two main objectives: first, explain what observation missions are, then analyze the different techniques used to improve these missions.

In order to better understand the observation or surveillance missions, different contexts requiring these missions have been highlighted: environmental analyses, protection of territories, etc. In addition to this, it has been shown that the images collected during the missions have an impact on several research areas, in particular ML. Emphasis was also placed on mission planning to achieve satisfactory results.

From a technical point of view, several methods used to optimize observation missions were analyzed. A particular emphasis has been placed on AI methods which make it possible: to quantify the objectives that can be achieved for each mission plan, to find the

best mission plans when these objectives are in conflict, and also to estimate the qualities of the images afterwards acquired according to the mission plans.

Chapter 3

Multi-Objective Heterogeneous Multi-Asset Collection Scheduling Optimization with High-Level Information Fusion

This chapter presents a surveillance missions' CSO: the Multi-Objective Heterogeneous Multi-Asset Collection Scheduling Optimization with High-Level Information Fusion (MOHMA-CSO-HLIF). MOHMA-CSO-HLIF's main contribution will be its ability to consider the benefit of sensor fusion in the optimization process. Other than that, three different variants of MOHMA-CSO-HLIF are proposed, each prioritizing either a certain number of platforms used per AOI or a minimum coverage of each AOI.

3.1 Problem Definition

MOO problems are quite suitable when looking for solutions, MOHMA-CSO-HLIF will have to take into account more than one objective or criterion among which some could be in conflict. The choice of solutions must then take into account the trade-off between the different criteria. In this work, the type of MOO problem to be solved can be defined as follows:

- Let A be a number of platforms (UAV, vessel, satellite, UGV, etc.) having well-defined trajectories and each equipped with at least one sensor.
- These platforms are managed by B SPs, B being less than or equal to A .
- Let C be the number of TRs submitted by agencies.

The questions that need to be addressed become:

- How to assign these TRs to SPs, given the trajectories of their platforms, so that the objectives (which will be presented later on in this chapter) can be maximized?
- Additionally, for each TR that is assigned to a SP, how to optimally use the platforms in order to maximize the objectives?

3.2 Methodology

The mission planning problems to solve in this work can handle heterogeneous types of assets (UAVs, UGVs, Satellites, etc.). However the scenarios used in the experiment section

only use UAVs and satellites as assets. A TR is an area or a moving target for which agencies or SPs require imagery products. MOHMA-CSO-HLIF has four types of TRs: AOIs, Points of Interest (POIs), dynamic tracks and circuits. In this work, TRs are limited to AOIs and POIs. A TR will be qualified as local to a SP if, in the definition of the problem, it is assumed that it will be accomplished by that SP. A TR that is not a Local Task Request (LTR) to a SP is a System-level Task Request (STR).

Each platform will have an image acquisition schedule: different periods of time when they turn on their sensors to acquire images of AOIs or POIs. Platforms can observe TRs by using different loitering trajectories: circle, spiral, racetrack, snake, etc. In this thesis, MOHMA-CSO-HLIF handled two different types of sensors models used: SAR with multiple beam modes, and EO/IR with different surveillance modes. Total::PerceptionTM¹ will be used to run user-based scenarios and generate Collection Opportunities (COs). A CO represents the opportunity of a platform's sensor model to acquire images of a specific TR. Each AOI will be divided into a number of surface tiles, while a POI is considered to be represented by a single tile. A CO will then have as attributes: the cost of the observation, the Quality of Observation (QoO), the start time and end time of the observation, the platform observing the AOI or POI, the sensor used to observe the AOI or POI, the name of the AOI/POI (only one AOI/POI per CO) being observed, and the list of tiles of the AOI/POI being observed.

Research in the sensor fusion field shows that an image resulting from the fusion of two images from different sensors can provide more information than the original images [47]. This work is based on this in order to create novel capabilities in the field of mission planning. This innovation, termed MOHMA-CSO-HLIF, can be summed up in two points:

1. It takes into account the image quality that a sensor can offer in the suggested solu-

¹Total::PerceptionTM is a proprietary ISR Systems Simulation Engine developed by Larus Technologies

tion. A reminder that the main purpose of these surveillance missions is to obtain images of AOIs/POIs. Thus, taking into account the image quality that one sensor can provide compared to another is more than crucial. 2. MOHMA-CSO-HLIF does not stop there, it also takes into account the image fusion factor. This second point can push the optimizer to select solutions where one or more platform(s) equipped with different sensors monitors the same area so that the resulting image (fusion) is one of superior quality. Without HLIF, MOHMA-CSO-HLIF becomes Multi-Objective Heterogeneous Multi-Asset Collection Scheduling Optimization (MOHMA-CSO). The difference between these two frameworks is that MOHMA-CSO-HLIF takes into account the QoO when assigning STRs to SPs while MOHMA-CSO does not. To take into account the QoO of STRs observed by more than one sensor, MOHMA-CSO-HLIF will use COs generated by Total::Perception™ to create new COs, Fused Collection Opportunities (FCOs), with tiles observed by more than one type of sensor. These FCOs will have a new QoO. Figure 3.1 shows a TR divided into equal tiles, some tiles are covered by COs (including one FCO) and others are not covered.

3.3 Proposed Solution

The output of MOHMA-CSO-HLIF is a set of Task Assignment Plans (TAPs) representing assignments of STRs to SPs. These TAPs are binary numbers of $M \times N$ bits, M being the number of SPs and N being the number of STRs. The i^{th} bit of this binary number represents the assignment (1) or not (0) of the STR d (the latter being the result of the integer division of i by M) to the SP e (the latter being the result of i modulo M). Thus, the MOEAs (NSGA-II [62], NSGA-III [63] and SPEA2 [64]) will be able to generate several TAPs and evaluate them using the objectives which will be defined in the following sections.

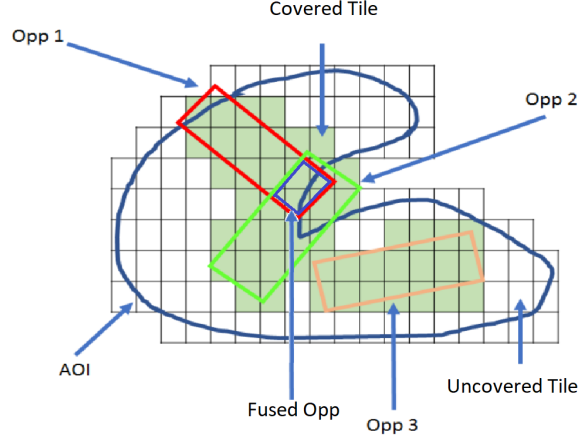


Figure 3.1: A TR observed by three different COs. Opp1, Opp2 and Opp3 are COs using different types of sensors. Since Opp1 and Opp2 have some tiles in common, there will be a FCO, Fused Opp, covering their common tiles.

After the assignment of STRs to SPs, each SP will execute Multi-Objective - Genetic Algorithm-based collecTion scHedulER (MO-GATHER) [2] to optimize the realization of the TRs assigned to it and obtain as output a Collection Plan (CP). The latter can be simulated and visualized using Total::Perception™.

3.3.1 Motivation behind Strategies in MOHMA-CSO-HLIF

MOHMA-CSO-HLIF has a mechanism for finding the best solutions taking into account different strategies. The purpose of using strategies is to capture what the mission planners are most sensitive to during the mission. Three types of strategies are available in MOHMA-CSO-HLIF. The first is All-Asset Coverage Maximization (AACM): choosing this strategy pushes the SPs to maximize the coverage of STRs by using all their platforms. In the second strategy, Single-Asset Coverage Maximization (SACM), the system

pushes each SP to maximize the coverage of each STR by using only one platform. Finally, Cost-Aware Coverage Maximization (CACM) aims to reach a minimum coverage for each STR in order to reduce the cost of the mission. Since finding the optimal solutions is directed by evaluating the objectives, depending on the strategy chosen, objective function evaluation when assigning a STR to a SP will differ. Depending on the strategy, the only modification in the evaluation of an objective will be the selected platforms. For example, if the strategy chosen is SACM and a STR is assigned to a SP of three platforms, the different objective function evaluations will only use the platform that has best covered the AOI or POI (one wants to push the SP to take into account only one platform); whereas if the strategy was AACM, they would use the three platforms. For the same example, if the strategy chosen was CACM, the minimum coverage was 60% and two specific platforms of these three were sufficient to reach at least 60% (no other combination allowed to have more than 60% with a lowest cost), then these two platforms would be used to compute the different objectives. See Algorithm 3.1 for more details on how platforms are selected for CACM.

Algorithm 3.1 Selection of a Sub-planner's Platforms with CACM Strategy

Input: STR S , sub-planner's assets A , set of Collection Opportunities CO , minimum coverage threshold γ

Output: The subset of assets required to achieve the minimum user-specified coverage threshold γ or \emptyset if γ cannot be achieved by the sub-planner

```
1:  $\Delta_a \leftarrow$  the coverage on  $S$  achieved by all assets  $a \in A$  using all the collection opportunities  $o_{a,k} \in CO$ .
2: if ( $\Delta_a < \gamma$ ) then
3:   return  $\emptyset$ 
4: end if
5:  $B = A; \Delta = \Delta_a; notTried = A$ 
6: while ( $(\Delta > \gamma) \& (notTried \neq \emptyset)$ ) do
7:    $b \leftarrow$  the asset in  $notTried$  with the highest estimated cost  $C_b$  while covering the STR  $S$ 
8:    $\Delta_b \leftarrow$  the coverage on  $S$  achieved by all assets in  $B - \{b\}$ 
9:   if ( $\Delta_b > \gamma$ ) then
10:     $B = B - \{b\}$ 
11:     $\Delta = \Delta_b$ 
12:   end if
13:    $notTried = notTried - \{b\}$ 
14: end while
15: return  $B$ 
```

3.3.2 Objectives Definition

When assigning STRs to SPs, MOHMA-CSO-HLIF uses four objectives in the evaluation of solutions.

Local Conflict Cost

The first objective is the Local Conflict (LC) cost. The idea behind LC is to assess the degree of conflict if a STR X is assigned to a SP Y . This degree of conflict is evaluated by considering LTRs to SP Y . If the STR X is performed by the SP Y during a moment when the SP Y can also perform its LTRs then there is a conflict. The LC will be a function of the intersection between the time when the SP can perform an assigned TR X (which is a STR) and the time when it can perform its LTRs. The goal is to minimize LC. The Equation 3.1 details how to compute the LC when assigning a TR to a SP using as parameters: the STR, the SP, the list of COs in the scenario and the list of local COs (COs used to collect images of a LTR) to SPs. Equation 3.2 computes the LC for a specific solution i.e. TAP.

$$LC_{i,j} = \sum_{k=1}^K \sum_{l=1}^L \text{Overlap}(Opp_k, LOpp_{l,j}) x_{i,j,k} \quad (3.1)$$

$$LC_{TAP} = \sum_{i=1}^I \sum_{j=1}^J LC_{i,j} y_{i,j} \quad (3.2)$$

where:

- Opp_k is an interval representing the interval: [start time, end time] of the k^{th} CO.
- K is the number of COs in the scenario.

- $LOpp_{i,j}$ is an interval representing the interval: [start time, end time] of the l^{th} local CO (to fulfill a LTR) of the j^{th} SP.
- L is the number of local COs associated with the j^{th} SP in the scenario.
- $Overlap(Opp_i, Opp_j)$ is the amount of time when Opp_i and Opp_j are overlapping.
- $x_{i,j,k}$ is 1 if the TR associated with the k^{th} CO is the i^{th} STR and the platform associated with the k^{th} CO is one of the selected platforms (to fulfill the i^{th} STR depending on the strategy) of the j^{th} SP. Otherwise it is 0.
- $LC_{i,j}$ is the LC of assigning the i^{th} STR to the j^{th} SP.
- I and J are respectively the number of STRs and SPs.
- $y_{i,j}$ is 1 if the i^{th} STR is assigned to the j^{th} SP in the TAP . Otherwise it is 0.
- LC_{TAP} is the LC of the TAP .

Resource Cost

The second objective is the Resource Cost (RC). The RC of a solution represents the cost, in monetary value, spent in order to carry out this mission: having sensors switched on for a certain period of time, going through an entire area by UAV, UGV, satellite or boat (the cost of the battery or gasoline), capacity of the memory to store the images. Similarly, the value of RC will have to be minimized. The Equation 3.3 computes the RC of assigning a STR to a SP by using as parameters: the STR, the SP, all the COs and their RCs. Then Equation 3.4 computes the RC of a TAP.

$$RC_{i,j} = \sum_{k=1}^K rc_k x_{i,j,k} \quad (3.3)$$

$$RC_{TAP} = \sum_{i=1}^I \sum_{j=1}^J RC_{i,j} y_{i,j} \quad (3.4)$$

where:

- rc_k is the RC of the k^{th} CO.
- K is the number of COs in the scenario.
- $x_{i,j,k}$ is 1 if the TR associated with the k^{th} CO is the i^{th} STR and the platform associated with the k^{th} CO is one of the selected platforms (to fulfill the i^{th} STR depending on the strategy) of the j^{th} SP. Otherwise it is 0.
- $RC_{i,j}$ is the RC of assigning the i^{th} STR to the j^{th} SP.
- I and J are respectively the number of STRs and SPs.
- $y_{i,j}$ is 1 if the i^{th} STR is assigned to the j^{th} SP in the TAP . Otherwise it is 0.
- RC_{TAP} is the RC of the TAP.

Profit

The third objective is the profit. The latter represents the execution rate of the STRs. The more images of different zones of AOIs or POIs a solution has collected or has monitored, the greater the profit will be. Unlike the first two objectives, the value of profit will have to be maximized. The Equation 3.5 computes the number of tiles observed when assigning a STR i to a SP j . It uses the STR, the SP, the list of COs of the scenario and their list of

tiles as parameters. Then, the profit of a specific TAP is computed as shown in Equation 3.6.

$$Tiles_{i,j} = Tiles_{i,j,1} \cup \dots \cup Tiles_{i,j,K} \quad (3.5)$$

$$Profit_{TAP} = \sum_{i=1}^I \sum_{j=1}^J Size[(Tiles_{i,j} \cap X_{i,j})] Priority_i / Size_i \quad (3.6)$$

where:

- $Tiles_{i,j,k}$ is equivalent to the set of tiles of the k^{th} CO if the TR associated with the k^{th} CO is the i^{th} STR and the platform associated with the k^{th} CO is one of the selected platforms (to fulfill the i^{th} STR depending on the strategy) of the j^{th} SP. Otherwise it is \emptyset .
- K is the number of COs in the scenario.
- $Tiles_{i,j}$ is the set of tiles of the i^{th} STR observed by the j^{th} SP's selected platforms.
- I and J are respectively the number of STRs and SPs.
- $Priority_i$ and $Size_i$ are respectively the priority of the i^{th} STR and its size (number of tiles).
- $X_{i,j}$ is \emptyset if the i^{th} STR is not assigned to the j^{th} SP in the TAP, otherwise it is the set of positive integers.
- $Profit_{TAP}$ is the Profit of the TAP.

Quality of Observation

The transition from MOHMA-CSO to MOHMA-CSO-HLIF is made possible thanks to the addition of another objective, the QoO, in the assignment of STRs to SPs. Using the result of Equation 3.7, which computes the QoO of each tile, Equation 3.8 will compute the QoO of a specific TAP. These Equations use as parameters: the TAP, the list of COs, the QoOs associated with COs and the list of tiles of COs.

$$QoOTile_{a,i,j} = \max_{\forall k \in \mathbb{N}, 0 < k < K+1} (qOpp_k x_{a,k} y_{i,j,k}) \quad (3.7)$$

$$QoOTAP = \sum_{i=1}^I \left[\sum_{j=1}^J \sum_{a=a_i}^{A_i} (QoOTile_{a,i,j} z_{i,j}) / Size_i \right] \quad (3.8)$$

where:

- $qOpp_k$ is the QoO associated with the k^{th} CO. Note that here, FCOs (resulting from the fusion of two COs with different types of sensors) are included in the list of COs.
- $x_{a,k}$ is 1 if the a^{th} tile (of the scenario) is one of the tiles associated with the k^{th} CO. Otherwise it is 0.
- $y_{i,j,k}$ is 1 if the TR associated with the k^{th} CO is the i^{th} STR and the platform associated with the k^{th} CO is one of the selected platforms (to fulfill the i^{th} STR depending on the strategy) of the j^{th} SP. Otherwise it is 0.
- K is the number of COs (including the FCOs) in the scenario.
- $QoOTile_{a,i,j}$ is the quality of the a^{th} tile when assigning the i^{th} STR to the j^{th} SP.
- a_i is the first tile (with the smallest id) of the i^{th} STR.

- A_i is the last tile (with the biggest id) of the i^{th} STR.
- $Size_i$ is the number of tiles of the i^{th} STR.
- I and J are respectively the number of STRs and SPs.
- $z_{i,j}$ is 1 if the i^{th} STR is assigned to the j^{th} SP in the TAP . Otherwise it is 0.
- QoO_{TAP} is the QoO of the TAP.

3.4 Experiments and Results

In order to demonstrate the operation and utility of MOHMA-CSO-HLIF, this section will be divided into three parts. First, an analysis will be performed to underscore the added value of the QoO. In the second part, a comparison between the three different variants of MOHMA-CSO-HLIF will be made using their results after their executions on the same scenario. Then, a comparison of the results of this framework will be made with those of other frameworks with different architectures.

The last two scenarios used in this section are created using a meta-tool that generates scenarios by using the number of platforms as a hyper-parameter. For all the cases where CACM is the selected strategy, the minimum coverage, which is an end-user entry, was set at 70%. The minimum coverage was experimentally set at that threshold since if it is too high (i.e. 90%), the profit and QoO will be low since most SPs will not be able to achieve that minimum coverage percentage for STRs. Moreover, on the other hand, if the threshold is too low, then it will behave similarly to SACM since that constraint will only need one or two platforms per SP to reach the minimum coverage. The use of the meta-tool confirmed the relative impact of the number of platforms on the objectives.

Without platforms, there is no possibility to collect imagery, the QoO will then be 0. On the other hand, the more platforms there are in a scenario, the greater the probability to obtain a good QoO which will ultimately depend on the sensors used and on the platforms' coverage of STRs. Figure 3.2 shows the impact of the number of platforms on QoO.

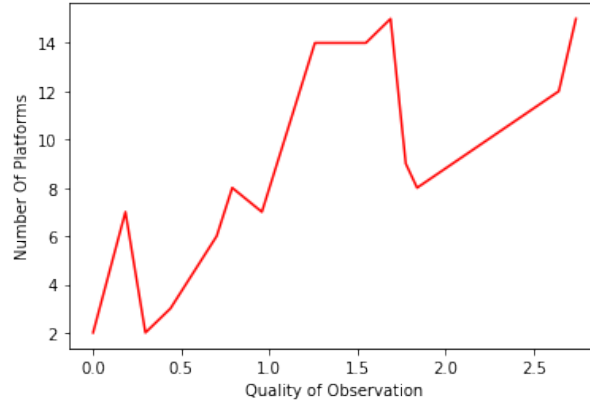


Figure 3.2: Impact of the Number of Platforms on QoO.

3.4.1 Added Value of the QoO

One of the indicators to measure the impact of the objectives in an MOO is the independence of the objectives. If all the objectives have a perfect dependence, their collective value will be diminished since having one of them would be enough to estimate the value of the others. On the other hand, if each objective is independent from the others, each of them becomes even more important since replacing one by another will lose an important indicator.

The PCC between each of the four objectives will therefore be examined. The emphasis will be placed on the correlations between the QoO and each of the other objectives in order to confirm or not that its inclusion as an objective in MOHMA-CSO-HLIF is not

vain. In the case of a mission planning system, with the objectives like those proposed, it would be almost abnormal not to have any dependence between the objectives: an increase of the QoO or of the profit will necessarily have an effect on the RC. However, it is still interesting to know if the value of PCC is the same regardless of the strategy.

The TAPs of the scenario described in Figure 3.3 were selected in order to measure the PCCs between each of the objectives.

The PCCs of Table 3.4 confirm what was mentioned above. The majority of the objective values implemented often have fairly strong positive linear correlations between them. However, the correlation coefficients are not always the same when switching TAPs from one strategy to another. This is also confirmed between QoO and the other objectives. This variability of the PCCs confirms that each of the objectives remains important since it is not possible in each scenario or each strategy to exactly predict one of them from the others. The PCCs of CACM are even more reassuring about this: the QoO is only fairly linearly correlated with the profit and the LC. This is because the threshold in CACM cancels out several TAPs that do not reach the minimum coverage required for each STR.

The importance of an objective also lies in its impact when the end user has to choose between several solutions. Two TAPs of the scenario described in Figure 3.3, obtained with AACM, were selected to confirm the importance of the QoO as an objective. Their objective values are mentioned in Table 3.1. In the situation described by Table 3.1, without the QoO as an objective, the end user might wonder whether it is justified to choose the solution TAP 1 since its cost increases by 15% while profit only increases by 4%. With the QoO, the user is led to reconsider their decision since the growth percentage of the QoO is almost equivalent to the cost's. In this case, the QoO is an indicator highlighting the benefit of one solution against another for the end user.



Figure 3.3: Snapshots of a scenario in Google Earth. In the top image, the three SPs deploy their platforms to observe six TRs. The bottom image shows the execution of the scenario several hours later.

Table 3.1: Comparison of Objective Values.

TAPs	QoO	Profit	RC	LC
TAP 1	3.27	0.76	7.94×10^6	0.0
TAP 2	2.89	0.73	6.90×10^6	0.0

AACM					SACM				
	QoO	Profit	RC	LC		QoO	Profit	RC	LC
QoO	1.000000	0.941209	0.976144	0.727423	QoO	1.000000	0.913165	0.969168	0.758058
Profit	0.941209	1.000000	0.903849	0.652885	Profit	0.913165	1.000000	0.872818	0.650631
RC	0.976144	0.903849	1.000000	0.664706	RC	0.969168	0.872818	1.000000	0.703670
LC	0.727423	0.652885	0.664706	1.000000	LC	0.758058	0.650631	0.703670	1.000000

CACM				
	QoO	Profit	RC	LC
QoO	1.000000	0.515364	0.911453	0.787379
Profit	0.515364	1.000000	0.274740	0.270886
RC	0.911453	0.274740	1.000000	0.872631
LC	0.787379	0.270886	0.872631	1.000000

Figure 3.4: PCCs of Objectives.

3.4.2 MOHMA-CSO-HLIF Variants

Tables 3.2, 3.3 and Figure 3.5 describe a scenario in which there are 29 TRs submitted by 2 SPs and 7 agencies. Two types of TRs are in Table 3.2: STRs which are submitted by the agencies and LTRs submitted by the SPs. Recall that the first goal of MOHMA-CSO-HLIF is to optimize the assignment of STRs to SPs using the four objectives defined in the previous section.

Table 3.4 gives the different results obtained after the execution of MOHMA-CSO-HLIF using AACM, SACM and CACM strategies. For each of these variants, MOHMA-CSO-HLIF presents non-dominant solutions in a Pareto Front (see Figure 3.6 for a sample Pareto front where three of the four objective variables were selected). Then, in order to compare the solutions, we chose, for each variant, the solution with the highest QoO.

Let us note that with these results, the highest profit and the highest quality are obtained with AACM. This is very logical since with this strategy, each SP uses all its platforms (even those covering exact same areas) in order to carry out the STRs entrusted

Table 3.2: Scenario 2's Requests.

Requester	AOIs	POIs
Agency-1	Somali land	Liverpool Airport, Hormuz, Quebec City Airport, Montreal Airport Trudeau
Agency-2	Kosovo1, Gaden Mid, Azov Ukraine	Atlantic Canada
Agency-3	Hormozegan, Damerdjog	Finlay Air Park, T4, Artic North
Agency-4	North Alaska, Azov Russia	Base5, FOL Yellow Knife
Agency-5	Op Box1, Hurmoze	McArthur River Mine Airport
Agency-6	North Arctic Circle, Coldbrook Caledonia , Annapolis	-
Agency-7	-	T1, Base1
SP-1	Aegean to Marmara	-
SP-4	-	Halifax Airport

Table 3.3: Scenario 2's Sub-planners' Assets.

Sub-planner	Number of UAVs	Number of Satellites
SP-1	6	2
SP-2	10	1
SP-3	0	0
SP-4	6	1
SP-5	4	1
SP-6	0	0
SP-7	2	1
SP-8	3	0
SP-9	3	0

Table 3.4: Scenario 2's Results.

Strategy	QoO	Profit	RC	LC
AACM	55.56	12.94	7.99×10^7	1.89×10^7
SACM	54.63	12.17	3.74×10^7	1.79×10^7
CACM	50.63	12.62	1.58×10^7	2.29×10^6

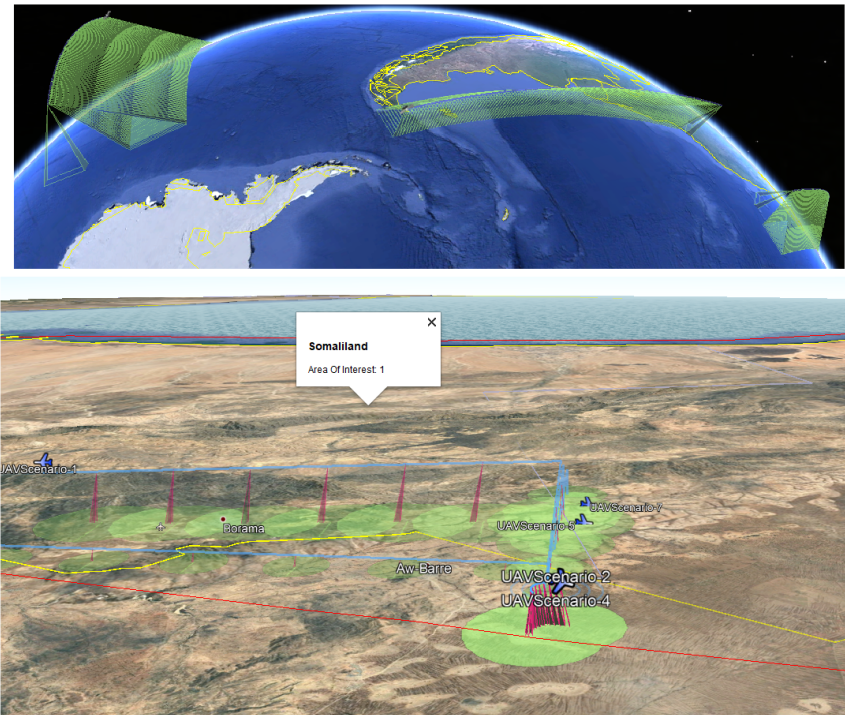


Figure 3.5: Snapshots of a TR and some platforms of Scenario 2.

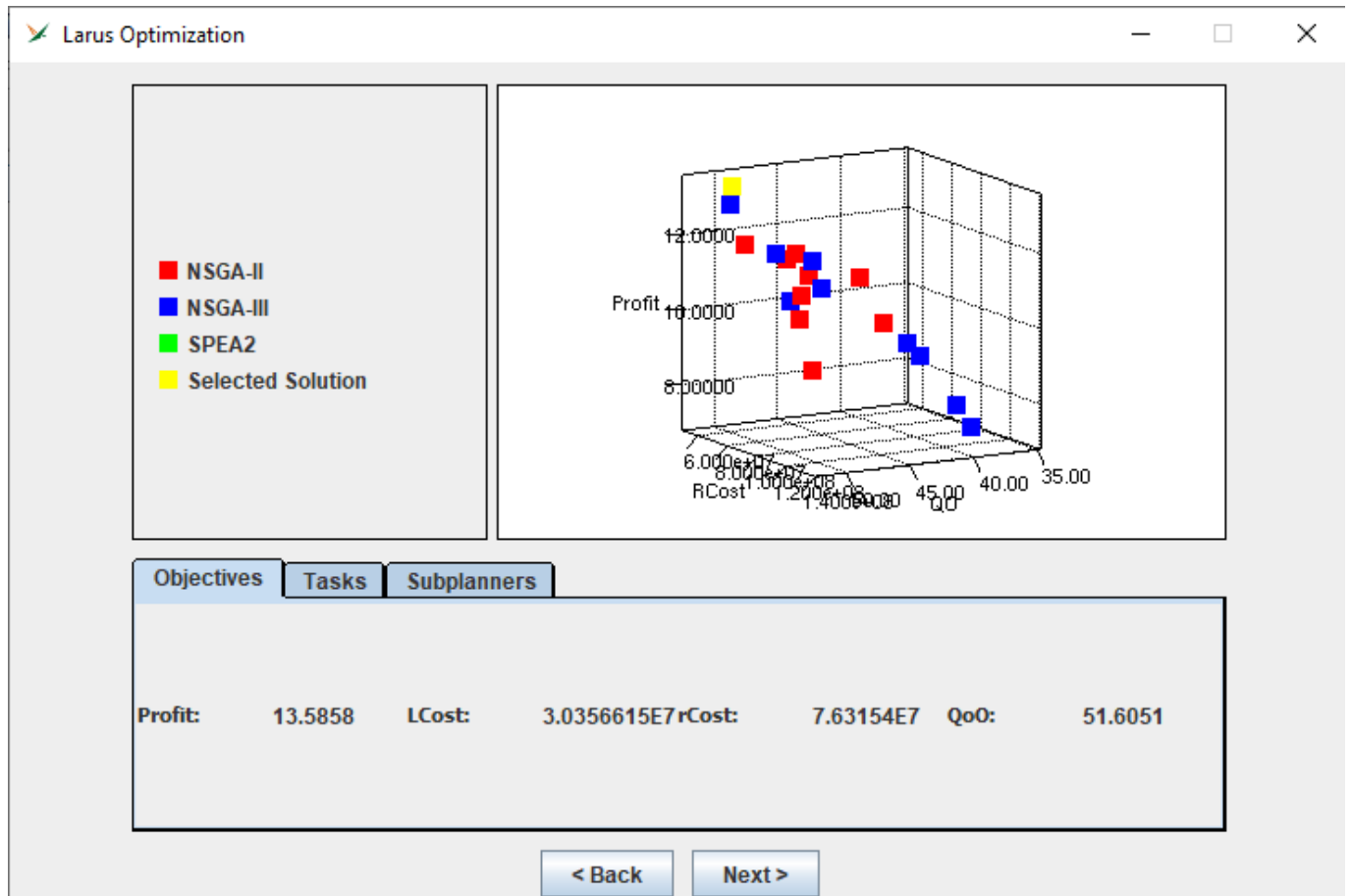


Figure 3.6: 3D Chart with the non-dominant solutions obtained by MOHMA-CSO-HLIF.

to it. But this result is obtained at the expense of the RC and the LC. Let us also realize that compared to SACM which uses a maximum of one platform per SP for each STR, CACM gets the highest profit. Although this will not happen in all scenarios, in this specific case, this is explained by the fact that with CACM no SP will be assigned with a STR if it cannot cover at least 70% of its tiles. This forces MOHMA-CSO-HLIF to assign STRs to SPs that can contribute with highest profit. CACM does it by only using the necessary platforms per SP per STR to reach 70%, this is why the RC is low.

There are several metrics to analyze the quality of Pareto fronts including: the HyperVolume (HV) and the Inverted Generational Distance (IGD). The HV measures the volume of space dominated by the approximation set (the set of solutions provided by MOHMA-CSO-HLIF) while the IGD measures the average of distances of solutions in the reference set (estimated set of best solutions) to their closest solutions in the approximation set. These values are normalized to an interval from 0 to 1 where 1 is the optimal value. The author of [56] gives more details and explanations on those metrics and on how the reference set is constructed.

Table 3.5 provides the median HV and the median IGD for each strategy. For the HV, which takes into account almost all the Pareto front's solutions to calculate the volume, it is SACM which provides the best set for this scenario. This is explained by the fact that each SACM's solution constitutes a type of compromise since the number of platforms per SP for each STR is limited to 1. Thus, even if a STR is assigned to X SPs to increase the profit and the QoO, the RC will always be minimized since the number of platforms used will be X (it would be greater than X for the other strategies). On the other hand for IGD, which takes into account only one solution (the closest in the approximation set) for each solution of the reference set, one notes that it is AACM which provides the best set. This means that although several of AACM's solutions favour certain objectives to

Table 3.5: Scenario 2’s Pareto Front Quality.

Strategy	HV_{Mean}	IGD_{Mean}
AACM	0.21	0.20
SACM	0.28	0.15
CACM	0.21	0.09

the detriment of others, the fact remains that it also contains the best solutions since one can play on the assignment of STRs to SPs to select solutions that create compromises. These inputs turn out to be vital during the choice of which strategy to undertake.

3.4.3 Comparison of MOHMA-CSO-HLIF with MOHMA-CSO, DCSO and MO-GATHER

Using the scenario described in Tables 3.6, 3.7 and Figure 3.7, the results of four different configurations were analyzed and compared: MOHMA-CSO-HLIF (decentralized coordinated architecture with HLIF), MOHMA-CSO (decentralized coordinated architecture without HLIF), MO-GATHER [2] (centralized architecture) and Distributed Collection Schedule Optimization (DCSO) [6] (Distributed Architecture). These frameworks were chosen given that their outputs (CPs) use the same objectives (and metrics): Collection Value (CV), Demand Satisfaction (DS) and Dollar Cost (DC) ². The CV is proportional to the coverage percentage of all the TRs in the scenario by taking in consideration their priorities. The DS is the ratio of TRs whose tiles are completely covered. The DC is the

²For MOHMA-CSO-HLIF, the comparison will use the final CP as a result and not the TAP’s objective values. The CP is also evaluated in terms of CV, DS, and DC.

Table 3.6: Scenario 3's Requests.

Requester	AOIs	POIs
Agency-1	Bridgewater, Lassqoray, Stanley	Hormuz
Agency-2	Yarmouth, Polygon, North Bearing Sea, Labrador	Quebec City Airport, Ugolny Airport, McArthur River Mine Airport, Yarmouth Airport, Liverpool Airport, Russia North1

cost of acquiring the different images as suggested by the solution.

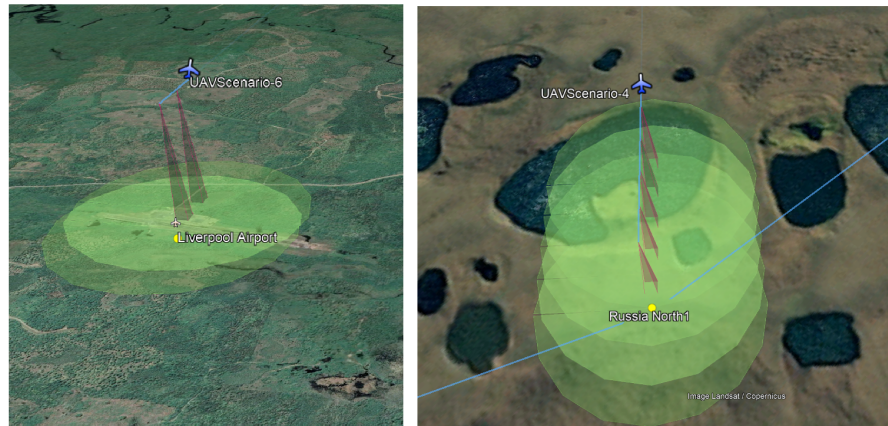


Figure 3.7: Snapshots of some TRs of Scenario 3.

Table 3.7: Scenario 3’s Sub-planners’ Assets.

Sub-planner	Number of UAVs	Number of Satellites
SP-2	1	0
SP-3	2	1
SP-4	2	0
SP-5	3	0

The results of Table 3.8 show that although the cost to complete a mission suggested by MOHMA-CSO-HLIF (AACM) is high compared to other missions, the best CV is obtained with this framework. It goes from a CV of 1.30 with MO-GATHER and MOHMA-CSO (AACM) (second best solutions) to 1.33 with MOHMA-CSO-HLIF (AACM), an increase of 2% with a much lower cost. This proves that when the different SPs are efficiently used, the results obtained are better in some scenarios. In situations where the cost can be a problem, one can always take into account the different strategies and their non-dominant solutions (see Figure 3.6) that MOHMA-CSO-HLIF displays in order to choose the most suitable one. By comparing the results of MOHMA-CSO and MOHMA-CSO-HLIF, strategy by strategy, it is clear that the HLIF feature obtains better CVs with almost equivalent costs. This is explained by the fact that pushing SPs to have a better QoO also pushes them to better cover STRs. One can also notice that even if the CV just increased by 2% from MOHMA-CSO (CACM) to MOHMA-CSO-HLIF (CACM), the DC increased by 40%. This contrast between the increase of DC and that of CV can be explained by the type of platforms used to obtain a better CV, satellites for example may cost more, but also by the distance traveled by platforms to increase the coverage of TRs.

Table 3.8: Scenario 3's Results.

Optimizer	CV	DS	DC
MO-GATHER	1.30	0.36	6.09×10^6
MOHMA-CSO (AACM)	1.30	0.36	3.77×10^6
MOHMA-CSO (SACM)	1.27	0.36	3.68×10^6
MOHMA-CSO (CACM)	1.17	0.36	4.87×10^5
MOHMA-CSO-HLIF (AACM)	1.33	0.36	3.51×10^6
MOHMA-CSO-HLIF (SACM)	1.29	0.36	3.68×10^6
MOHMA-CSO-HLIF (CACM)	1.19	0.36	6.90×10^5
DCSO-MB_coop	0.76	0.21	7.42×10^5
DCSO-MB_comp	0.74	0.21	8.83×10^5
DCSO-CC_coop	0.68	0.21	4.40×10^4
DCSO-CC_comp	0.76	0.21	1.59×10^6

3.5 Chapter Summary

The objective of this chapter was to propose a CSO mission planning system whose particularity is to consider the quality of future images including fused ones.

The optimization process was done using MOO algorithms with four different objectives:

- The first objective was to maximize profit to allow the optimizer to cover as many STRs as possible.
- The RC's goal was to estimate and reduce the cost of each solution presented to end users.
- The LC aim was to reduce conflicts between the LTRs of the SP and those submitted by the agencies.
- Finally, the objective of the QoO was to maximize the quality of acquired images.

In addition to this, MOHMA-CSO-HLIF has an added value by proposing different strategies to maximize the objectives when assigning STRs to SPs. The strategy will depend on how to maximize the objectives: whether we want to use a single platform per SP, as many as possible platforms or the minimum number of platforms to reach a certain coverage percentage and minimize the cost of the mission. The experiments detailed in the previous section demonstrate indeed that choosing a specific strategy has an effect on the proposed solutions.

Chapter 4

High-Level Information Fusion in a Mission Planning Context

The imagery collected during observation missions are subject to several analyses. Some are used for real-time analysis by decision support systems while others are used by computer models or humans [65–68]. These applications highlight the importance of collecting good quality imagery. This chapter will propose image quality estimation methods. Several articles on image quality estimation do not consider the benefit of sensor fusion during mission planning. Therefore, the main innovation of this chapter will be the prediction of the quality of fused images.

4.1 Problem Definition

Some mission planning articles [2, 3, 6, 7] and mission planning software use the notion of COs to represent image acquisition opportunities. A CO encapsulates information such as

the start time and end time of the observation, the zone being covered, the type of sensor being used, the type of platform being used and other characteristics. See Figure 4.1 for an illustration of COs. For zones being covered by more than one CO, there will be FCOs, with each FCO encapsulating information of a pair of COs covering a common zone.



Figure 4.1: Illustration of UAVs' Collection Opportunities (in white and pink).

Since a CO encapsulates information of an image acquisition opportunity, predicting the quality of future images will then lead to predicting the quality of COs (including FCOs).

4.2 Methodology

Assessing or predicting the quality of an image should take into consideration how the mission planners would use those images. Depending on whether the image should be used by humans or computer models and on the usage of the image, the quality should differ. This work proposes three techniques to predict the quality of images based on two different contexts. The first context is one where the images will be analyzed by humans in order to perceive and extract as much information as possible. There are also contexts where the images obtained will be only processed by computer models. This second context can particularly be useful to automatically recognize objects in imagery.

4.3 Proposed Solutions

4.3.1 Expert-Driven Approach

The objective of this method is to predict the Quantity of Information (QoI) that humans would be able to detect in subsequently-acquired aerial images from EO and IR sensors. This prediction will be based on the information encapsulated in the COs. The GIQE will be used to predict the NIIRS, each rating level of which indeed corresponds to what humans can detect in an image.

The authors of [14] proposed a risk-aware fusion effectiveness metric of hard and soft data fusion in maritime domain awareness. Given that the main purpose of our work is also to predict the quality of fused images, the concepts of the risk-aware fusion effectiveness metric with the GIQE can be combined to predict the QoI of both fused and non-fused images.

Equation 4.1 estimates the QoI in future images using the Information Benefit (IB), the Information Confidence (IC) and the Fusion Possibility and Revelance (FPR).

$$QoI = IB.IC.FPR \quad (4.1)$$

In Equation 4.2, IB measures the completeness of the amount of information an image can contain given the type(s) of sensor(s) used.

$$IB = RV_1.IB_1 + RV_2.IB_2 \quad (4.2)$$

Where:

- IB_i will be 1 if the sensor I is used, and 0 otherwise.

- RV: relevance value. RV_i will be 0.5 considering that the EO and IR sensors are complementary.

This formulation is justified considering that EO and IR sensors are complementary. As stated in the introduction, a fusion of images from EO and IR sensors gives a better situational picture within the AOI. Figure 4.2 illustrates this with images extracted from [69].

As for IC, its value will be proportional to the NIIRS and computed using the GIQE given a CO.

Equation 4.3 describes how to compute IC for cases where research has demonstrated that if the fusion is well performed the fused images would give more information compared to the individual images. Since the added value of the fused image depends on many factors, it will be assumed that the fused image gives at least as much information as the best of the two images. Another way of saying that is that the fused image should not be worse than the best of the two images.

$$IC = \text{Max}(IC_1, IC_2) \quad (4.3)$$

where:

- $IC_i = NIIRS_i / 10$. The NIIRS value is divided by 10 to keep IC_i between 0 and 1.

The FPR will measure the utility of performing fusion taking into account the types of platforms and the time separating the two COs. FPR will depend on the Fusion Relevance (FR) and the Fusion Possibility (FP). FPR will be determined using propositional logic.

- FPR values: *good*, *middle*, *bad*.

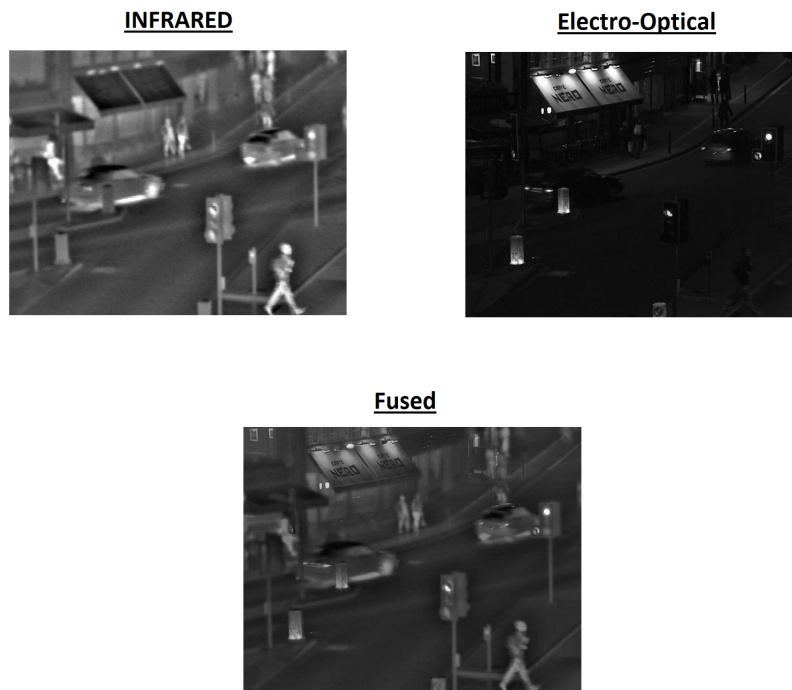


Figure 4.2: An AOI was captured within the IR spectrum and the EO spectrum. Notice that in both of the top images some information is missing: the name of the store is clearly readable in the EO image while it is not in the IR; the pedestrians that can be seen in the IR image are hardly visible the EO image. The fused image contains almost all the features of the original images.

- FR values: *relevant*, *moderately relevant*, *irrelevant*.
- FP values: *yes*, *no*.

The propositions to determine FPR are the following:

- If there is just one CO (one image from one sensor, the system will consider that same image as being fused), FPR will be *good*.
- If there is a FCO and (FR is *irrelevant* or FP is *no*), FPR will be *bad*.
- If there is a FCO and FR is *moderately relevant* and FP is *yes*, FPR will be *middle*.
- If there is a FCO and FR is *relevant* and FP is *yes*, FPR will be *good*.

The proposition to determine the FP is: FP is *yes* if the COs' platforms are of the same type and their COs have a common covered zone. Otherwise, it's *no*. This will have the role of avoiding fusion of images obtained by platforms of different types (e.g. fusion of images obtained by satellites and ground vehicles).

The propositions for FR are:

- FR is *relevant* if the COs' time intervals are intersecting.
- FR is *moderately relevant* if the COs' time intervals are not intersecting and their start times differ by less than one hour.
- FR is *irrelevant* otherwise.

If FPR is *good*, its value will be 1, *middle*: 0.5 and *bad*: 0.1.

4.3.2 Distributed Data Fusion-Based Approach

Among the various observation missions, there are some whose main goal is to automatically analyze the objects on collected imagery. This type of analysis is often done by computer models and can be grouped into four types: Detection, Recognition, Classification or Identification (DRCI) of targets. The detection of targets consists of assessing if there is an object or not in the imagery. On the other hand the recognition of targets consists of assessing which type of object is it (is it a vessel, a building, a computer, etc.). Target classification comes down to selecting the class or category to which the object belongs to. If the goal is to classify vessels, the system should choose whether it is a merchant, a cargo, etc. Finally, target identification consists of identifying the specific object as an individual different from others. The identification of humans could consist of stating if the human in the imagery is Person A, Person B, etc.

The objective of the Distributed Data Fusion (DDF) method will be to predict how accurate the results of DRCI would be given a mission plan. Performing such an operation is important since it will aim to guide the mission planners on the best way to carry out the mission. The accuracy of the detection will not be the same if a satellite is chosen instead of a ground vehicle; or if the flying altitude of an UAV is 400 meters rather than 1400 meters. By prediction of quality, we mean predicting of the ability of our models to detect, recognize, classify or identify targets in a subsequently-acquired imagery given a CO.

In order to predict the quality, the proposed method will be divided into two main stages: (1) Training and Evaluation Stage, (2) Real-Time Prediction of Quality Stage. The training and evaluation stage will consist of training models to predict the quality. This stage can be compared to a process when the model learns how the quality (capacity) of

DRCI changes according to the different categories of COs whereas the real-time prediction of quality corresponds to a process when the quality of each CO is determined according to what the model has learned in the previous stage for a better planning of the mission.

The Training and Evaluation Stage will be done by using datasets (each corresponding to a specific category of COs) where each instance of the dataset will have an image and a label to signify the presence or not of objects, the type of object, the class of the object or the identity of the object in the image. The label of each instance will be the ground truth to be predicted by the model. For each categorical model, an accuracy value corresponding to the ability of the model to correctly predict the label of the images during the evaluation will be obtained. In the Real-Time Prediction of Quality Stage, the quality of a CO will be the accuracy value of the category to which it pertains.

Figures 4.3 and 4.4 respectively describe how the Training and Evaluation Stage for non-fused and fused imagery is carried out. Figure 4.5 shows how the quality of the COs is determined according to their categories during the Real-Time Prediction of Quality Stage.

Figure 4.3 describes how different categories of datasets are used to train models to detect, recognize, classify or identify objects in EO and IR imagery. This process is divided into different steps. Firstly, if the main dataset is composed of several images acquired from different sources and with varying characteristics, it should be divided into several categories of datasets, for each category there should be a dataset for each type of sensors. Several criteria can be used to divide the datasets into different categories, in particular the type of vehicle used to acquire these images, on the sole condition of having a sufficient number of images for each dataset. Secondly, each new dataset will be used to train and evaluate a CNN. The last step is to bring out the evaluation accuracy of each CNN. Thus for each category and each type of sensor, there will be an evaluation accuracy as a result

of the process.

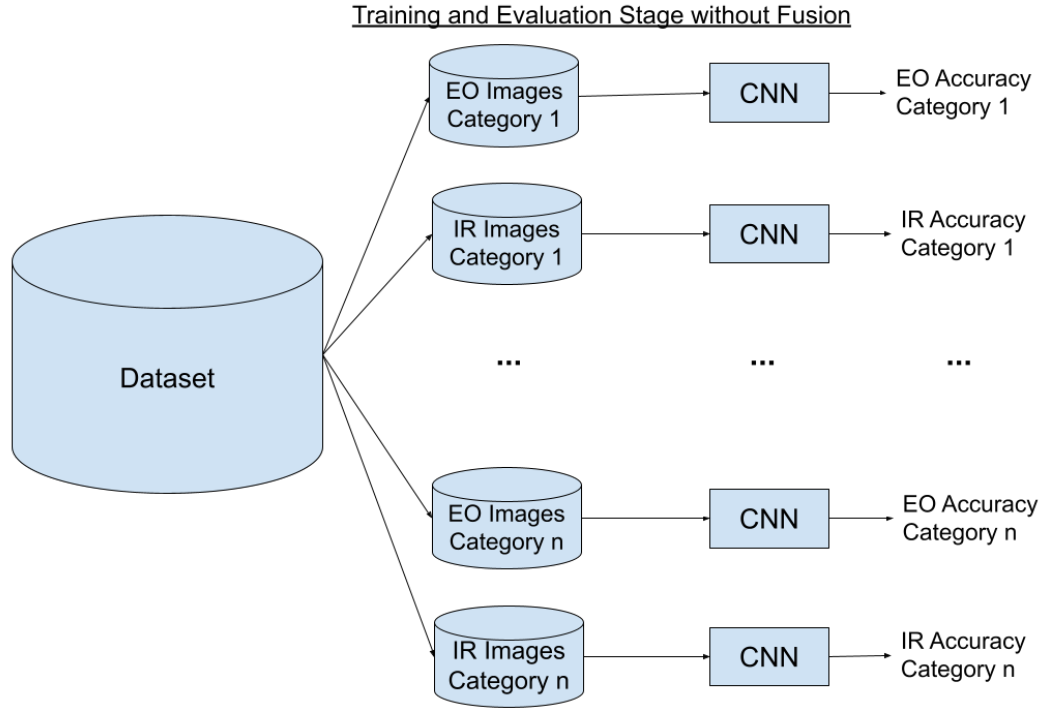


Figure 4.3: Different categories of datasets are used to train models to detect, recognize, classify or identify objects in EO and IR imagery.

The purpose of the process described in Figure 4.4 is to estimate the DRCI rate of fused images. Given this, it is required to have pairs of EO and IR images for this process. Then, similarly to the description given for Figure 4.3, the dataset should be divided into different categories. For each category, there will be a dataset with pairs of EO and IR images. Each new dataset should then also be used to train and evaluate three CNNs according to the three fusion methods (more details on these CNNs are given in the following texts and Figure 4.6). For each category, the evaluation accuracies of the three types of fusions will

thus be obtained.

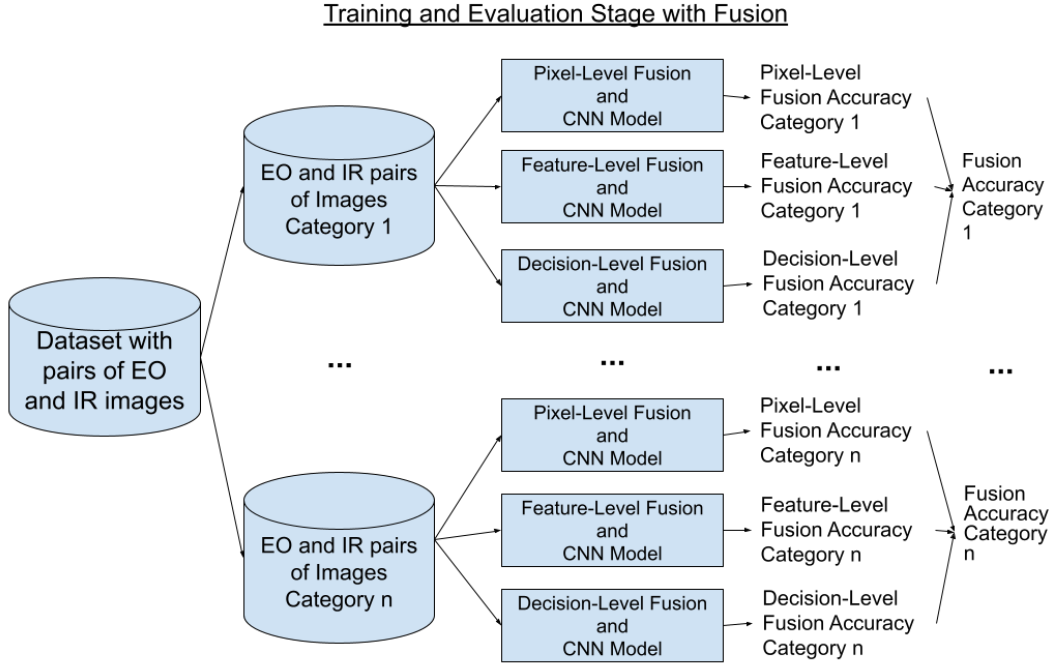


Figure 4.4: Models are trained to detect, recognize, classify or identify using three fusion methods.

Figure 4.5 describes how to determine the DRCI rate of a CO during the planning of missions. The DRCI rate will be determined according to the categories used during the Training and Evaluation Stage. If the categories were simply created based on the type of vehicle used, the CO's category will also be determined based on that. Then depending on whether it is an FCO or a CO obtained with an EO or IR sensor, the DRCI will be equal to the corresponding evaluation accuracy according to the results obtained in the process indicated by Figure 4.3 or Figure 4.4.

Automatic DRCI Rate - Real Time Stage



Figure 4.5: Prediction of DRCI ability given a CO.

Notice that for non-fused imagery, two accuracy values are obtained for the two types of sensors used in this work. On the other hand, for fused imagery, the three fusion methods described in Figure 4.6 (with images extracted from ¹ and [70]) are used. Each of these three methods will have a fusion accuracy among which the best one will be used for the real-time prediction of quality stage.

The pixel-level fusion will use DL techniques described in [52]. The fused imagery obtained from the fusion of pairs of EO and IR imagery will be used as inputs of CNNs.

The architecture of the feature-level fusion CNNs consists of two steps: (1) The extraction of features through features maps. Subsequently, these features are summed up (using weighting for EO and IR) to fuse features extracted from pairs of EO and IR images. In order to ensure that the best values were chosen for weighting, an experimental approach was chosen. The latter consists of using different weight values ranging from 0 to 1 and 1 to 0 respectively for the features extracted from EO and IR images. Thus, by performing

¹<https://towardsdatascience.com/a-comprehensive-guide-to-convolutional-neural-networks-the-eli5-way-3bd2b1164a53>

several experiments with pairs of weights, the analysis would allow to choose according to the results, values leading to better results for the fusion. (2) The results of these summations will be entries of the fully connected network to obtain the output of each pair of images.

Two CNNs will be used for decision-level fusion, one for EO images and another one for IR images. The first step of decision-level fusion will consist of training both CNNs, after which predictions of those CNNs on each pair of images would be inferred. Subsequently, these predictions (pairs of confidence levels) serve as entry points of an Ensemble classifier. The latter also uses the weighted sum of the predictions to determine the output of each pair of images.

4.3.3 Neural Network - Based Approach

The last metric that this chapter proposes is the Quality of Perception (QoP). Some observation missions may aim to provide end users with images whose value is measured according to human perception. Thus, in this section, a method will be proposed to predict the QoP of images, including subsequently fused images, by using COs' attributes.

This method uses an ANN that will be trained, evaluated and then used to infer the predictions. Faced with the lack of dataset allowing to perform such an accurate model training and inference, the following steps are proposed to form a dataset:

- Select datasets with images from observation or surveillance missions. These datasets must also contain information on the means and contexts for obtaining those images.
- Fuse (pixel-level fusion) pairs of images if any.

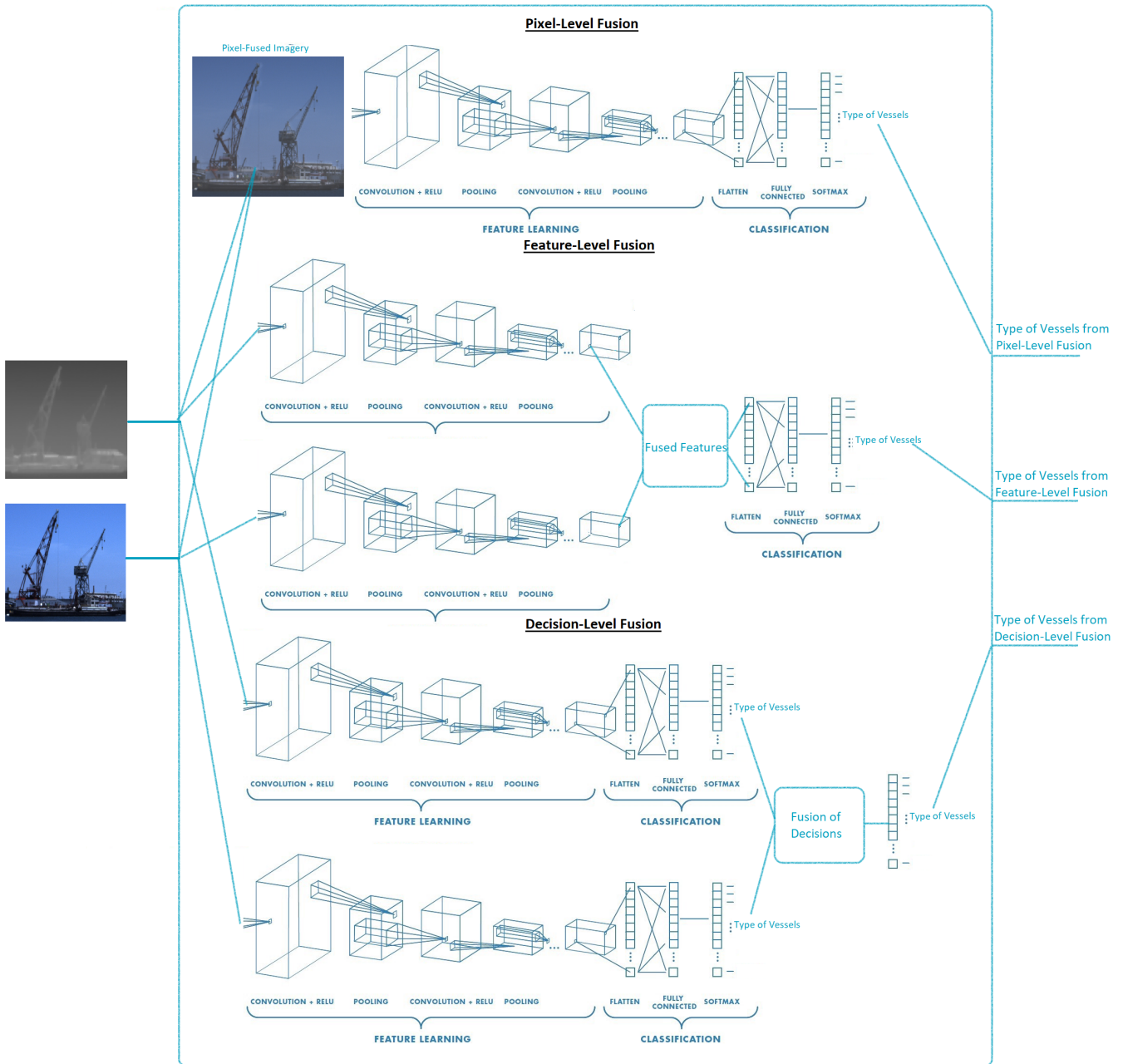


Figure 4.6: Classifications of vessels done with the three levels of fusion.

- Determine the quality of each image. Since the PIQE method, used to determine the quality of the images, gives values between 0 and 100 (the lower the values, the better the perception), the following formula was used to keep the quality between 0 and 1 (with 1 being the higher quality): $QoP = 1 - PIQE(Image)/100$.
- The dataset will therefore be formed of attributes characterizing the context and the means of obtaining the image, as well as the QoP of the image.

4.4 Experiments and Results

4.4.1 Expert-Driven Approach

Sample COs of UAVs have been selected and will be used to validate the proposed method. This experiment will allow us to understand what are the key factors of the QoI. [46] will be used to compute the NIIRS using the GIQE. Figure 4.7 lists the attributes of sample COs and the results obtained for their QoIs.

Line	Sensor 1	Altitude 1 (m)	Start Time 1	End Time 1	Sensor 2	Altitude 2 (m)	Start Time 2	End Time 2	QoI
1	eo	8000	2021-06-29 8:15	2021-06-30 15:54	ir	8000	2021-08-29 8:17	2021-08-30 5:26	0.097
2	ir	8000	2021-06-29 8:15	2021-06-30 15:54	-	-	-	-	0.480
3	eo	1000	2021-06-29 8:15	2021-06-30 15:54	-	-	-	-	0.495
4	ir	8000	2021-12-22 18:15	2021-12-23 0:04	eo	5000	2021-12-22 18:55	2021-12-23 0:03	0.990
5	eo	3000	2021-12-22 18:15	2021-12-23 0:04	-	-	-	-	0.495
6	eo	6000	2021-04-01 22:15	2021-04-03 22:17	ir	3000	2021-04-02 22:51	2021-04-05 2:07	0.990
7	ir	1000	2021-04-01 22:15	2021-04-03 22:17	-	-	-	-	0.495
8	ir	4000	2021-11-19 2:18	2021-11-19 7:07	eo	2000	2021-11-19 2:58	2021-11-19 5:08	0.990
9	eo	5000	2021-11-19 2:18	2021-11-19 7:07	-	-	-	-	0.495

Figure 4.7: Sample QoI Values of COs.

The QoIs of all these COs are computed with the same values excepted for the attributes in Figure 4.7. The lines with the best QoI are lines 4, 6 and 8. They are all lines with fusions of COs. In contrast, line 1, although performing a fusion, has a low QoI value given

the huge time difference between the two COs. The QoI of line 2 is lower than the one of line 7 because of its fairly high altitude.

In the case of fusion, a great time difference could bias the relevance of the information that will be contained in the fused image. As for the altitude, these results confirm the observation of [44] which affirmed that the more one UAV rises in altitude, the less the quality will be. These results also show that fusing the EO and IR images, if possible and pertinent, increases the QoI.

4.4.2 DDF-Driven Approach

Consider this real-world scenario: the maritime surveillance organization of a country X wants to gather statistics on the types of vessels navigating its waters. They plan to send a dozen coast guard vessels, equipped with EO and IR sensors, to the sea in order to identify the different types of vessels. They would like the tracking and classification to be done automatically in order to minimize labor. They would also like to get an idea of the classifier's performance given their mission plan and the sensors they will be using.

The task will consist of classifying vessels on EO, IR and fused images. The images of [70] will be used to train, evaluate models and fusion methods. The dataset described in [70] contains more than 1000 pairs of EO and IR imagery of vessels labeled with their classes (merchant, sailing, etc). The imagery of this dataset were obtained using vessels equipped with sensors. Given the small amount of images in the dataset, K-Fold Cross Validation was used with $k = 10$.

[60] was selected as CNN architecture. Still considering the size of the dataset, a pre-trained version of [60] was used to achieve satisfactory results. The pre-trained version of [60] was trained with ImageNet, a dataset containing 14 million of images [71].

Table 4.1: Mean Accuracies after 10 Experiments.

Model Number	Fusion Method	Mean Evaluation Accuracy
Model 1	No Fusion EO Images Only	0.875
Model 2	No Fusion IR Images Only	0.635
Model 3	[52] Fusion Model	0.801
Model 4	Proposed Feature Level Fusion	0.871
Model 5	Proposed Decision Level Fusion	0.884

The proposed fusion methods will be compared to [52]. Table 4.1 lists the results of classification of EO, IR and of the three aforementioned fusion methods. In order to confirm statistical significance of the results, they are presented in Table 4.1 as an average of the 10 experiments that were carried out.

The results of Table 4.1 not only show that it is possible to obtain an accuracy of almost 90% but they also highlight the performance of the accuracy through fusion methods, particularly the decision-level fusion proposed in this work.

4.4.3 Neural Network - Based Approach

The efficiency of this method will be proven by evaluating the results of ANN models trained to predict the QoP by taking into account some characteristics of COs.

Figure 4.8 shows some images used to form the dataset using the steps described in Section 4.3.3. The selected datasets have specificities that will be used in this experiment. First, [72, 73] are datasets with EO and IR imagery respectively obtained with ground vehicles and UAVs. [70]’s dataset, described in the previous section, whose images are obtained using vessels also contains information on the period of the day during which each image was obtained as well as the type of sensor used. This will be an added value given the complementary of EO and IR imagery during day and night. In addition, the images from [74] are obtained with satellites equipped with EO sensors. Apart from that, for each image used, the season in which the image was obtained is mentioned.

Table 4.2 shows sample instances of the dataset formed using data from [70, 72–74] according to the steps indicated in 4.3.3. The ’unknown’ values have been replaced by the mode (for the same feature) of the samples with closest qualities [75].

The results in Table 4.3 show that the QoP can be predicted using a trained model and COs’ attributes. These results also provide information on the efficiency of models with hidden layers compared to linear regression. Figure 4.9 illustrate how the predictions of the experimented models approach the ground truth values. As one can notice, for all the three models, the predicted values are close to the ground truth ones. This not only confirms the results in Table 4.3 but also highlights the efficiency of the method.

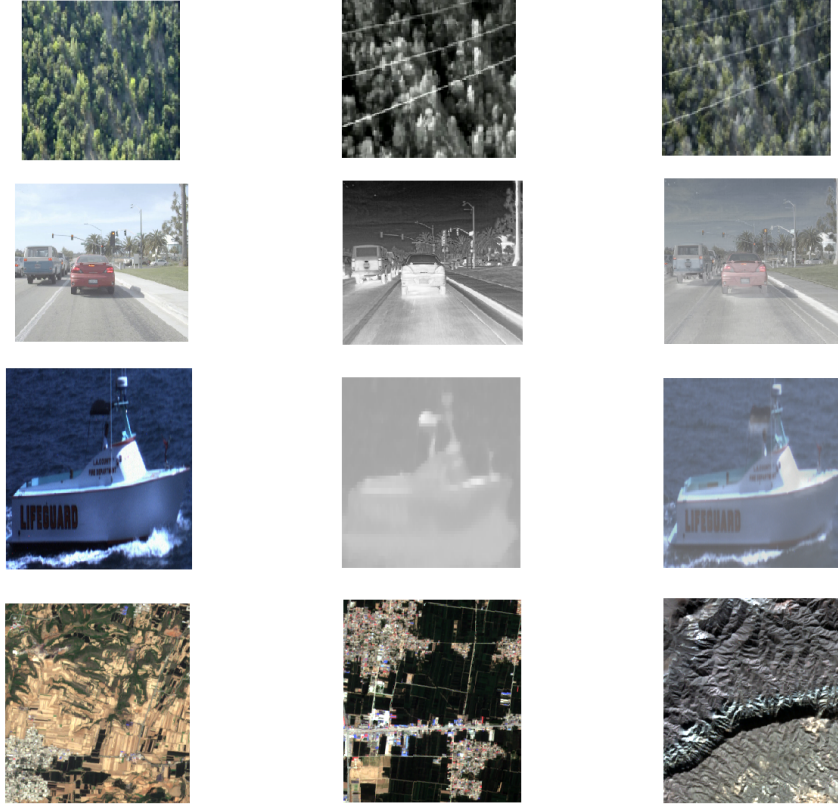


Figure 4.8: Images whose qualities and characteristics were used to experiment with some models. The images of the first line are those obtained with UAVs [72], those of the second line with ground vehicles [73], those of the third one with vessels [70] while those of the last one are obtained with satellites [74]. Except the last row, where all the images are obtained with EO sensors, the images of the first column are obtained with EO sensors, the second one with IR sensors and the last column contains their fusions.

Table 4.2: Platform, Time, Season, Sensor of the Synthesized Dataset.

Vehicle Type	Day or Night	Season	Sensor Type	Fusion or not	QoP
UAV	unknown	unknown	IR	No Fusion	0.72362
Satellite	unknown	fall	EO	No Fusion	0.68756
Vessel	day	unknown	EO_IR	Fusion	0.78098

Table 4.3: Testing Mean Squarred Error.

Model Number	ANN's Architecture	Mean Squarred Error
Model 1	Linear Regression	0.0185
Model 2	2 hidden layers of 10 and 5 neurons	0.0152
Model 3	2 hidden layers of 150 neurons	0.0146

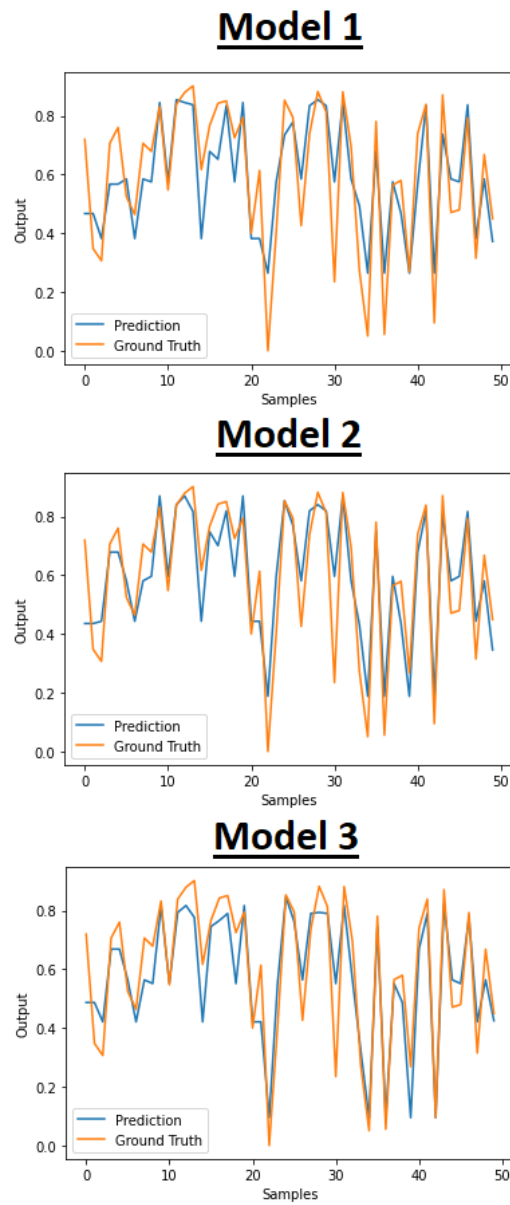


Figure 4.9: Prediction values of models 1, 2 & 3 and the associated ground truth values.

4.5 Chapter Summary

The objective of this chapter was to propose different methods in order to estimate the quality of the images subsequently acquired given a surveillance mission plan. The difference with several existing methods is the emphasis on sensor fusion.

It was first shown that depending on the context and the objective of the missions, the estimation of the quality of the images would differ. Thus, three methods, each with a specific metric, have been proposed to predict the quality of images in different contexts:

- The QoI is a metric used to measure the amount of information that the future image will contain.
- The DRCI rate is a metric used to predict the ability of models to detect, recognize, classify or identify objects in future images.
- Finally, the role of QoP is to predict the quality of perception of future images given their COs.

Chapter 5

Future Work and Conclusion

This chapter concludes this thesis by giving some perspectives for future work in this domain and summarizing the contributions of the conducted research.

5.1 Future Work

The observation missions optimizer proposed in chapter 3 is a CSO which receives as inputs the STRs, the planned trajectories of the SPs and their LTRs in order to assign STRs to the SPs . Having to submit platform planned trajectories as inputs to the system could be a disadvantage in cases where SPs also want to know what would be the best way to observe their LTRs. So as a perspective for the future, it would be interesting to see how the integration of a path planner could make the optimizer more usable. The role of the path planner will be to suggest trajectories of vehicles given their starting point and their main tasks locations, which will eventually be the LTRs of their SPs.

As for the prediction of the quality of images, the existence of a version of the GIQE

taking into account the fused images could improve this work. Still regarding the GIQE, the NIIRS values were designed to predict the quality of aerial images (captured by UAVs or aircraft), it would also be interesting to extend it to other types of platforms or simply generalize it.

Two of the proposed image quality prediction methods use ML to predict image quality. These methods were faced with the lack of suitable datasets to predict the quality for different categories of images and the lack of datasets containing as many attributes as desired. [76, 77] highlight these problems and suggest solutions that can lead to datasets with synthetic images.

5.2 Conclusion

The first proposal of this thesis was an observation missions' optimization framework that allows platforms to carry out the tasks of more than one organization in order to possibly reduce the individual cost of missions. The proposed framework brings two main innovations. It takes into account the quality of the images to be acquired and three strategies during optimization. The strategy depends on how to maximize the objectives: whether we want to use a single platform per SP, as many as possible platforms or the minimum number of platforms to reach a certain coverage percentage and minimize the cost of the mission. The experiments have indeed demonstrated that choosing a specific strategy has an effect on the proposed solutions. These experiments have also demonstrated that having the QoO as an objective can increase the CV while keeping DC low. This has been proven with two of the three strategies: from MOHMA-CSO (AACM) to MOHMA-CSO-HLIF (AACM), the CV went from 1.30 to 1.33 while the DC went from 3.77 to 3.51; with SACM, the CV went from 1.27 to 1.29 for the same cost.

The second major proposition was the prediction of image quality taking into account different contexts. Different methods were proposed to take into account different mission objectives and contexts. The first context was a one where the goal of the mission was to obtain images containing as much information as possible. The second was to take into account the use of models to automatically categorize the objects on the images. One of the innovations of these methods is to take into account the potentiality of fused images in the prediction of qualities. The effectiveness of each of these methods has been demonstrated. The results obtained in the QoI experiments have demonstrated their relevance by aligning with some validations of other research cited in Chapter 4: fused images have better QoI, the higher the altitude of an UAV, the worse its QoI will be. As for the DRCI rate, thanks to the methods used, the accuracy rates of the models were around 90%. Another observation to note: the proposed decision-level fusion method obtained the best accuracy. The models trained to predict the QoP, despite the challenges mentioned in the previous section, gave mean squared errors of less than 2%.

APPENDIX

The purpose of this appendix is to provide more information on the general architecture of CNNs. As mentioned in Chapter 2, CNNs are composed of two main stages: the feature extraction stage and the fully connected layers stage.

CNNs are often used for classifying objects on images. They are based on the recognition of certain features in order to recognize the type of objects on an image. These features can be lines or different shapes whose detection on an image helps CNNs to recognize objects.

Figure 1, extracted from ¹ illustrates how a feature learned (or being learned), in a feature map, is dragged over the whole image in order to detect all the areas where that line could be found. The two-dimensional array described as destination will then be considered as the "new image", a pooled feature map, through which other feature maps will be dragged to detect shapes and lines.

Figure 2, from the same source as Figure 1, describes a more global architecture of CNNs. The feature extraction stage is a succession of feature maps (filters) and pooled feature maps (results of convolutional operations between an image and feature maps).

¹<https://towardsdatascience.com/simple-introduction-to-convolutional-neural-networks-cdf8d3077bac>

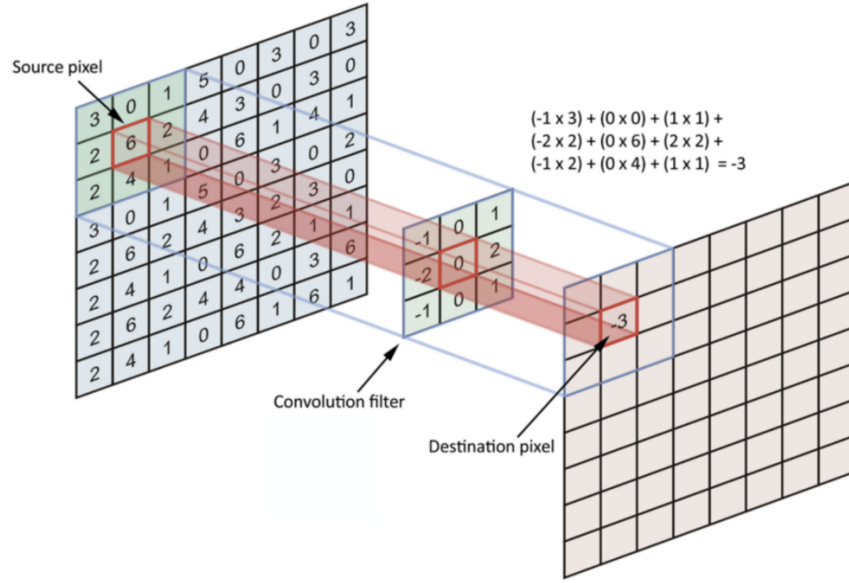


Figure 1: Convolutional operation between a filter and an input image.

At the end of the extraction of features, the last pooled feature maps will be flattened to become inputs of an ANN, composed with fully connected layers. The training of a CNN consists of learning the weights of the fully connected layers and the best filters to use for feature extraction. More details on CNNs can be found in [58].

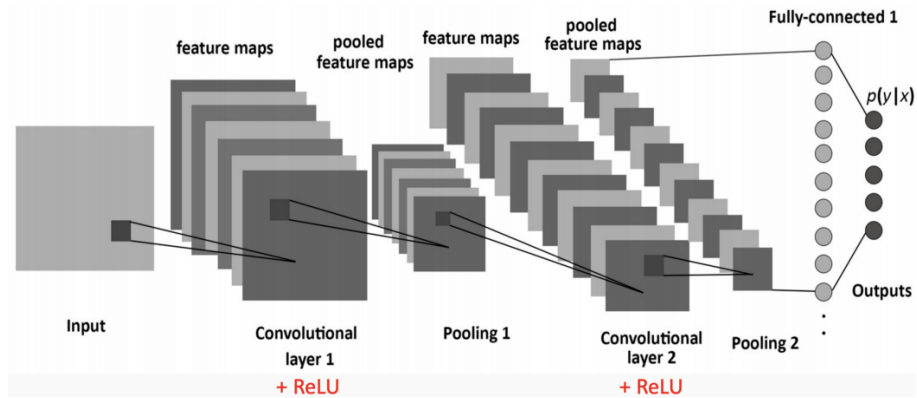


Figure 2: General architecture of a CNN.

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