2017-09

Mission planning for heterogeneous UxVs operating in a post-disaster urban environment

Tan, Choon Seng Leon Mark

Monterey, California: Naval Postgraduate School

https://hdl.handle.net/10945/56182

NAVAL POSTGRADUATE SCHOOL

MONTEREY, CALIFORNIA

THESIS

MISSION PLANNING FOR HETEROGENEOUS UxVs OPERATING IN A POST-DISASTER URBAN ENVIRONMENT

by

Choon Seng Leon Mark Tan

September 2017

Thesis Advisor:	Oleg Yakimenko
Second Reader:	Brian Bingham

Approved for public release. Distribution is unlimited.

THIS PAGE INTENTIONALLY LEFT BLANK

REPORT DOCUMENTATION PAGE			Form Approved OMB No. 0704-0188
Public reporting burden for this collection of information is estimated to average 1 hour per response, including the time for reviewing instruction, searching existing data sources, gathering and maintaining the data needed, and completing and reviewing the collection of information. Send comments regarding this burden estimate or any other aspect of this collection of information, including suggestions for reducing this burden, to Washington headquarters Services, Directorate for Information Operations and Reports, 1215 Jefferson Davis Highway, Suite 1204, Arlington, VA 22202-4302, and to the Office of Management and Budget, Paperwork Reduction Project (0704-0188) Washington DC 20503.			
1. AGENCY USE ONLY ***(Leave blank)***	**2. REPORT DATE** September 2017	**3. REPORT TYPE AND DATES COVERED** Master's thesis	
4. TITLE AND SUBTITLE MISSION PLANNING FOR HETEROGENEOUS UxVs OPERATING IN A POST-DISASTER URBAN ENVIRONMENT			**5. FUNDING NUMBERS**
6. AUTHOR(S) Choon Seng Leon Mark Tan			
7. PERFORMING ORGANIZATION NAME(S) AND ADDRESS(ES) Naval Postgraduate School Monterey, CA 93943-5000			**8. PERFORMING ORGANIZATION REPORT NUMBER**
9. SPONSORING /MONITORING AGENCY NAME(S) AND ADDRESS(ES) N/A			**10. SPONSORING / MONITORING AGENCY REPORT NUMBER**
11. SUPPLEMENTARY NOTES The views expressed in this thesis are those of the author and do not reflect the official policy or position of the Department of Defense or the U.S. Government. IRB number ____N/A____.			
12a. DISTRIBUTION / AVAILABILITY STATEMENT Approved for public release. Distribution is unlimited.			**12b. DISTRIBUTION CODE**

13. ABSTRACT (maximum 200 words)

Time is critical during search and rescue operations, as human survival diminishes exponentially if survivors are not located and recovered efficiently. This thesis sought to integrate technologies into a solution that helps rescuers plan for a mission utilizing multiple autonomous unmanned systems for search operations. It exploits methods of image analysis to fuse data into a common map and identify key areas of search interest. The key mission areas were developed by comparing edge detection techniques on images obtained from remote sensing platforms in the DigitalGlobe database. Together with close-up snapshots of the environment obtained from drones, three-dimensional maps were developed by stitching the images together into a comprehensive model for a mission commander's use. With the mission bubbles developed, a probabilistic road map was used to develop an optimal trajectory to the search area. It was found that by connecting to the 20 nearest neighboring points in the K-dimensional graph instead of all the points, and using the weighted heuristic method for the A* search, formed the most optimal means to obtain a solution. Together with a tool to generate search patterns for multiple drones, an experiment at Camp Roberts was conducted successfully. Technology was effectively used in the development of a mission-planning tool utilizing a set of heterogeneous unmanned systems for a search mission, which can be expanded for various types of military applications.

14. SUBJECT TERMS search and rescue, unmanned system, mission planning, heterogeneous swarm of unmanned systems			**15. NUMBER OF PAGES** 145
			16. PRICE CODE
17. SECURITY CLASSIFICATION OF REPORT Unclassified	**18. SECURITY CLASSIFICATION OF THIS PAGE** Unclassified	**19. SECURITY CLASSIFICATION OF ABSTRACT** Unclassified	**20. LIMITATION OF ABSTRACT** UU

NSN 7540-01-280-5500 Standard Form 298 (Rev. 2-89) Prescribed by ANSI Std. 239-18

THIS PAGE INTENTIONALLY LEFT BLANK

Approved for public release. Distribution is unlimited.

MISSION PLANNING FOR HETEROGENEOUS UxVs OPERATING IN A POST-DISASTER URBAN ENVIRONMENT

Choon Seng Leon Mark Tan
Civilian Engineer, ST Aerospace Ltd., Singapore
B. Eng (Hons), Nanyang Technological University of Singapore, 2005
M. Eng, Nanyang Technological University of Singapore, 2007

Submitted in partial fulfillment of the
requirements for the degree of

MASTER OF SCIENCE IN MECHANICAL ENGINEERING

from the

NAVAL POSTGRADUATE SCHOOL
September 2017

Approved by: Oleg Yakimenko
Thesis Advisor

Brian Bingham
Second Reader

Garth Hobson
Chair, Department of Mechanical and Aerospace Engineering

THIS PAGE INTENTIONALLY LEFT BLANK

ABSTRACT

Time is critical during search and rescue operations, as human survival diminishes exponentially if survivors are not located and recovered efficiently. This thesis sought to integrate technologies into a solution that helps rescuers plan for a mission utilizing multiple autonomous unmanned systems for search operations. It exploits methods of image analysis to fuse data into a common map and identify key areas of search interest. The key mission areas were developed by comparing edge detection techniques on images obtained from remote sensing platforms in the DigitalGlobe database. Together with close-up snapshots of the environment obtained from drones, three-dimensional maps were developed by stitching the images together into a comprehensive model for a mission commander's use. With the mission bubbles developed, a probabilistic road map was used to develop an optimal trajectory to the search area. It was found that by connecting to the 20 nearest neighboring points in the K-dimensional graph instead of all the points, and using the weighted heuristic method for the A* search, formed the most optimal means to obtain a solution. Together with a tool to generate search patterns for multiple drones, an experiment at Camp Roberts was conducted successfully. Technology was effectively used in the development of a mission-planning tool utilizing a set of heterogeneous unmanned systems for a search mission, which can be expanded for various types of military applications.

THIS PAGE INTENTIONALLY LEFT BLANK

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

THIS PAGE INTENTIONALLY LEFT BLANK

LIST OF ACRONYMS AND ABBREVIATIONS

AI	Artificial Intelligence
ASWORG	Anti-Submarine Warfare Operations Research Group
COTS	Commercially Off-The-Shelf
CRASAR	Center for Robot-Assisted Search and Rescue
DARPA	Defense Advanced Research Projects Agency
DJI	Da Jiang Innovations
EO	Electro-optical
GBDX	Geospatial Big Data
GPS	Global Positioning System
IAMSAR	International Aeronautical and Maritime Search and Rescue
LIDAR	Light Detection and Ranging
LOCUST	Low-Cost UAV Swarming Technology
MCMC	Markov Chain Monte Carlo
NPS	Naval Postgraduate School
ONR	Office of Naval Research
OODA	Observe, Orientate, Decide and Action
PDF	Probability Density Function
PRM	Probabilistic Roadmap
RRT	Rapidly Exploring Random Trees
SAR	Search and Rescue
SOP	Standard Operating Procedures
SPOT-1	Satellite Pour l'Observation
UAS	Unmanned Aerial Systems
UGV	Unmanned Ground Vehicles
UxV	Unmanned Systems (including aerial, ground, surface and undersea systems)
USV	Unmanned Surface Vehicle

THIS PAGE INTENTIONALLY LEFT BLANK

ACKNOWLEDGMENTS

The words of the late Steve Jobs were always inspirational. The ones that are always in my mind, and the more appropriate with which to thank those who have inspired me, is: "*You can't connect the dots looking forward; you can only connect them looking backwards. So you have to trust that the dots will somehow connect in your future. You have to trust in something—our gut, destiny, life, karma, whatever. This approach has never let me down, and it has made all the difference in my life."* These words of Mr. Jobs have never failed to inspire me: to have faith that you know where you are going, and when you connect the dots after going through them, you will appreciate the meaning of each step you took.

Connecting the dots to the beginning of my NPS journey, it could not have started better than to select my thesis advisor based on the positive vibes and feedback from LT Ryan Beall. This piece of work would not have been possible without Professor Oleg Yakimenko graciously agreeing to be my advisor when I first approached him in Fall 2016. His knowledge and expertise in the unmanned technology domain was the main guiding star throughout the research, a mentor that I can always fall back on when any doubt arose. There is no code or problem too big for him to solve! Professor Yakimenko constantly encouraged and pushed us to the boundaries, guiding us and evolving our work into a potential capability that is practical and can be applicable in both the military and homeland security domain. His introduction to Professor Brian Bingham was also pivotal in connecting the dots and completing the puzzle. Without this opportunity to work with Professor Bingham, I would not have the possibility to learn from the expert in multirobot controls and their applications. His knowledge in the robotics environment is second to none, and his ability to translate complex problems to simplified tasking made the learning journey enjoyable and enriching.

As I pursued my research, I got to see the amazing skills of both a drone pilot and an aerial photographer in Jeremy Metcalf, faculty associate in the Physics Department, and CPT Ang Wee Kiong. They expertly flew the DJI

drones to capture images that made it possible to generate the necessary results in this thesis; without their expertise in obtaining the images, there would not be any thesis at the end of this summer quarter. Special mention must also be made to Jeremy's passion in analyzing remote sensing imagery; his commitment in piecing and cleaning up the finer details of each model to get a perfect image in the computer environment is without a doubt commendable.

Looking further back, this would not have been possible without the support of MINDEF, ST Engineering LTD and TDSI who gave me this opportunity to set forth into such a unique learning environment in a world-class institute in the form of the Naval Postgraduate School. The NPS professors' ability to blend in operational problems into the academic curriculum was an eye-opener. Special acknowledgement must be made to Professor Garth Hobson, chair of Mechanical and Aerospace Engineering, whose patience and selflessness allowed me to explore options in the aerospace engineering domain during my studies. The flow of the thesis would not have been possible without the coaching and guidance from Kate Egerton at the Graduate Writing Center as well as Janice Long and Sue Hawthorne from the Thesis Processing Office, including Meg Beresik, my international editor, who made this work written professionally.

Although there were many obstacles as I journeyed through my studies, notwithstanding the magnitude of completing this thesis, I had a very smooth journey. The reason for the journey being so smooth was the selfless support and sacrifices of my understanding wife, Nicole, who took the time off work to support me as well as to nurture our two wonderful kids, Kate and Matthew, during this one-year eventful stay in the United States. Their playfulness and chirpy laughter always served as an encouragement and brightened each day, especially during the most stressful moments in my studies.

Finally, a special shout-out should go to the Singapore contingent here in our little "kampong" in Monterey. The many gatherings and celebrations reminded us of our roots and bonded the community; whipping up local delicacies like chicken rice and Nasi Lemak burger created a small Singapore

within Monterey. This one year has passed in a blink of the eye, but the time spent is nothing short of magical; it has been a great year of fun, laughter and joy. I would like to take this opportunity to thank all my family, friends and colleagues whom I am unable to thank here personally for offering advice and guidance throughout the journey.

THIS PAGE INTENTIONALLY LEFT BLANK

I. INTRODUCTION

On August 23, 2005, Hurricane Katrina formed over the south-eastern Bahamas, caused by the interaction of a tropical wave and the remnants of Tropical Depression Ten. Tropical Depression Ten, emerging from western Africa in early August, was the tenth tropical cyclone of the 2005 Atlantic hurricane season. The storm swept across the Gulf Coast from Florida to Texas, causing severe destruction over the next few days. Major roads were impassable and there was minimal access to buildings due to the massive floods, as seen in Figure 1. The operational environment was dynamically changing each day with victims scattered across the massive disaster area. Time is critical during any search and rescue (SAR) operation. The survival of human beings will diminish exponentially with time if they are not located and recovered efficiently. These searches can vary in scale and magnitude, ranging from a single target in the form of a wandering hiker in Grand Canyon National Park to a massive operational scenario as described here. Hurricane Katrina happens to be one of the costliest and among the top five deadliest natural disasters in the history of the United States.

Figure 1. Impact of Hurricane Katrina. Source: Herbert (2005).

In the aftermath of a hurricane, emergency responses must adapt to the changing conditions, complete their missions and work with different teams to respond to the situation. Rescuers must piece together the available data obtained from the various sources to reconstruct the operational area and develop plans to optimally execute their rescue successfully. Based on the data, the commander in chief must identify potential hot spots to dispatch rescue teams to locate and extract victims safely. In the past, these tasks have been performed by utilizing a large pool of human resources to consolidate information and identify the search area. Subsequently, the rescue teams are dispatched to the ground for physical search and rescue only if the location is accessible. With the advancement of technologies, unmanned systems (UxS) are now equipped with an integrated sensor suite utilizing state-of-the-art computational power and processing capabilities to generate search plans to increase the success rate of the rescue mission. The efficiency of reading large amounts of data and development of plans allow the responders to locate the lost individual or groups more efficiently. Research in image recognition and detection of victims, development of optimal path planning and search path algorithms deriving from traditional search theory, and control of heterogeneous sets of unmanned systems have been completed independently over the past decade, however. The goal of the thesis is to integrate the various concepts into an integrated solution that provides a capability for the rescuers to utilize multiple autonomous UxSs for rescue operations. This cooperative swarm of heterogeneous UxSs can plan and execute a search rescue mission optimally to enhance the survivability of the victims.

A. THE FOURTH INDUSTRIAL REVOLUTION

The evolution of the previous industrial revolutions was pivotal in shaping the world today. The first industrial revolution in the 1800s to 1900s helped humans achieve mechanized production using natural resources. The birth of steam engines was made possible by the ability to convert water into steam to power engines, whilst the second industrial revolution prior to World War I from

1907 to 1914 saw the utilization of electrical power for mass production of products. The current third industrial revolution, commonly known as the digital revolution, started in the 1980s and saw the advancement of technologies that brought computers and the Internet to the mass population. The increase of computer power today has grown to the extent that our mobile devices are more powerful than the computer that was used to fly the first man to the moon. From the foundations of the digital revolution, the fourth industrial revolution is evolving exponentially and disrupting almost every industry in the world today. The fusion of technologies that integrate sensory information obtained from the physical and biological world merge the data into a digital environment that allows computers to simulate, predict and provide recommendations to decision makers.

These emerging technologies, coupled with the unprecedented computational processing and storage capacity, pave the way for many applications where large data sets are required to be crunched by human analysts within a short time. These applications can range from the financial industry to military applications. The powerful computers can identify patterns with the data and simulate various possible scenarios to provide recommendations. In addition, the ability to handle high bandwidth of data and process them on miniature computers that can be packed on board unmanned systems resolves past challenges of large avionics required to control multiple unmanned aerial systems (UASs) for missions. The impressive progress in research and development in the computer science discipline has seen the growth of artificial intelligence (AI) algorithms. The algorithms observe patterns from the vast resources, learn from these sets of data to provide the operators with predictions, and suggest possible solutions to a task within seconds. This path shows the way toward potential usage of robotics and unmanned technology in the application of a search and rescue operation.

B. CHALLENGES OF SEARCH AND RESCUE OPERATIONS

The biggest challenge in any search and rescue operation is the ability to obtain and disseminate information to the relevant party to get an overview of the operational area, to derive a plan to execute the rescue mission. The pieces of information might not be consistent as they are collected based on different perspectives and interpretation. For the search and rescue mission to achieve a higher success rate, multiple stakeholders must work closely to piece the data collectively to form a consistent view of the operational environment and disseminate to the right party.

Time becomes the critical factor as any delay will diminish the survival probability of any human in such a harsh environment. With time as an important factor in the operation, the usage of multiple unmanned platforms working together and sharing information of the environment from various perspectives will speed up the search and rescue operations. These sets of autonomous heterogeneous or homogenous unmanned systems can work in swarms, actively sharing information to collectively achieve the goal of identifying victims and deriving optimal paths for rescuers to reach them.

C. MOTIVATION FOR USING SWARM UNMANNED SYSTEMS

Technologies have matured, but reservations on the use of swarm unmanned systems must be resolved. The control of unmanned systems or drones, both in the commercial and military sector, have been inspired by the natural world. The emergent behavior to accomplish a complex task with simple agents working collectively has shifted the paradigm from an operator controlling a single platform to multiple platforms. An influential report by John Arquilla and David Ronfeldt (2000) defined swarming doctrine, which some war strategists envisaged as a potential “game-changer” in the evolution of war, as a “deliberately structured, coordinated, and strategic means to strike from multi directions, through a sustainable pulsing force and/or fire, close-in as well as from a standoff position.” Arquilla and Ronfeldt argued that swarming tactics

should not be purely used as a military tactic but can be expanded and applied to crowd control or SAR missions.

Following this argument, the question is how can swarm be leveraged and used in SAR? The capability to be structured and coordinated to extract a large amount of information at a greater speed will thus shorten the search time, which will be pivotal in the survival of the victims during the operations. Paul Scharre, a fellow and director from the Center for a New American Security, articulated in the report “Robotics on the Battlefield Part II: The Coming Swarm” that the dispersion of small and inexpensive drones in place of the expensive versatile platforms like the F-35 Joint Strike Fighter (with its attendant risk of losing a pilot) can extract a larger amount of information at a greater speed with lower cost and disaggregate risk from any enemy location, thus reinforcing the possibilities of utilizing drones for SAR applications (Scharre 2014).

There is a need to handle multiple platforms without the increase of limited human resources, however. The Office of Naval Research (ONR) utilized 30 Raytheon-built Coyote UASs as part of the Low-Cost UAV Swarming Technology (LOCUST) program to demonstrate the capabilities whereby a single operator can manage multiple platforms. “We have an operator that’s monitoring it [the drones], keeping eyes on what’s going on, and can reach in and change things if they want to,” LOCUST program manager Lee Mastroianni said. “But the reality is, [the drones are] flying themselves, they’re performing their mission and the operator’s supervisory. So, it tremendously reduces the workload to be able to control large numbers of UAVs” (Hope 2016). This demonstration showcases that with the right application of autonomy in the drones, a single operator could control multiple platforms.

These successful demonstrations have been completed in a controlled environment in which prior intelligence of the environment is known. Much swarm research has been completed on homogeneous platforms as inspired by the natural world. Each robot is unware of its teammates’ actions but completes shared goals collectively. The robots apply relatively simple local control laws,

which, when combined with the other robots, result in the global goal being achieved. Apart from the public resistance in the extent of automating machines as highlighted in “The Coming Age of Autonomous Systems” by Tan (2017), the drones’ inability to adapt and evolve in a dynamic environment restricts mission capabilities. Nevertheless, the potential to effectively handle a task that can enhance the efficiency for a mission that is time critical is too attractive to be ignored.

The fourth industrial revolution paves the way for robotics in many applications as the world evolves. The rise of hybrid warfare in an urban environment as well as operations in a post-disaster arena brings about a dynamic and uncertain environment for systems to be operated in. This creates an opportunity for robotics technologies. With the exponential growth of autonomous robotics systems embedded with data-mining technologies, the future is without doubt driving toward more autonomy amongst the robots to overcome the ageing population. It was reiterated in “Disruptive Technology and US Defense Strategy” that these advances in capabilities are the underlying technologies that will support the autonomous systems (Shawn Brimley et al. 2013). With the integration of the disruptive technological capabilities to be able to observe and orient the robots collectively with lightweight and commercially off-the-shelf (COTS) components, a wide latitude of applications is made available for autonomous platforms to be explored, operated both individually or collectively in a swarm, to accomplish any type of mission.

These systems will not be replacing human tasks but instead should complement them in a manned-unmanned teaming environment. Many in the military, due to the lack of personnel resources, have pushed for an autonomous system to replace manned aerial and ground capabilities. The key intent is to push for increased autonomy for the system to make decisions and accomplish tasks with minimal user input. The debate on the use of robots to attack an adversary, like drone strikes executed in Yemen and Pakistan by the United States, has proven to be highly controversial. Human Rights Watch has

campaigned to ban such actions since in their position, they believe it is immoral to kill any humans remotely. Collectively, this is also being discussed and debated at the United Nations level. Therefore, there is a need to understand the possible implication and select tasks that are practical in complementing the human factor prior to the application of autonomy in these platforms.

D. RESEARCH PROBLEM

The utilization of the swarm technologies in which a network of drones overwhelms the enemy through a massive onslaught, drawing fire and thus expending enemy resources, was a possible scenario painted by Defense Advanced Research Projects Agency (DARPA). Alternatively, it can be used as a means of intelligence gathering or sent in as a form of jamming against enemy communications systems. This thesis attempts to expand swarm operations on military applications and address the problem of whether such a concept of operations, a swarm of UASs as shown in Figure 2, can be used to enhance the search operations of the responders? Specifically, this thesis exploits methods of image analysis and generation of optimal paths and search patterns for a rescue mission by a set of drones.

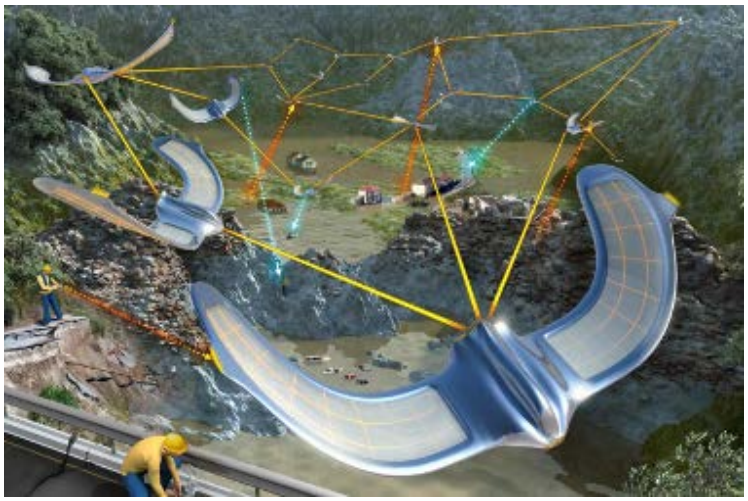


Figure 2. Swarm of UASs flying in operations. Source: Laboratory of Intelligence Systems (2010).

To narrow down, this thesis deals with consolidating information and navigating through an ever-changing and dynamic environment created in the aftermath of natural disaster. To solve this problem, several tasks in the various disciplines must be addressed. (1) The operational environment needs to be fused together by extracting information from various sources including remote sensing equipment, local surveys completed by the UAS and imagery obtained from the ground; (2) optimal trajectory and search plans must be developed for the swarm of heterogeneous UxSs to obtain the best path and search pattern in the respective mission bubbles; (3) image processing in the detection and identification of victims has to be processed and the information of the location of potential victims or hazardous areas has to be constantly shared amongst the various rescue teams for the safe extraction of the victims.

E. PROPOSED APPROACH

Based on the research challenges, a proposed approach to solving the problem was established. The concept of operations must be defined with key requirements of the mission established. The extent of the consolidated information to obtain the situational awareness will determine the success in most operations. Apart from rescuing victims, the stakeholders will also require vital information on the status of key infrastructure (e.g., the functionality of the power grid, water treatment plant or potential temporary housing areas) as well as the accessibility around these locations for the recovery phase. Thus, information needs to be constantly updated and shared amongst all stakeholders.

The proposed approach was based on five phases in a closed-loop sequence for the operational mission as shown in Figure 3. In the first phase, all the information will be gathered from the various sources obtained prior and after the disaster to be pieced together to form an operational area. The stake-holders utilize this operational map to plan and develop mission goals for the swarm UxSs to complete at the tactical level. Based on the given mission, an optimal

trajectory to the search area and search patterns are developed for the UxSs to search autonomously.

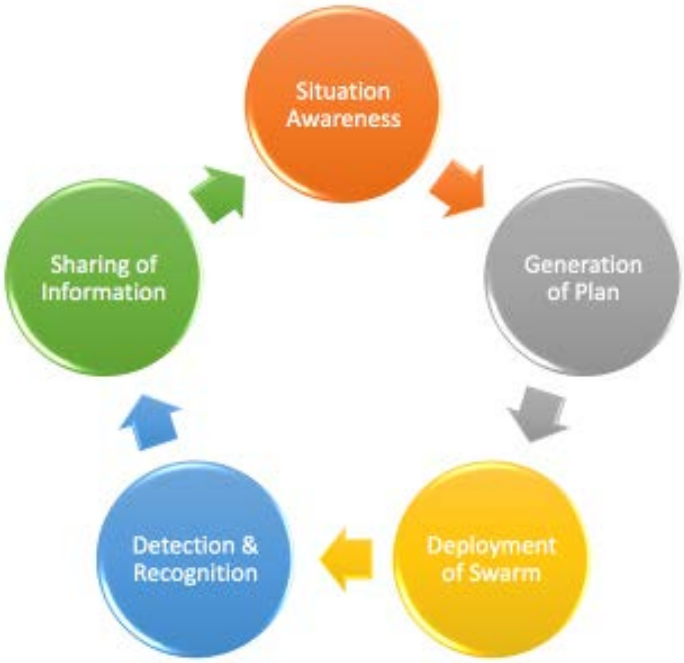


Figure 3. Proposed approach to search and rescue operations

As the operations are executed in an uncertain environment, the search plan formulations will be based on a belief map obtained through a probabilistic function. These probabilities are derived from information that was received throughout the mission. The three-dimensional map based on the initial information, supplemented with the updated images either from satellite or other UxSs obtained during the mission, are used to optimally plan its trajectory and to complete the search mission. The optimal trajectory path planning can be enhanced with machine learning to adapt to various scenarios in future studies. With the given trajectory in the form of waypoints, the UxSs will embark on the search mission, detecting and identifying the potential survivors in the area. Constant updates to the rescue teams will be sent for them to execute the rescue operations and to the main control station for planning and coordination.

F. THESIS ORGANIZATION

The key areas of research are based on the five phases of the search and rescue operation as described above, with the key thrust being the integration of the various technological concepts and evolving them through experimentation via computational simulations and live demonstration. As such, this thesis is organized as follows. The various concepts of operations are explored in Chapter II. A literature review in the various disciplines applicable to the search problems is performed to derive the proposed concept of operations. This will translate to the framework of the heterogeneous swarm of UxSs to operate and complete a search mission.

The theoretical method with the mathematical implementation associated with the various concepts in developing the situational awareness and optimal UASs path planning will be explored prior to the discussion of the proposed resolution of each task in the subsequent chapters. In Chapter III, image analysis to develop mission bubbles and identification of points of interest are developed. Subsequently, a three-dimensional map based on the images obtained from remote sensing or other means will be developed in the MATLAB environment to give the commander an overview of the situation. With the maps developed, the optimal trajectory to complete the search is discussed in Chapter IV. The results for each chapter will be presented in a simulated environment in MATLAB. Evaluation for the optimal method in the various phases will be based on measurable metrics and tangible outputs. Finally, in Chapter V the results of the demonstration of the search and rescue operation in conjunction with the research completed by Ang at Camp Roberts will be presented before concluding with the findings and recommendations of the thesis.

II. REVIEW OF CONCEPTS

In this chapter, a literature review in the various disciplines, including search theory, path planning, and imagery for detection and recognition, will be completed. Based on the concepts and technological maturity, a proposed concept of operations will be defined for a search and rescue operation. Prior to the formulation of the problem statement, it is essential to understand the scope of the task required in a search and rescue operation.

A. SEARCH AND RESCUE OPERATIONS

SAR is a complex operation whereby multiple groups with different skill sets work together in response to the disaster. Pieces of information are being obtained from multiple sources with mixed reliability. In the initial phase, information is either obtained through aerial surveys with manned helicopters and/or aircraft or from images obtained from those at the heart of the disaster and fed back to the personnel on the ground for the rescue operation. These challenging tasks are being undertaken visually, which means that the information received might be limited. With the scale of the area to be searched, it is challenging for the observer as shown in Figure 4 on board the USAF helicopter to be able to scan such a wide area without occasionally missing critical information during the search.

Local rescue teams or the population on the ground are alternative sources of information. They might be emotional because of the disaster, however, reporting biased information that might hinder decision makers. All this is being communicated through a congested network to a small pool of data analysts who attempt to piece the information together. Based on the ability and experience of the data analyst, an operational picture is painted for the decision makers to draw plans for rescue operations to be executed. Without the full awareness of the situation, however, decision makers might allocate resources poorly and thus hinder rescue operations. All these tasks completed by the

limited pool of emotionally charged humans are available for the rescue operations, draining their energy, and potentially degrading their decision-making capabilities.

Figure 4. Rescue personnel during a search operation. Source: U.S. Air Force (2005).

With time as the critical element in search and rescue operations, various technological concepts can be integrated into a capability that will aid rescuers in the disaster response. Multiple heterogeneous unmanned systems can collaborate autonomously to work in tandem with the rescuers to respond effectively in an urban search and rescue operation. The derivation of the concept of cooperation of an unmanned-manned teaming in rescue operations will be presented in this chapter. Prior to conceptualizing the operations, it is essential for the tasks in a mission to be analyzed to apply the right set of robotics technology to optimize the mission.

B. URBAN ENVIRONMENT

Search and rescue operations are typically split into two types: wilderness and urban. In the context of this research, search and rescue operations will occur in an urban domain characterized by destruction of man-made structures as shown in Figure 5, where rescuers are operating in the aftermath of the earthquake in Nepal. The chaotic environment is dynamically changing after each day with the possibility of further collapse when the rubble is displaced unnecessarily by anxious or inexperienced rescuers. A false negative of not reporting a victim, even though he or she is there, or a false positive that requires a fruitless search, are some of the challenges that the rescuers must face during the search and rescue operations.

Figure 5. Rescue workers in operations. Source: USAID Disaster Assistance Response Team (2015).

Schwab describes three main phases of an emergency management and disaster life cycle: response, recovery and preparedness with mitigation encompassing these phases, as shown in the flowchart in Figure 6 (Schwab 2014). Of the three phases, response is the most critical in terms of locating survivors. The key challenges are to identify the areas of search and locate them

with limited resources in an ever-changing terrain. The SAR operations are executed at two distinct levels: a strategic level for overall coordination and planning, and a tactical level on the ground for rescue. Upon the occurrence of the disaster, responding to the situation and recovering from the destruction is naturally the first step. Response is a critical phase, which is typically led by the first responders from the local fire rescue department who directly deal with the immediate threat to the victims in the area.

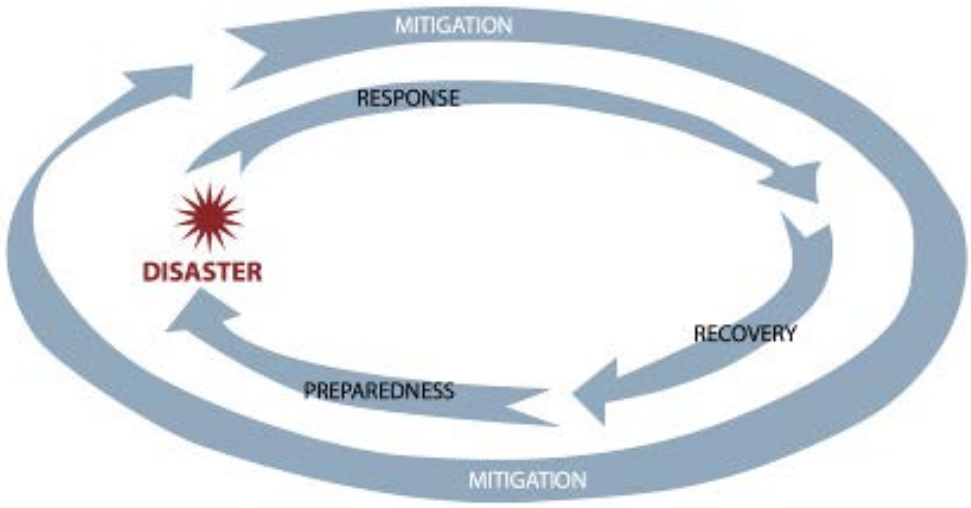


Figure 6. Phases of a disaster life cycle. Source: Schwab (2014).

The goal of the rescue team is to search for victims and rescue them. Rescue includes the assessment of the victim's medical condition, stabilizing them, and extricating them to a safe location. At the strategic level, the stakeholders will focus on the broad mission planning and coordination among the different parties. At the tactical level, on the other hand, the ground rescuers will be tasked to locate and rescue the victims at the site. To understand the specific task required to be completed at the tactical level, a review of the operating procedures (SOP) for first responders was completed to solve the research problem. Although this is mainly completed by personnel on the ground,

it is essential to understand the whole process before conceptualizing a solution for the search problem. Based on the United States Fire Administration, the SOP for a search and rescue operation in a collapsed building is based on two main phases: (1) scene management, which includes the establishment of command and control of the area and defining rescue sectors for the teams, and (2) technical rescue operations, which define the specific procedures for rescue in confined space, rope rescue, rescue under structural collapse and trenches (U.S. Fire Administration 1996).

The commander on the ground is required to complete the initial assessment of the area to derive an optimal but safe plan for the search operations. With the assessment completed, the rescue will commence for casualties on the surface before expanding to the concealed victims who are lightly trapped or possibly in the voids of the collapsed building. The global survey of the site covers a wide scope of tasks to be completed in a very short time. Depending on the environment, the assessment can be simple or complex. An experienced commander might be able to complete the task quickly. The scale and nature of each mission is different and unique in terms of the environment and the dynamics of the personnel involved, however. Moreover, the environment is likely to be unorganized, coupled with the potential risk due to tampering with the rubble by volunteers or civilians eager to save their families and friends. The key objectives of the damage assessment include (1) determining the severity of the damage, (2) identifying safe entries and exits, and (3) exploring the possibility of removal of debris to commence further rescue operations in a safe manner, among others. Subsequently, during the rescue operations, the commander must constantly report to higher command.

Based on various applications, technologies can help provide, collect, and store information that can be promulgated to a wider audience in a short time. Will unmanned platforms be used to aid the commanders and relieve their stress by completing information intensive tasks? Murphy et al. (2008) suggested that unmanned technologies can aid the commander in several areas. Tactical search

and strategic planning through reconnaissance and mapping have been two fundamental elements in which current technologies have matured sufficiently to enhance the speed and completeness of the rescue mission. They further defined search as the activity of identifying victims or potential hazards, while the reconnaissance and mapping task provides the responders a general situational awareness through maps constantly being updated with the changes in the environment (Murphy et al. 2008). This distinguishes the two levels of tasks robots take to aid the rescuers. Tactical search and rescue are usually executed by the first responders to find and extract survivors based on local information. This will cascade to the strategic level, where all the information will be consolidated and communicated throughout the whole operational area. In search and rescue operations, however, it is not always clear which will occur first. Unlike a military operation, where a strategic plan will be derived prior to the execution of the tactical plan, in search and rescue the information is likely to be generated from the tactical level up.

An aerial view, which can cover a large area, provides the best perspective of the environment. Such a view will be dependent on the severity of the disaster, however, which will dictate the resources available for such a survey. Moreover, in the aftermath of a disaster where major roads are impassable, the aerial vehicles provide a significant advantage in collecting data compared to ground elements. As the mission requires a large coverage of the area to obtain information required, unmanned technologies present a unique cheap and light solution. Drones have been in fact utilized in small quantities during search and rescue operations in the aftermath of several natural disasters in the United States. An iSENSYS UAS (Figure 7) from the Center for Robot-Assisted Search and Rescue (CRASAR), an experimentation institute in Texas, was used as part of the Florida State Emergency Response Team to search inaccessible rural areas in Mississippi in the aftermath of Hurricane Katrina. The Department of Defense utilized the BAE fixed wing Silver Fox in New Orleans to search for potential rescue sites. This clearly shows aerial footage used in both

the tactical and strategic levels of search operations. In the tactical environment, it will provide a vantage point of the area, especially when it is inaccessible, while the UAS can be used at the strategic level to identify potential rescue sites.

Figure 7. CRASAR UAS used in Hurricane Katrina. Source: Murphy et al. (2008).

Even though the research focuses on the search, it is essential to understand what the rescuers are looking out for at the tactical level to apply the right solutions for their search at the higher level. Upon the establishment of command and control, the rescue teams are sent into the area to provide medical treatment and evacuate the victims to a safe location. The rescue teams will save those victims on the surface prior to rescuing those victims who are lightly trapped under the debris. These victims under the rubble are typically located by search dog or acoustic or thermal sensors. Robotic applications have been discussed since the early 1980s, but not many successful platforms have been implemented. Robots with manipulator arms were used to observe in accessible areas, for example, over railings or voids under collapsed buildings after the World Trade Center collapsed on September 11, 2001. Specialist teams are required in the search for victims inside void spaces or under debris. The high-risk operation in an enclosed place and the need to remove rubble as they

entered the voids required well-trained personnel. The conventional approach for this search under rubble for survivors involves the inefficient method of removal of rubble through passing of buckets. This large amount of human resources is time consuming and draining, and at times might complicate the situation as the removal of debris might be completed by inexperienced personnel leading to further collapse. Mini and micro robots designed based on the movement of snakes might be able to search for survivors safely by wriggling through voids. Such robots have not been fielded and are still being tested, however.

The search and rescue operation is clearly segregated into two main tasks. The rescue operations must be completed by responders who need to interact with and assess the victims. In the future, this could be automated, however. With the available technologies, the focus for the research essentially will be in the search phase. The key aim is to shorten the time to locate the victims. With increased autonomy of platforms, Macwan (2013) envisioned that human SAR teams will eventually be augmented and work closely with teams of autonomous robots in the search aspect of the operations. The vision of an augmented framework presents two challenges: to overcome the energy limitation of the individual UASs and the quality of sensory data that the UASs can accommodate. Based on understanding the tasks required at the tactical and strategic level, it is essential to review search methods within the discipline of search theory and expand the concept from single to multiple robots, to include the ability to collate and share information to optimize the energy limitation and payload capacity that each drone can handle.

C. SEARCH THEORY

In search operations, the teams have an area of responsibility to search for an object of interest. In all disasters, some form of information about the location of interest should be available. As the search evolves, however, this information will be updated based on the data obtained on the ground. Thus, the

teams will be operating in a dynamic environment where changes to the trajectory will depend on the information received at any moment.

Modern search theory evolved during World War II and subsequently became a field within the discipline of Operations Research. Bernard Osgood Koopman and his team at the United States Navy's Anti-Submarine Warfare Operations Research Group (ASWORG) developed techniques to optimally hunt for German U-boats, which led to the theoretical foundation for search theory. Koopman defined basic search concepts based on the probability model. He developed probabilistic models for search areas and techniques to optimally search for the target in the area. Although the method was successfully implemented, Koopman's research was specified for a stationary target. Dennis Kelly applied the concept to a dynamic environment for search and rescue missions in 1973. The motivation for the development of search algorithms for optimal search was made possible with the availability of computer technologies. Search theory described analytical methods in identifying the shortest or most efficient solution that governs the allocation of resources in achieving its desired goal by maximizing the probability of success while minimizing the efforts based on the defined metrics. The metrics typically take the form of distance travelled or amount of time required to complete each task.

Monte Carlo computation to obtain distribution of a target for a multi-scenario environment was employed as a dynamic planning tool in searching for ships lost at sea. The probability map was built based on a grid of cells that described the distribution of the search. A detection probability of the target based on the prior information was tagged to each cell. Based on the map that was developed, a search plan was derived. The probability map in Figure 8 was developed for the search for USS Scorpion (SSN-589), a nuclear submarine, in 1968. The probability developed based on the consolidation of data from various experts who postulated the possible location of the submarine. According to Richardson and Stone, after several months of search operations, the USS Scorpion (SSN-589) was found at the base of the peak of the probability map.

Throughout the search, decisions were evolving based on the results obtained during the search process (Richardson and Stone 1971).

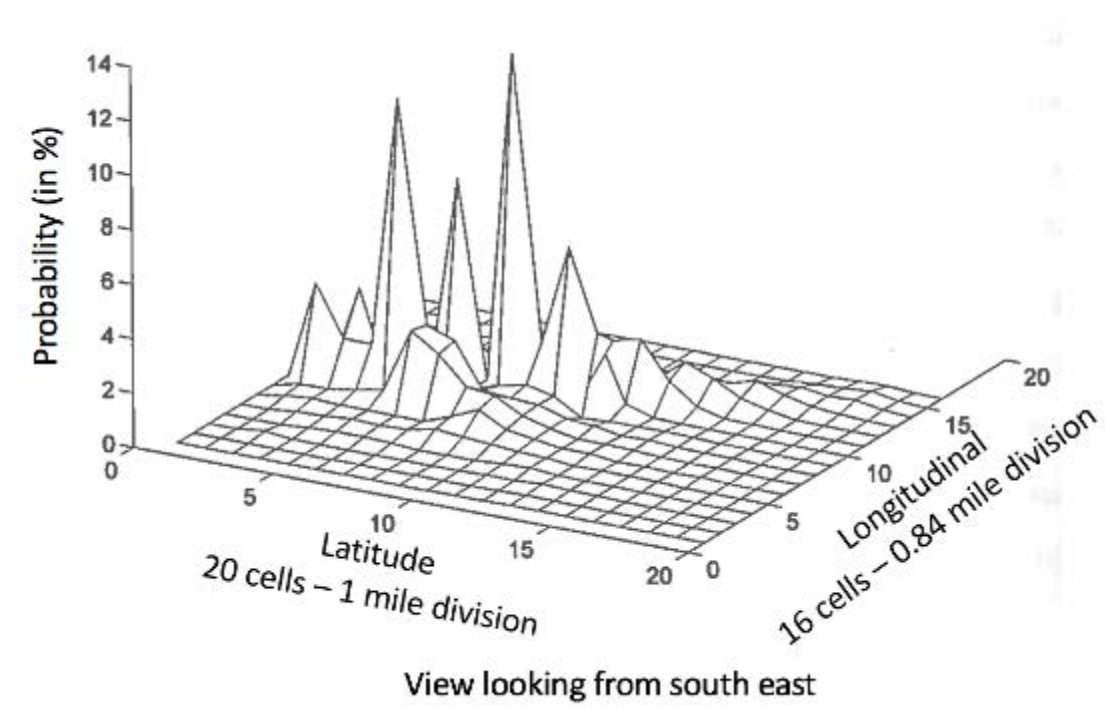


Figure 8. Initial distribution of the search for USS Scorpion (SSN-589)

Bayesian analysis is a recursive method that computes the probability based on unknown parameters. The estimation of the distribution is based on a posterior of the parameter of interest. The posterior distribution encompasses a prior distribution about the parameter and its likelihood of occurrence based on observed data. The posterior distribution can be obtained analytically or approximated in the form of the Markov chain Monte Carlo (MCMC) method. The motion model of the target is recursively combined with the sensor measurement model to compute the probability distribution of the target location. This Bayesian approach will determine the location of the target state probability density function (PDF). A prior probability distribution based on the initial information of the possible target location is used as the starting point of the search problem.

The Gaussian distribution of the target location is based on experience of past natural disasters, where survivors were likely to be in areas of collapsed buildings or along main roads. The search algorithm will choose a strategy that minimizes the time to find the target or maximizes the probability of finding the target based on the limitation of its energy. The probability of target in each cell is updated and recomputed once each cell has been evaluated or when information of the belief map is shared among the various resources.

1. Situation Mapping and Damage Assessment

The biggest challenge is to derive optimal plans for a search and rescue operation when information of the situation is either incomplete or inaccurate. To obtain an optimal solution of any search problem, it is essential that a map of the area can be pieced together as accurately as possible. This complete situational awareness map can be obtained through multiple sensors. To get an overview of the operational area at the strategic level, one of the means is to obtain high resolution geospatial data from commercial satellites orbiting around the Earth. In their research on the aftermath of an earthquake in the city of Port-au-Prince, Haiti, Hussain et al. (2011) reiterated that imagery obtained and analyzed from remote sensing platforms greatly assisted the authorities and the rescuers in providing damage assessment for the stakeholders to develop a plan for remedial measures in the response and recovery phase.

Remote sensing is a field designated as a discipline to enable people to look beyond the range of our visual and spectral range. Research has tapped into these remote sensing platforms and utilized sensors of different disciplines—for example, electro-optical (EO) cameras, synthetic aperture radar, light detection and ranging (LIDAR) sensing equipment—or a combination of such sensors for assessment of a post-earthquake environment. One simple method that was discussed was based on comparing the pixels based on the fused data obtained from the EO and synthetic aperture radar satellite images.

The most accurate library of Earth imagery and analytics is provided by DigitalGlobe in the U.S. and France's Airbus Defense and Space, utilizing the SPOT constellation satellite. These high-resolution wide-area optical images are used by the defense and commercial community. Federal agencies utilize them to observe changes in the environment, while commercial enterprises mainly use those that provide navigation information (e.g., Google and Apple utilize them to obtain updates on road conditions). These images are also often used by meteorologists to study weather patterns. The French Satellite Pour l'Observation (SPOT-1), launched in 1986, was one of the first satellites providing high-definition images of the Earth. At that point in time, a panchromatic (black-and-white) camera with a ground-spatial resolution of 10m and a multispectral camera with a resolution of 20m was used. This set of satellites evolved with the addition of SPOT 6 and 7, which will assure the provision of imagery until 2024. In 1997, Earth Watch Inc. launched an improved version of the sensor with a 3m-resolution panchromatic camera and a 15m-resolution multispectral camera on the EarlyBird-1 satellite. As sensor technologies advanced, the resolution has improved to a more accurate sub-meter resolution for the panchromatic and to a meter resolution for the multispectral camera.

The high-resolution multispectral or panchromatic imagery was obtained from DigitalGlobe's suite of geospatial big data (GBDX) for this research. Data obtained from various time frames was used to develop the initial mission bubbles for the search operations. Comparisons were made to identify potential areas to be searched. With the mission bubbles defined, a belief map based on the posterior distribution was constructed for the automated generation of the path and search plan. Five satellites operating in sun-synchronous orbits provided the data: WorldView-I, Geo-Eye-1, WorldView-2, WorldView-3 and WorldView-4 (Figure 9). Each of them operates at a different altitude and has different resolution, with the best being WorldView-3 and WorldView-4 with a 0.31m resolution for the panchromatic and 1.24m for the multispectral. Samples

of the imagery as extracted from the technical data sheet are shown in Figure 10. The details and specification of each satellites are summarized in Table 1.

Table 1. Specification of DigitalGlobe satellite. Source: DigitalGlobe (2015).

Specifications	WorldView-1	GeoEye-1	WorldView-2	WorldView-3	WorldView-4 (GeoEye-2)
Operational Altitude, km	496	681	770	617	617
Spectral Characteristics	Pan	Pan + 4 MS	Pan + 8 MS	Pan + 8 MS + 8 SWIR	Pan + 4 MS
Panchromatic resolutions, m	0.50	0.41	0.46	0.31	0.31
Multispectral resolution, m	N/A	1.64	1.85	1.24	1.24
Weight Class, kg	2500	1955	2800	2800	2800
Launch Date	Sep 18, 2007	Sep 6, 2008	Oct 8, 2009	Aug 13, 2014	Nov 11, 2016

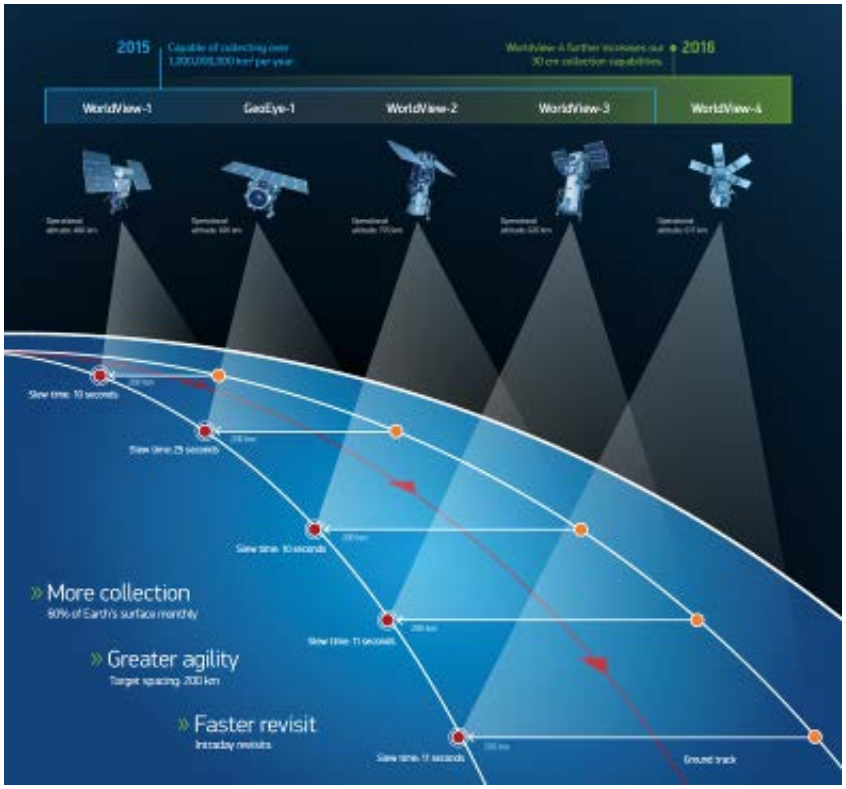


Figure 9. DigitalGlobe suite of satellites. Source: DigitalGlobe (2015).

Figure 10. Sample images from the various satellite. Source: DigitalGlobe (2015).

2. Multi-robot Coordination

Multi-robot coordination generally requires the planning, directing, and controlling of a team of multiple autonomous robots operating in the same environment to carry out either a single task or multiple tasks individually or collectively to achieve a global-level goal. This set of robots can have similar capabilities in a homogenous swarm or have varying capabilities in a heterogeneous swarm. In a heterogeneous set of robots, each robot will have a specialized set of skills, like the special forces in the military. To be self-contained to execute the mission, each team will be staffed with an explosives expert, a medic to provide first aid, and a communications specialist to handle the signal equipment. This type of arrangement is common in our everyday life; whereby, an individual will be required to complete a specific task to resolve a larger goal.

This concept of distributed intelligence allows multiple robots to work together to achieve a larger goal that might not be possible to be completed individually. Parker defines distributed intelligence as systems of entities working together to solve a problem. The domain space in the distributed intelligence can be broken down in terms of the interaction between the systems, as in the four main categories illustrated in Figure 11 (Parker 2008). In this illustration, there are three main axes: the awareness of the other platforms on the team, the classification of the goals (individual or shared), and if each robot's action will advance the goals of the others on the team. The collective, cooperative and collaborative interaction tends to advance the goals of the others, while the coordinative does not, despite its name. In a simple grouping, the awareness is split into two categories: awareness or lack of awareness. Awareness can be defined as the means for the robots to exchange and share information to execute an action. Being unaware is based on the robots operating on the principle of stigmergy, whereby communication between entities is not direct but reacts based on the traces left in the environment by the other robots. For the advancement of goals, a robot can advance the goals of a team if its actions are

helpful to the team, whereby, the other robots will not be required to repeat the same actions. An example will be in search and rescue; as a member of the team of robots, each robot is required to search a small area. Each robot's search action is helpful to the other robots who will not be required to search the exact location again since it has been completed by another teammate.

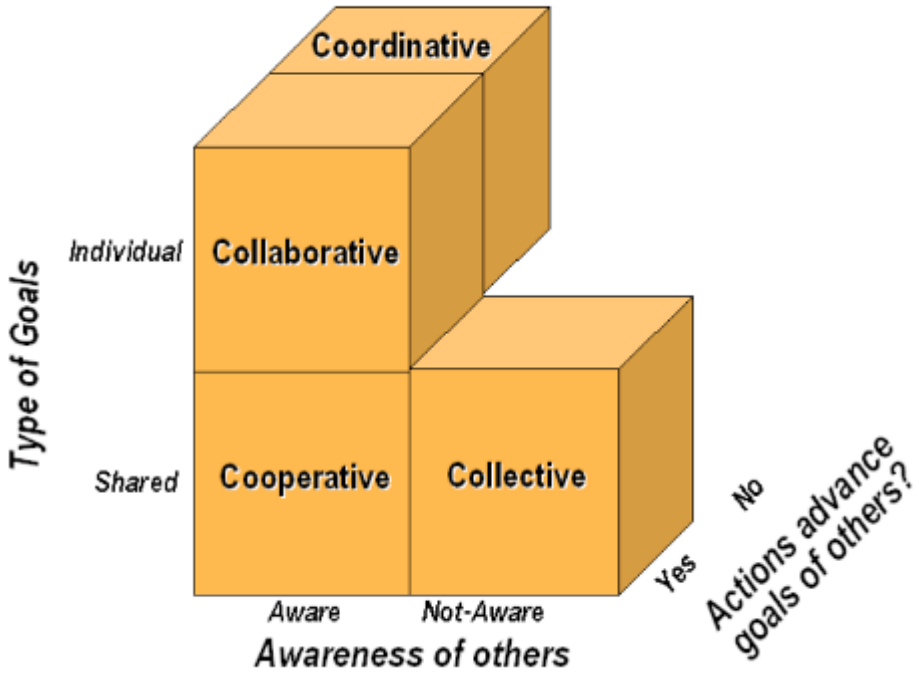


Figure 11. Categorization of distributed intelligence

Based on the common forms of interaction, each type of interaction is explained further for clarity. The simplest form or interaction, the collective interaction, evolved based on biological tasks seen in the natural world. Examples of such tasks includes bear foraging, swarming of locusts, the flocking of birds and the herding of cows. Not all the animals are aware of the other animals except that they share a common goal to either hunt for food or to move to a specific location. Although they are not aware of each other, their individual actions are beneficial to the others in the group. Robots in such interactions are

based on simple local control laws and, when combined, result in an emergent property that allows them to achieve a global goal.

As the exchange of information is made possible by higher bandwidth in communications, providing awareness allows for more cooperative and collaborative interactions between robots. From a collective interaction, a lateral shift is a robot's ability to be aware of the actions of its teammates and, at the same time, have a shared goal where its actions are beneficial to the others. In such interaction, each robot due to its limited capacity can only complete a specific task to achieve a bigger goal. In the context of search and rescue, the global objective or goal is to identify victims, but each robot has limited energy capacity. Thus, the area can be split into smaller regions for each robot to search, working together to achieve a common goal of identifying victims in the search area. There is a grey line between this form of interaction and the collaborative classification. In the collaborative classification, everyone has an individual goal to achieve; this form of interaction is typically applied in complex problems to achieve a global goal; it is necessary to split the task to simpler individual goals for each robot to tackle. The distinction between the collaborative and cooperative is characterized by each robot helping each other to accomplish its individual goals as each might have a specific skill set not present in others. The example of the search and rescue in the cooperative was a simplistic scenario. To extend from a cooperative to a collaborative interaction, while the individual robots are navigating to the specific location for the search operations, some robots because of interference from the global position system (GPS) coverage cannot reach their search area independently. If they work together and obtain GPS positions from the other robots that have a clear coverage of the satellites, however, the individual goal of reaching the search area can be completed with the help of the teammates. This is a form of collaborative interaction that can be seen in multi-robot systems. The last type of interaction is more applicable to a factory whereby the robots are aware of each other, but

must coordinate to ensure that they do not clash with each other during the completion of their individual goals.

Based on the understanding of the categorization of interaction in a distributed intelligence domain, the cooperative and collaborative means of interacting is the likely choice for the search and rescue operation. A global goal is to rescue victims, but to do that you will need to search for them. Thus, there is a shared goal between the robots. As the magnitude of the area becomes bigger, however, an individual goal might be required at the tactical level, and thus, a more collaborative interaction will be implemented. Therefore, the application is dependent on the requirements and nature of the operations. The next question is the means to control the interaction: Should it be via a centralized system or a decentralized method? Each has its own pros and cons, so a review of past research completed in this area is required to understand the strengths and weaknesses of the two schemes.

a. Centralized Multi-robot Coordination

Centralized coordination is akin to a hierarchical control whereby all commands are given by a single chain of command, like military operations. A single control unit allocates the various tasks to the robots. For this to happen, a communication link between the robot and the central command is always essential. With such a coordination strategy, a large amount of information will be generated and transferred through the network to the master controller. The master controller will require crunching a large set of information obtained from the various robots to disseminate the next set of instructions to them. Thus, it might take a longer time to complete the analysis of the data received. Since all the information resides within the master controller, however, it can consolidate a more complete picture to optimize the plan and allocate the necessary resources to complete the mission more effectively.

The application of the centralized approach for coordination of multiple robots was completed in multiple research, but in the application for specialized

and specific tasks. The research areas include motion planning, both in the static and dynamic environment, formation control of robot agents in specific formations, and search coverage and exploration problems. An example of such central coordination was implemented with a refueling system. A schedule for the refueling of multiple UAS by a single tanker that acted as a central controller was also explored by Shima and Schumacher in their research (Jin et al. 2006). In that study, the UAS reported to a centralized command. Fierro and Spletzer (2005) expanded such a concept into an optimization tool whereby a centralized command developed to coordinate multiple unmanned vehicles in real time. The optimization tool solved the problem with a receding-horizon mixed-integer program. The coordination strategy developed paths and input the control commands to the robots to accomplish the mission. Although the mission objectives could be varied, the targets for the robots to explore were fixed (Fierro and Spletzer 2005).

As the targets were fixed, however, the multiple robots' coordination was completed in a controlled environment, which is not likely to occur in a search mission. Brumitt and Stentz (1996) extended their research in centralized coordination of multiple robots in a dynamic environment by designing a method that allows changing the robot's plan and assigning new paths based on knowledge of the updated data. With such an implementation, multiple robots can handle unforeseen circumstances like what is expected in the aftermath of a natural disaster. The centralized planner updates the assignment of the robots to achieve the goals based on minimizing the mission cost (Brumitt and Stentz 1996). Tan et al. (2017a) implemented a centralized control for multiple ground robots in a search mission in a detect-to-engage robotics challenge. The dependency on the central command to make the decision and transmit commands, however, reduced the flexibility and did not tap into the full potential of the autonomous ground vehicles. Since the platforms can be autonomously controlled, each should handle its own navigation based on the global targets set by higher command. On the other hand, with the full assessment of information,

the central command utilized the resources more effectively (Tan et al. 2017). The approach of centralized command has its advantages; it will provide the optimal solution since all the information pertaining to the situation resides with the central command. If the scale of the mission is too huge, however, the central command system might be overloaded and not ideal for such implementation.

b. Decentralized Multi-robot Coordination

In contrast to the centralized control, in a decentralized approach each team member receives a task and completes it independently acting solely on the local information that it received. Although working independently, there must be a cooperative element to accomplish a global goal. The decentralized approach allows each robot to complete its own navigation to avoid obstacles and correct its path based on the environmental conditions. Their cooperative or collaborative elements come in the form of interaction between the robots when they are within range of each other or at designated points.

This can be applied in a context of a complex search environment where each robot will go about completing some tasks or search a specific area to aid the rescuers in identifying the victims. Cao et al. (2006) demonstrated this concept by applying a distributed control approach to a hunting mission. Each robot searched for its targets independently. When they were within the sensing range of each other, they exchanged information. During the exchange of information, the robots synchronized their data to get an updated situational awareness of the environment and modified their actions accordingly (Cao et al. 2006).

Another example of a decentralized coordination is insect behavior in the natural world. Insects are influenced by the behavior of their others who are operating independently to achieve a bigger goal. It has been observed that more purposeful cooperation and collaboration can achieve more intelligence and capabilities when operating as a swarm. Cortez et al. (2009) presented a decentralized algorithm for a coordinated search by a robot team. Each robot

maintained its own map of the search area and navigated based on the belief map that was loaded in the system. Upon interaction with the other robots, the belief map was updated to reduce the search scope (Cortez 2009).

Thus, decentralized approaches can be utilized where the global task is too complex and must be sub-divided into smaller sub-tasks. As they do not require intensive communication and computation during the operation, the platforms need not be equipped with big and bulky computers. Instead, miniaturized avionics can be used, which is ideal for search and rescue operations. Lightweight drones are an ideal solution for the first responders in tactical search. Eventually, the individual robot can aggregate the data to the global system to give a more complete situational awareness at the strategic level.

c. Multi-robot Search and Rescue

The potential of multiple robots in the search and rescue application is huge. The application in searching for survivors in an urban environment was studied by Chan et al. (2004). The application for search and rescue, however, followed a simple search strategy. Chan et al. (2004) used a simple random walk algorithm. Research in multi-robot control mainly focused on the control of robots in the formation or simple search methods. Few applications or solutions rely on remote sensing equipment to enhance the search mission and optimize the coordination between the strategic and tactical level in a post-disaster situation. As more UASs are evolving into full autonomy, multiple robot coordination to assist the rescuers in hybrid environments of centralized and decentralized control are evolving. Based on the review of the different types of interactions, it can be verified that a collaborative or cooperative interaction paradigm in a decentralized coordination scheme is an ideal means for the implementation of multiple robots for search and rescue.

3. PATH PLANNING

A path planning algorithm has several tiers, but an initial path can be derived based on the utilization of probabilistic path-planners. These path planners include the Probabilistic Roadmap (PRM) and the Rapidly-Exploring Random Trees (RRT) approaches. Subsequently, the robots can interact with the environment through sensory information to obtain a spatial model of the area. The sensor resource management problem is a major challenge, whereby multiple sensors determine the measurements in the dynamic environment and fuse the data to improve the perception of the robot. This model allows the drones to safely navigate past objects and obstacles and thus have the flexibility to deal with unexpected situations.

Wagner et al. (2012) address the curse of dimensionality by suggesting the implementation of the sub-dimensional expansion technique for large sets of multiple robots (Wagner et al. 2012). This technique dynamically varies the dimension of the path planning problem by restricting the planning to the configuration space that is within proximity. This approach reduces the computation time significantly to less than ten minutes for a 32-robot team. The Probabilistic Roadmap (PRM) planner will plan and generate a path that is free of any obstacles and has a feasible solution for the robot's motion to maneuver from a given start to a goal point. The solution, in the form of the black lines for the PRM defined in the workspace with obstacles represented by the blue blocks, is shown in Figure 12. The basic idea behind the PRM is to take a random sample from the defined configuration space of the robot and use a local planner to connect these points. With the given start and goal point, the resulting graph can be determined based on a search method. The effectiveness depends on how densely the roadmaps fill the configuration space.

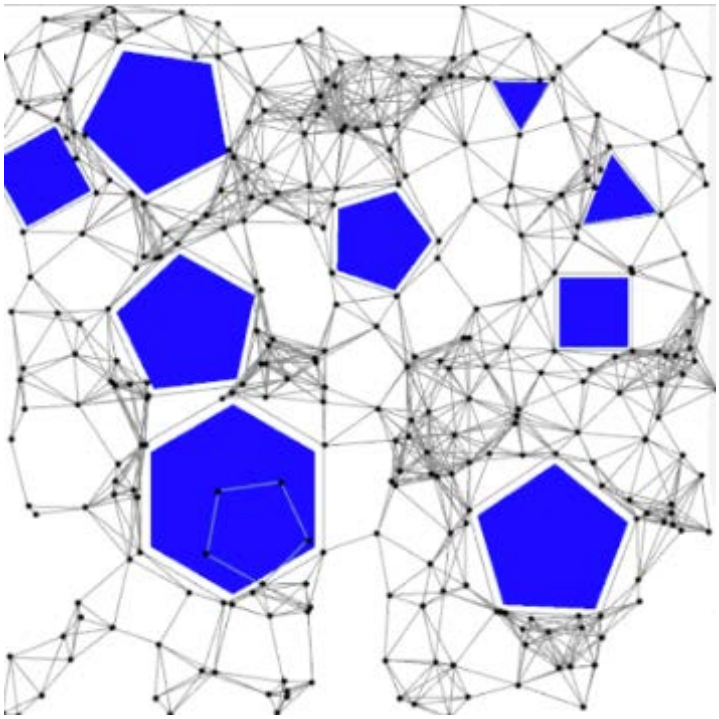


Figure 12. The various options generated by the PRM

A path planning method for a search and coverage problem was devised by Karimoddini et al. (2011) to address a multi-UAV formation control problem. The means to converge the discrete decision making on a multi-robot system requires a hybrid supervisory control approach. Karimoddini's team considered a two-dimensional leader-follower formation in which the UAV must reach a location relative to the designated leader, maintain its formation and avoid colliding with another UAV. The decentralized path planner was based on a finite discrete event system model. In this model, the formation control system is reduced to a discrete state that can be controlled by an existing discrete control system under supervisory control theory (Karimoddini et al. 2011). For a search problem, however, the path planner must be able to be updated based on the data obtained and respond accordingly to fulfill the mission objectives.

4. IMAGE PROCESSING

Obviously in search operations, the quality of the sensory data affects the rescue effort. The rescue efforts will be dependent on a decision-making stage in which a target is present or not in operations. It is inevitable that, due to various circumstances, there will be mistakes in the interpretation of the imagery that will lead to false alarm.

If the data is not reliable, the thrust in data obtained from the drones by the rescue team will diminish. For example, if the false negative is high and a survivor is present in the vicinity but was missed by the computer, the rescue team might not visit that location, leading to the possible loss of a victim. Similarly, when there is a probability of false positive, where a victim is detected when there is not a physical survivor, the rescue team might be searching for a needle in a haystack, thus wasting unnecessary resources. The challenge is then to establish and ensure that the data obtained from the sensors are computed effectively. The UAS used for the experimentation is equipped with a basic camera looking downwards to detect the potential survivors on the ground. The size of the area increased with altitude, although the possibility of victim detection decreased with height. The balance is to complete the search at the optimal height where victims can still be identified accurately without compromising the search process.

D. PROPOSED CONCEPT OF OPERATIONS

From the research in the various disciplines, the proposed concept of operations for the rescuers can be developed. There are two broad mission objectives at the strategic and tactical levels for a search and rescue mission, with the global goal to reduce the load on the rescuers to focus on rescue operations.

At the strategic level, the aim is to collate all sources of information and identify a potential area of operations to allocate specific missions for the first

responders to “hit the ground” and commence their tactical mission. Remote sensing equipment will be used to obtain imagery, and the images can be integrated into a single picture to give the stakeholders an overview of the environment. The centralized command will segregate the operational area into smaller sections for the responders to visit for further search. The heterogeneous swarm at the tactical level is required to aid the rescuers in a manned-unmanned interface to detect and identify victims for the rescue mission. Subsequently, the data will be updated to the central command when new information is found. All this must be completed in the shortest time possible to enhance the survivability of the victims. Thus, the key metric is the number of survivors that it can find and rescue in the aftermath of the disaster. The efficiency comes in the form of finding the quickest path or route to the location by utilizing the fewest resources. The concept of operations is envisaged based on the five different phases described in detail below.

1. Situational Awareness

The vision is to utilize computational power to process multiple inputs of data obtained from various remote sensing equipment or ground sources to generate a comprehensive operational environment. This will be accomplished by completing three main tasks (Figure 13) as part of the situational awareness bubble. (1) The first is information gathering, where the overview of the environment is fused together, and hot spots and potential areas to search are selected as mission bubbles for first responders. (2) With the potential area identified, the imagery will be stitched together in a grid, both in the two-dimensional and three-dimensional environments. Based on information obtained, a probability of survivors will be allocated to each cell. (3) Finally, the three-dimensional environment will be converted into point clouds in the virtual environment for the heterogeneous set of robots to navigate through.

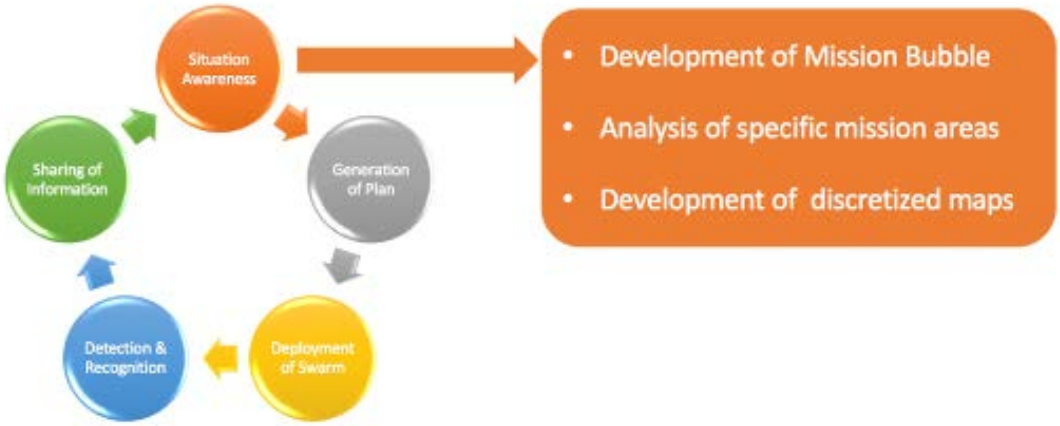


Figure 13. Tasks in the situational awareness phase

2. Generation of Plan

Typically, UxSs use pre-planned trajectories, but this may result in sub-optimal search strategies, especially in an uncertain environment following a disaster. Thus, a method must be applied to dynamically change the path and search pattern. Due to energy limitations, multiple UxSs of varying capabilities carrying different sensors will be utilized; thus, the term heterogeneous was used.

Two sets of plans must be generated in the generation of plan bubble by interpretation of the probabilistic maps called the belief maps to derive the optimal plans, as shown in Figure 14. An optimal path to reach the mission bubble and an optimal search must be derived for the designated search areas. This path and search pattern that the robots must undertake to complete the goal objective must be derived quickly with the fewest resources. With the situation mapped, the designated UxS rescue swarm will search the disaster zone, exploring and mapping potential locations of possible victims. The search patterns are generated based on traditional search theory and utilizing specialist UxSs for different aspects of the mission.

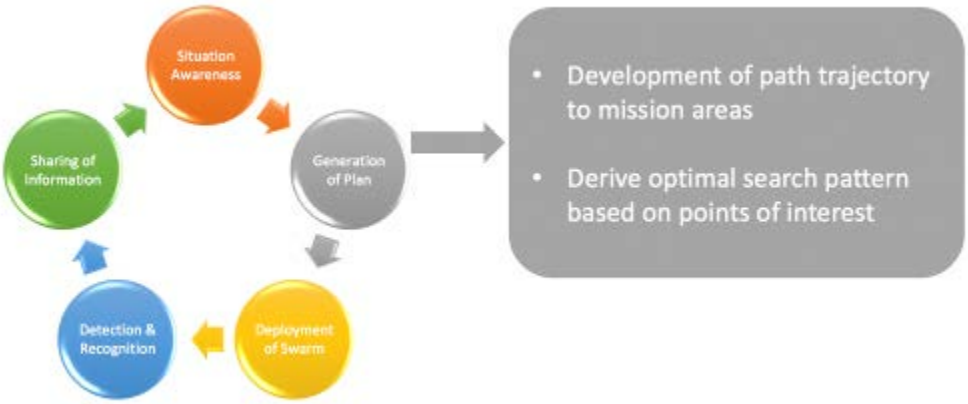


Figure 14. Tasks in the generation of plan phase

3. Deployment of Swarm

With the trajectory and search path developed, the waypoints are sent to the heterogeneous set of drones to be deployed. The navigation of the swarm and environmental sensing for collision avoidance is completed independently by the individual robots to ensure that the drones arrive at the specified location without hitting any obstacles.

4. Detection and Recognition of Victims

To reduce the burden of sensor operators, the detection and recognition of the imagery must be completed autonomously. The possibility of false positives and negative interpretation of the imagery by the computer must be addressed, however. The thin balance between flying higher for a larger coverage but less accurate detection and recognition capabilities must be resolved to aid the rescuers optimally in identifying the victims. Thus, an algorithm that is a function of the height from the object must be used to detect the differences of the pixels in the image. An estimator based on the field of view at different altitudes computes the probability of detection. This prior information from the estimator is used as a mechanism to tune the efficiency of the detection algorithm.

5. Sharing of Information

In the heterogeneous swarm at the tactical level, each UxS will maintain its own grid-based probabilities map that represents the discrete search space with a probability of the target present tagged to each cell. Typical uses of these maps include surface mapping, exploration or navigation in the research by Elfes (1989). The aim of this phase is to fuse the data from the various UASs and to share with each platform the updated components in each map to obtain a complete picture. There are two main challenges in the process of sharing information: the data fusion of the information as well as the network connectivity between the robots.

The challenge for the data fusion portion is mainly the computational power in the processing and memory storage. Network availability in the congested environment of the multiple UxSs is the main challenge for the network connectivity during the operations. Since the UxSs are required to be lightweight and small for easy handling at the tactical level, they are likely to have limited communication range. Thus, optimal points to exchange information must be defined to reduce unnecessary movement that consumes energy. The drones can only exchange data and update their belief maps when they are within each other's network communication range; an approach for such an exchange of information is shown in Figure 15. Each UxS have its own belief map generated in phase one and will synchronize the data when two UxSs are within the communication zone. With the updated data, the new belief map can be shared to give both UxSs the most updated search environment.

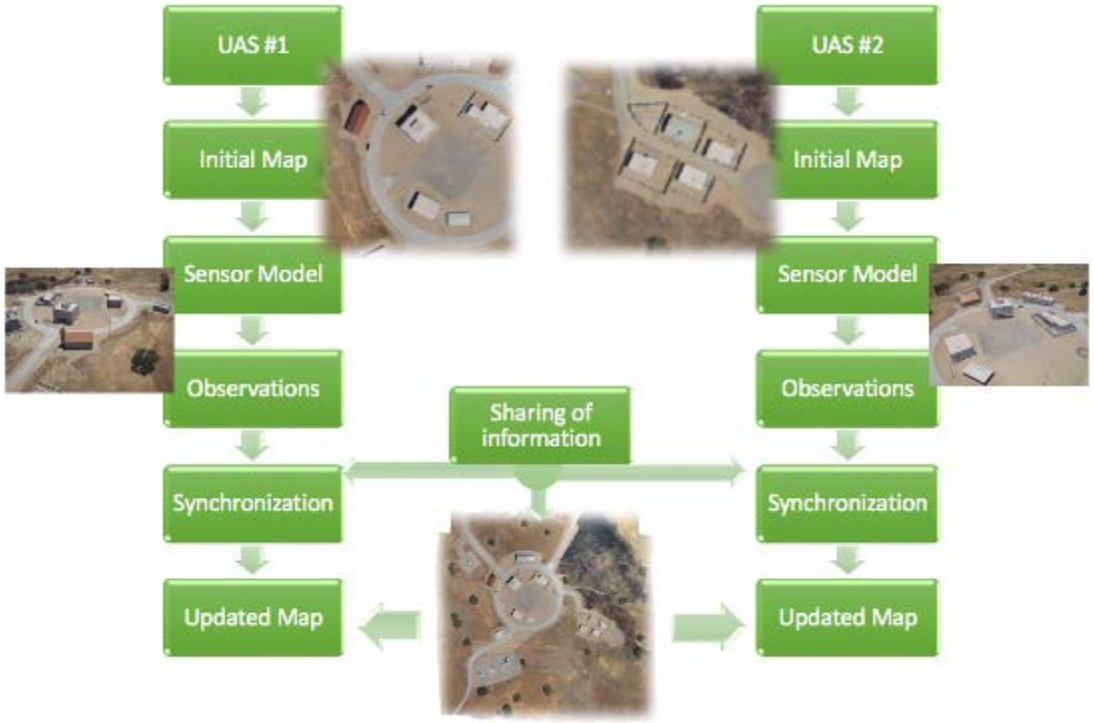


Figure 15. Concept of transfer of information

E. METRICS AND OBJECTIVE

The global goal for the use of the heterogeneous set of UxSs in the search and rescue mission is to reduce the overall victim discovery time and, thus, it is essential to estimate the time the robot requires when generating the optimal path and search pattern for the mission. Based on the global goal, the overarching metric is to obtain a solution and the shortest distance for the UASs to accomplish the desired mission.

To achieve the goals, however, it is also necessary to evaluate the performance of the algorithms during the processing. The most efficient frontier will be selected based on the evaluation criteria defined. The criteria were split into the global parameters and the task parameters. In the global parameters, an evaluation will be completed on the (1) probability of obtaining an optimal solution, (2) shortest distance that the solution will provide and (2) total resources required to process the solution.

The final set of parameters and strategies selected must be able to get an optimal solution in every instance; thus, the algorithm must ensure that an optimal solution can be obtained every time. The distance is an important function to minimize energy usage for the UxSs. Due to the limited battery power, a path generated that will result in a shortest distance will allow the UxSs to use the least energy and reserve them for other functions, thus enhancing their efficiency. The total time of computation will be completed at the global level while the individual time to complete each task will be done at the task level in selecting each strategy.

At the task level, analysis for the three tasks—(1) sampling, (2) connection and (3) search—will be evaluated based on the individual parameters in terms of time to complete each task and iteration required in generating the results. The time required to complete each task is essential to understand which strategy is suited for the selection of points in the configuration space. For the sampling strategy, the number of iterations required will be compared for the different implementations. This is the number of points generated to achieve the collision-free samples. The number of edges versus the number of collision-free edges will be evaluated for the connection strategy.

III. FUSION OF IMAGERY FOR SEARCH OPERATIONS

Based on the analysis of tasks in the previous chapter, the two main levels of search are the strategic and the tactical levels. The flow of information is not as clear for search and rescue (SAR) missions as it can be either top-down or bottom-up, as illustrated in Figure 16. Information can be obtained either from aerial images from remote sensing or airborne platforms, which give a global overview, or from the people on the ground equipped either with handheld devices or unmanned ground vehicles. In this chapter, the search problem will be defined before the development of the belief map that a survivor is present in the operational area, this operational map will be used in the subsequent chapters to develop a trajectory and optimal search pattern to locate the survivor. A belief map is defined as a map that was developed based on information obtained at that specific time. It is called a “belief map” as it was believed to give a true representation of the ground at the point when the information was obtained. To develop situational awareness, a top-down approach will be used. Starting from a global perspective, mission bubbles and areas of interest will be identified before the three-dimensional cloud maps are generated for the unmanned systems.

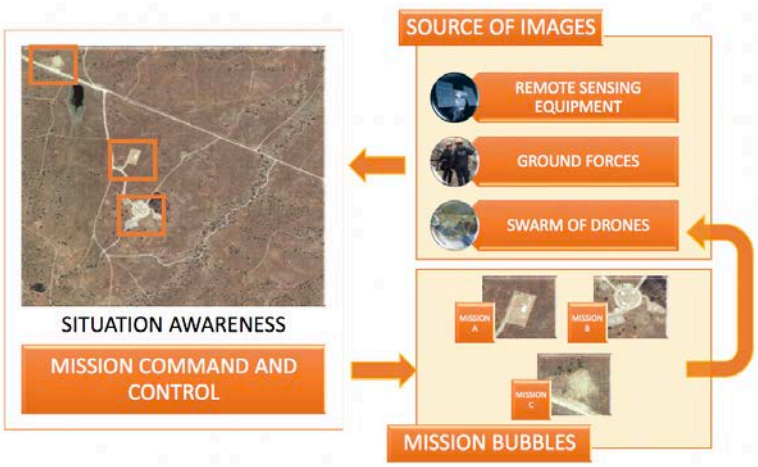


Figure 16. The exchange of information in a SAR mission

A. SEARCH PROBLEM

The goal is to search for survivors before rescue teams can be dispatched on the ground. The area of operation where the mission will be conducted will bound the configuration space. Within this configuration space, a search is conducted based on the current information that the decision maker has. The decision for each step of the search reflects the belief of the presence of the target in the specific location. The formulation also considers the evolution of information as data are being continuously updated during the operations. The measure of effectiveness of the decision based on the quality and robustness can be included.

A search and rescue mission will encompass a wide area, as described in Chapter I. The problem setup in this section is a simplified model that can be scaled to a bigger area of operations if required. It was developed based on the control strategies framework in a probabilistic search by Chung (2007). Starting by considering the task of searching stationary targets T_{S_i}, where i represents the number of targets present in a configuration space C, the environment can be discretized into $|C|$ cells. This configuration space is a grid-based probabilistic occupancy grid that is typically used in robot navigation or search operations. The discretization is based on the limitation of the platform chosen; it can be in terms of detection capabilities or ability to move in the environment. The choice of the size of the cells will dictate the effectiveness of the search model; if it is too small, the computation time for the reach will be too large for economical use. Similarly, if it is too big, there might not be a solution in generating a path through obstacles.

Thus, the expression $T_{S_1} \in C$ defines that the single stationary target is within the operational area, while $T_{S_1} \notin C$ will otherwise denote that the target is

not in the area. The configuration space is split into smaller cells and the expression $T_{S_1} = c \; and \; T_{S_1} \neq c$ indicates that the presence and absence of search elements in the cth cell, respectively. The representation of the cth cell is $c \in \mathbb{Z}^+ \leq |C|$.

1. Search Based on a Binary Hypothesis

The search problem determines if survivors are present in the defined configuration space, and thus the search can be simplified to a decision between a binary hypothesis, D such that

$$D = \begin{cases} 0, & if \; T_{S_1} \notin C \\ 1, & if \; T_{S_1} \in C \end{cases} \qquad \text{Equation 1}$$

The objective is to obtain the probability that the target is within the region that it is supposed to be in (i.e., to determine the probability when $P(D = 1)$). This probability is based on the measure of the consolidated belief that the target is somewhere within the region C. This probability assumption is based on the likelihood that a survivor will be in the region where there are buildings or near infrastructure, while it is lower possibility that they will be in a rural area in the aftermath of a disaster. The individual cell belief probability, which states that the target is within that cell, is represented by $P(T_{S_1} = c)$. This probability addresses the global problem of identifying the specific location of the target in the region. In general, the probability function can be represented by the Law of Disjoint Probabilities as

$$P(D = 1) = P(T_{S_1} = 1 \vee \ldots \vee T_{S_1} = |C|) = \sum_{c=1}^{|C|} P(T_{S_1} = c) \qquad \text{Equation 2}$$

The rationale in taking a decision methodology approach is due to the probabilistic nature of the sensor models. The detection models used to represent the sensors are not perfect and the possibility of a false alarm or missed detection is inevitable in the practical world.

2. Target Detection

The detection of a target is a function of altitude. The dimension or area of coverage at higher altitude increases, but the resolution in the sensing diminishes with time. The detection model is based on a binary random variable based on the decision of whether the object is in the specific cell or not. These measurements are typically taken in a noisy environment and there is no restriction to the distribution of the measurement noise being sampled. The simple detection model is based on defining $d_{c_i}^t$ as the measurement of the detection at the specific time step t taken in the ith cell of the specific cell c. The model for the imperfect measurement of detection considering the error probabilities of false positives (false alarm) and false negatives (incorrect detection) in the specific cell is given as

$$P\left(d_{c_i}^t \middle| T_{s_1}\right): \begin{cases} P\left(d_{c_i}^t = 0 \middle| T_{s_1} = c_i\right) & = \beta \\ P\left(d_{c_i}^t = 1 \middle| T_{s_1} = c_i\right) & = 1 - \beta \\ P\left(d_{c_i}^t = 0 \middle| T_{s_1} \neq c_i\right) & = 1 - \alpha \\ P\left(d_{c_i}^t = 1 \middle| T_{s_1} \neq c_i\right) & = \alpha \end{cases} \qquad \text{Equation 3}$$

where α and β are detection probabilities for false positive and false negatives, respectively.

These error rates can be obtained experimentally or be based on the sensor specifications. The experimentation method verifies the specifications that the original equipment manufacturer has stated. Symington et al. have conducted experiments on the probabilistic target detection by camera-equipped UASs in their research (Symington et al. 2010). The above model can be extended to

have a variation of height as the α and β values will be different at different altitudes. This detection model computes the likelihood of obtaining a measurement based on the error probability.

3. Development of the Search Problem

At the start of the search problem, based on the prior belief that a target is within the area, when $p_b = 1$ a target is in the region. The probability function is defined as

$$P(D = 1) = p_b, \qquad for\ 0 \leq p_b \leq 1 \qquad \text{Equation 4}$$

When the probability that the target is in the area, the search problem reduces to finding the target in the area. In the context of the defined operations for this research, this initial belief can be derived based on the assessment of the areas. The hot spots where there are likely to be survivors are areas that have infrastructure, while rural areas might have a lower probability, especially if they are in remote areas, which can converge to non-unity.

Thus, the search problem can be defined based on the initial belief obtained from prior information p_b and the probabilistic errors in the detection model α and β, determine location of the target T_{s_i} is present within the configuration space C as a function of the observation made until time t.This belief evolves constantly, which governs whether the target is located within the configuration space at the end of the search,

$$P(D = 1|d), \qquad where\ d = \{d^1, d^2, \ldots, d^t\} \qquad \text{Equation 5}$$

4. Grid Cell Dependency

The grid cell can be independent or dependent. In the independent approach, it is assumed that each cell will only be updated once the observation is complete. This is typically used when the number of targets is unknown or the target location is uncertain and it evolves over time. On the contrary, in the dependency assumption, the observation in any cell will affect the probability that the target is in the other cells. Thus, due to the dependency of each cell, a constant update of the belief map is required after every observation. The probability distribution of the area of interest is based on the belief function, $B(t)$ and can be defined. The computation of the cumulative belief is a sum of the belief at every individual cell,

$$B(t) = P(D = 1|d) = \sum_{c=1}^{|C|} P\left(T_{s_1} = c\middle|d\right) \qquad \text{Equation 6}$$

The computation of the belief probability can be obtained by Bayesian filtering that incorporates the proliferation of the target probability density function, as described in the book *Probabilistic Robotics* (Thrun and Burgard 2005). The Chapman-Kolmogorov equation, specifically the discrete analog component, was used to predict components of the discrete filter by combining the information from the previous time step. As the search problem entails how the observation affects the belief function, the observation can be computed for each cell based on the following equation. This equation includes the detection model and the belief function of the previous step, which allows the computation of the filter:

$$P\left(T_{s_1} = c_i\middle|d\right) = \frac{P\left(d_{c_i}^t\middle|T_{s_1} = c_i, d^{t\text{-}1}\right)P\left(T_{s_1} = c_i\middle|d^{t\text{-}1}\right)}{P\left(d_{c_i}^t\middle|d^{t-1}\right)} \qquad \text{Equation 7}$$

B. SITUATIONAL AWARENESS AND DAMAGE ASSESSMENT

The initial mission bubbles must be identified from the bigger operational area before the belief maps of the specific mission areas that the search operations will undertake can be developed. The situational awareness phase as described in the flow chart in Figure 17 encompasses three distinct tasks: (1) to develop mission bubbles for tactical search and rescue through means of analysis of imagery at the global level and (2) to analyze the specific mission areas for distinct difference in the forms of damage assessment to (3) develop a discretized map that can be used to generate a plan to go to the location and search for survivors. In the last phase, the development of the grid-based belief map will be completed.

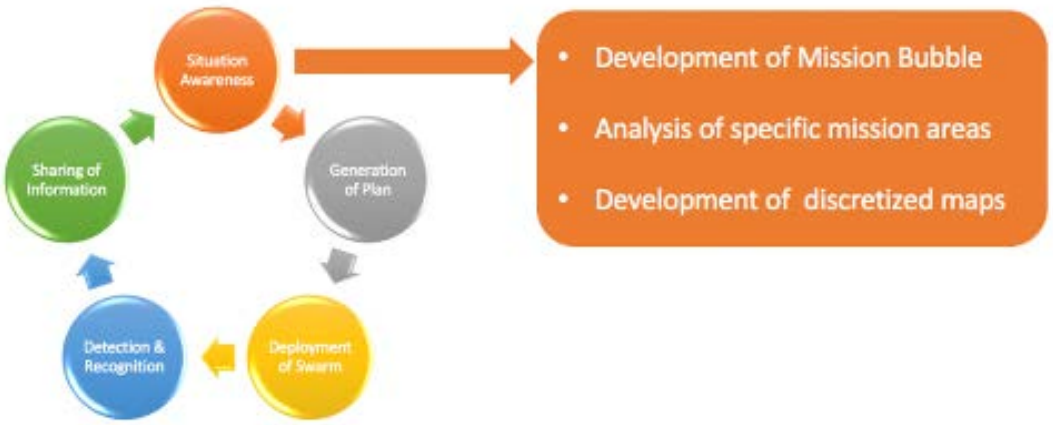


Figure 17. Task of the situational awareness phase

These tasks are basically taking a big picture at the strategic level and decomposing the problem into smaller pieces that can be executed at the tactical level. The maps must be translated from the human perspective to the computer perspective in the form of a discretized grid. The flow and snapshot of the image that is generated are shown in the summary flow chart in Figure 18. At the strategic level, an overview of the area is generated. Subsequently, a specific

tactical view based on the assessment that a survivor is likely to be in that region can be developed. Once the tactical area is identified, the environment must be converted into a discrete grid that the computers can use to identify an optimal trajectory to the location and generate a search pattern.

Figure 18. Flow of data generated

C. DEVELOPMENT OF MISSION BUBBLES

The first task was to obtain the area of operations in which the search and rescue mission will be conducted. The operational area defined was within Camp Roberts in California and panchromatic remote sensing data of the location was obtained by the WorldView-1 satellite (Figure 19). The data was assessed via DigitalGlobe's EnhanceView system. This imagery was captured on July 1, 2017, at a resolution of 0.5 m.

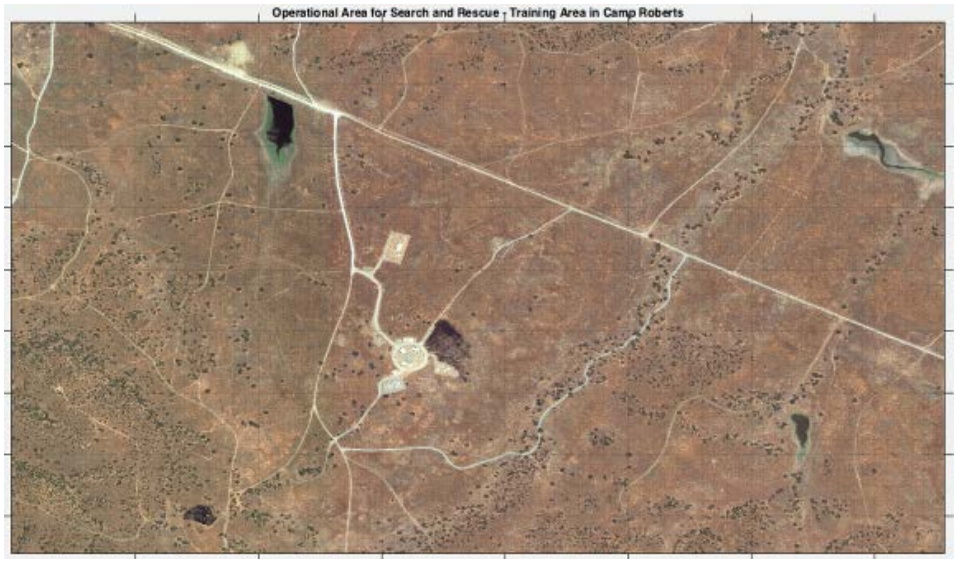


Figure 19. Overview of operational area at Camp Roberts. Source: DigitalGlobe (2017).

From the panchromatic image of the 2.0 by 0.8-kilometer area obtained for the area of operations, a conversion of the intensity of the image to double precision was first completed as shown in Figure 20. The image was further processed by extracting the pixels with the lowest and highest intensity into a binary image to distinguish the various features within the operational area. As observed in the binary image, an overview of the likely hotspots can be obtained. Three district areas within the area of operations can be identified as potential mission areas, as depicted by the orange boxes. Moreover, the roads and tracks are distinctly identified, which can be potential areas for search.

With the overall mission area decomposed into sectors, the commander can dictate strategies to complete the search operations dependent on the amount of resources that he or she has on hand. In such a situation, the commander might deploy three sets of heterogeneous drones or even unmanned ground vehicles to the three sectors, and instead of getting the drones to go directly to the location, they can scan the roads enroute to the three main mission bubbles. Alternatively, the roads can be scanned by a fourth team of UASs,

which might comprise fixed-wing UASs instead of multi-rotors, which might be more efficiently used in smaller sectors.

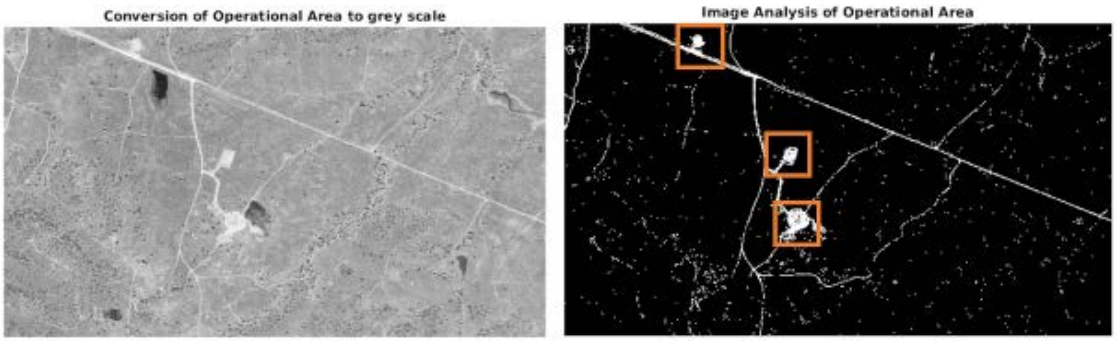


Figure 20. Processed data of the operational area

D. ANALYSIS OF CHANGES IN ENVIRONMENT

Vision-based intelligence has grown and scientists have developed techniques to add to the capabilities to see and analyze images more effectively. Techniques and algorithms are developed for identifying differences between images and edge detection to extract and identify key features from the digital image. Upon the identification of the mission bubbles, the area of operations must be analyzed for key differences for search operations to focus on. This can be accomplished by identifying differences in the disaster area based on prior information. Two different techniques commonly used are discussed in this section: (1) location differentiation via pixel analysis and (2) edge detection based on different algorithms.

A similar image processing of the mission area must be completed for further analysis, as illustrated in Figure 21. The latest image is extracted and post-processed to distinguish the vegetation from man-made structures. Typically, the vegetation areas will be on the higher end of the intensity range compared to the man-made structures. The image was analyzed based on the distribution of pixels, with the bulk of the pixels in the range of 0.55 to 0.65, as

shown in Figure 22. A scaling of the image is required to spread the distribution evenly to obtain an image that distinguishes the areas between the vegetation and man-made structures.

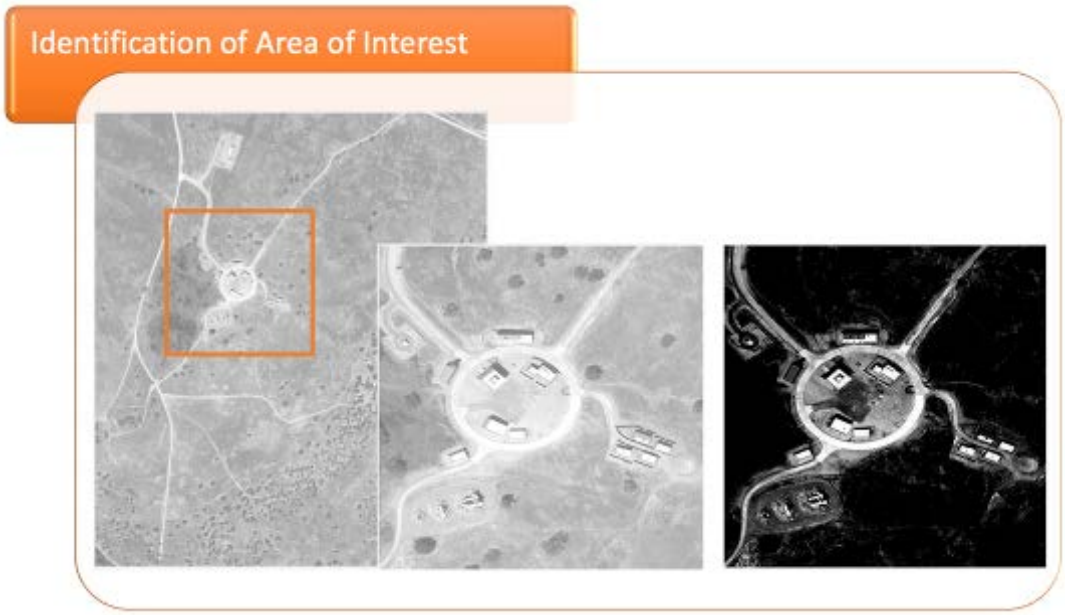


Figure 21. Identification of area of interest

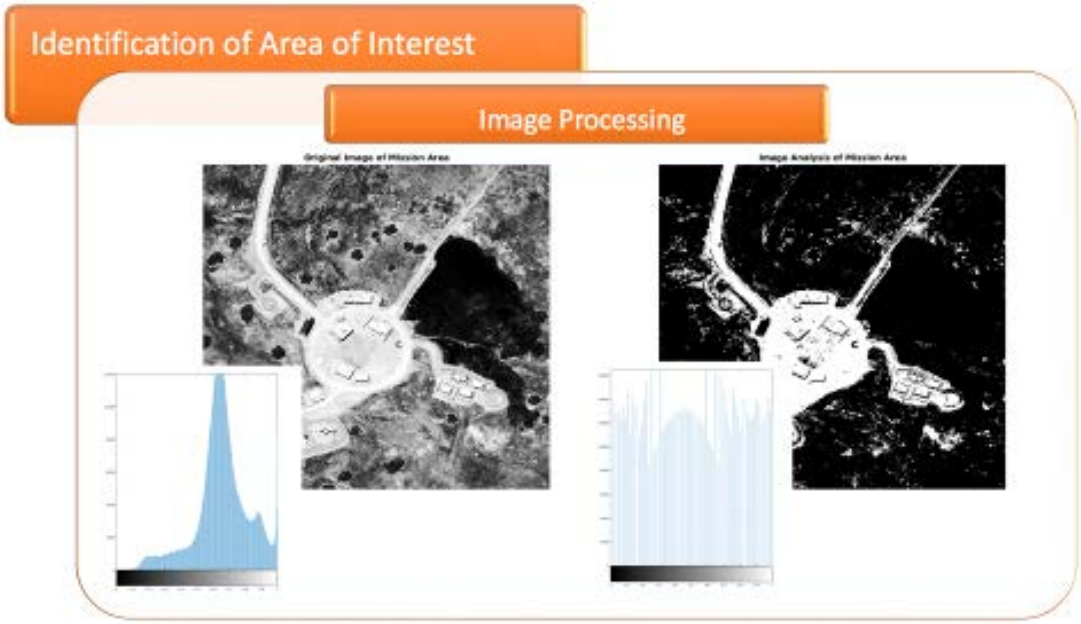


Figure 22. Image processing of the area of interest

1. Image Analysis for Differences in Pixels

A simple method of identifying the changes in a specific area can be accomplished by comparing images at different time steps of the area of interest. Specifically, an image obtained of the area of operations should be compared to the same area prior to the disaster. As the images are obtained from different time frames, it is likely that they were taken with varying illumination of the area and, thus, might have different variations of intensity. A correction can be completed before the cross-correlation to obtain sensible results. Cross-correlation is not the same as convolution. Instead, it will take the intensity of pixels in the two images and produce a third image that contains similar indices. When both images are similar, the correlation index tends towards its maximum value.

As stated, prior to the analysis of results of two images that might be obtained from different sources, they must be correlated to have the same reference frame and intensity. In the results shown in Figure 23, the maps of an area within Camp Roberts were obtained from open-source Google Maps and

DigitalGlobe. By glancing through the images, it was found that there is a new built-up area near the bottom left of the image. This difference is distinct in this example but it might not be as apparent in a post-disaster zone. Nevertheless, both the images must be geo-located to fixed their reference points, or else the comparison will not yield sensible results. If the reference index is not aligned, it will always yield differences in the imagery. Thus, this method is dependent not only on sensitivity of the geo-reference data but also the intensity of the image. The image on the left has a better illumination and thus is richer than the one on the right, which looks duller. This is mainly caused by environmental factors, ranging from sunlight to cloud cover. The images thus must be post-processed by analyzing the statistical data of the pixels as described in the previous section. The intensity of the pixels must be normalized to obtain a similar level of contrast for analysis.

Figure 23. Comparison of area of operation. Left image taken from Google Maps (2017); right image adapted from DigitalGlobe (2017).

To explore the effects and results of such methods, different areas with different characteristics were selected to identify the challenges and effects when identifying changes in operations. Two types of areas selected specifically were

(1) a rural area where a new building was developed on an empty piece of land within thick vegetation and (2) a development of a new building replacing past infrastructure. The areas were selected mainly for the application of a search and rescue operation. In the first case study, the area was chosen to identify the possibility of locating the position of a building that could have been destroyed by the disaster. Hypothetically, although the analysis was done based on the difference between an empty plot and a developed plot of land, it can also be completed in the opposite direction to find a building destroyed in a disaster. The second scenario was chosen to understand the complexity of comparing images based on a high intensity of features dominant in an urban environment, in which there are many elements that could have changed from the past to the present but must be located for search operations.

In the first scenario, the fishing harbor of Kokkari on Samos Island in Greece was selected. The town has small houses surrounded by undulating terrain, which is an ideal area for analysis of changes in a rural region. The images were extracted from DigitalGlobe captured by WorldView 1 on two different dates, September 11, 2015 and June 07, 2017. As noticed in Figure 24, both images have a distinct contrast between them; the vegetation in the image with no buildup area has a richer green compared to the one with the building, in which the vegetation is lighter in color. The cross-correlation image generated after the correction of the intensity between the images shows the areas that are correlated. The tracks can be seen to show significant correlation except for areas that were covered in vegetation. This is especially so on the top right area of the image, where vegetation was covering the tracks that were subsequently cleared, possibly during the commencement of the construction of buildings. In the third image, areas that are distinctly different from the combination of the images are identified as the black areas, which were extracted. The processed image returned the changes between the two images and this includes the changes that were picked up on the track as well as the new buildings that were built. The differences in the tracks are subtle to the naked eye, but on close

analysis, there were indeed changes in the region identified. The outline of the buildings was also distinct, as seen from the processed data. Thus, this method is verified to be effective in picking changes to the environment that humans might initially miss.

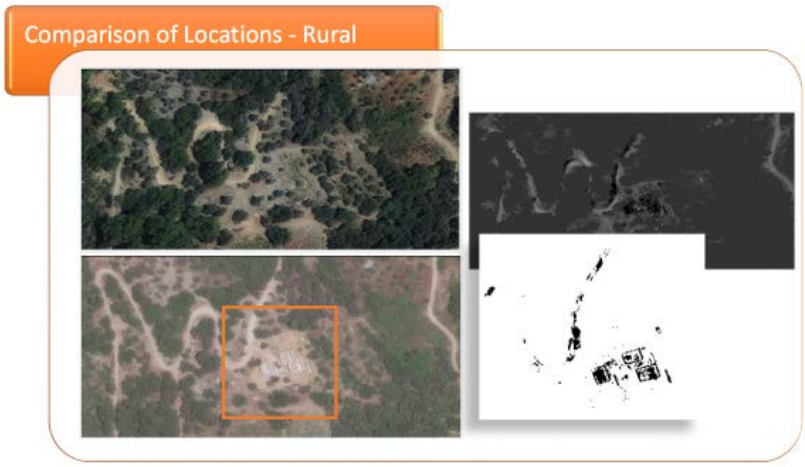
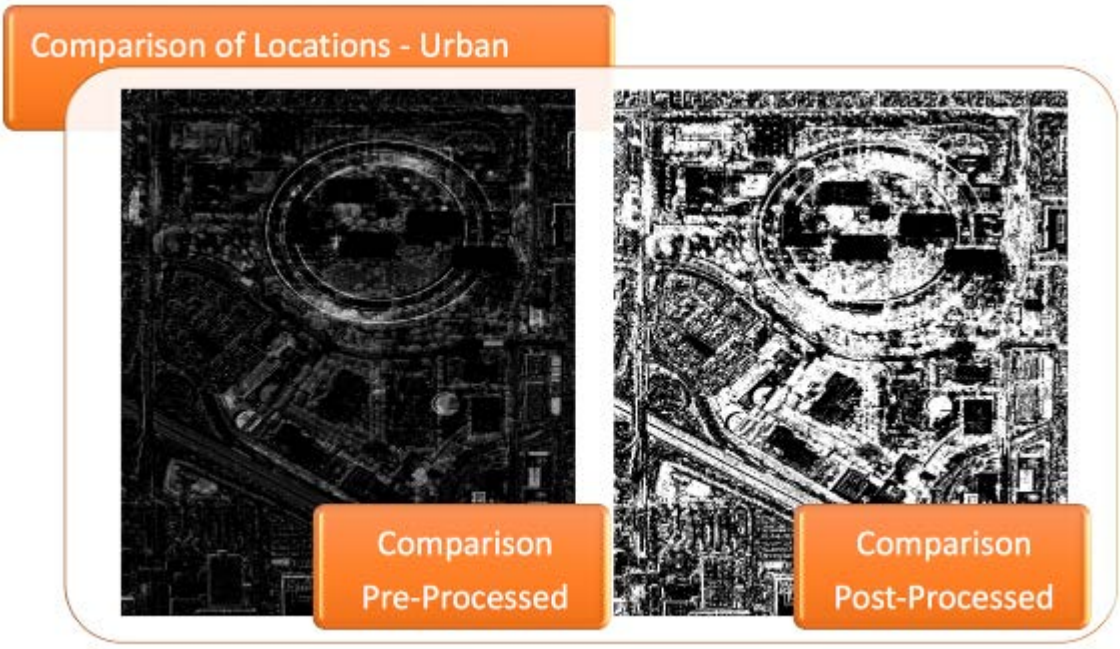


Figure 24. Comparison of changes in a rural environment

In the second scenario, an urban environment was analyzed. The much-acclaimed new headquarters of Apple Inc. in San Jose was selected, mainly for the massive change that it created in the region but also for its fixed boundary, as shown in Figure 25. The image was taken from a database dated August 30, 2012 prior to any construction in the area and compared to a recent capture of the area with the almost completed building on July 6, 2017. On August 30, 2012, the area has several other buildings within the region, thus posing a more challenging requirement to differentiate the changes.

Figure 25. Comparison in an urban environment. Adapted from DigitalGlobe (2017).

Based on the initial cross-correlation between the images, processed data is somewhat different from what was expected when the commonality between the image is more significant. In this example, the third image produces distinct markings with respect to the difference seen in the areas. The difference is distinctly marked in white and black; thus, by extracting the tail end of the intensity range of the image, we can sharpen the image as shown in Figure 26. With the post-processed image, the newer image is distinctly marked as white in the composite image, and in retrospect the black regions indicate the areas of the pass. The results show that this method can distinguish the differences in the infrastructure by cross-correlation, and data can be extracted for analysis. An example will be the three white buildings that were near the new building; based on the composite map, the location can be georeferenced and thus be used for rescue operations if required.



.

Figure 26. Processing of difference in urban environment

The difference in the images are obtained by correlation of the pixels in two different images. Based on this method, the results are sensitive to the location as well as the intensity of the images. It does provide good data for analysis and provides an insightful awareness for rescuers to identify areas to be searched, but it is subject to the two conditions stated above. The results show that the analysis in the rural and urban area is also different and must be handled differently. Although insightful, alternate means must be established as an alternative means of detection of differences in the region.

2. Image Analysis Based on Edge Detection

Edge detection is a technique for image processing based on finding the edges of key features in the image. This is completed by detecting any discontinuities within the image by identifying the change in intensity between them. Upon the identification of the possible boundaries, the derivatives at these areas are computed and measured against the surrounding pixels to verify if

each pixel is within the boundary or not. The result of the analysis is a binary image in which the edges will be displayed. This method in identifying the discontinuity is possible since all objects inherently have edges. These edges are produced due to a variety of factors, ranging from the discontinuity on the normal or due to changes in depth, changes in material properties for example from vegetation to concrete infrastructure, and possible variation of scene illumination. Scene illumination is a potential negative source of information and might lead to false positive results. A building under poor illumination will be represented in a dark color and thus might be confused with the vegetation around it as a single entity.

An edge as defined is a location on the image that has a rapid change in the image intensity function. The derivative with convolution can be obtained by partial differentiation. Convolution is a general-purpose filtering mathematical operation by implementing different matrices to give a value of a central pixel by adding the defined weighted values of the neighboring pixels. The key objective is to enhance the image by smoothing, sharpening or intensifying the pixels. The output of convolution is a new modified filtered image. The mathematical equation is based on the following derivative. The derivative of a two-dimensional function, $f(x, y)$ can be written in the following form:

$$\frac{\partial f(x,y)}{\partial x} = \lim_{\varepsilon \to 0} \frac{f(x+\varepsilon, y) - f(x,y)}{\varepsilon} \qquad \text{Equation 8}$$

For discrete data, it can be approximated using finite differences as:

$$\frac{\partial f(x,y)}{\partial x} \approx \frac{f(x_{i+1}, y) - f(x_i, y)}{x_{i+1} - x_i} \qquad \text{Equation 9}$$

Thus, the gradient of the image can be obtained as:

$$\nabla f = \left[\frac{\partial f}{\partial x}, \frac{\partial f}{\partial y}\right] \qquad \text{Equation 10}$$

The edge strength of the gradient can be obtained as:

$$\|\nabla f\| = \sqrt{\left(\frac{\partial f}{\partial x}\right)^2 + \left(\frac{\partial f}{\partial y}\right)^2} \qquad \text{Equation 11}$$

Both the Canny and Sobel methods use the gradient between the pixels to determine the edges. The first step is the convolution of images by using the gradient kernel on both axes. The Canny method, however, applies additional steps to suppress the non-maximum gradient magnitude.

a. Sobel Method

The Sobel filter (sometimes called the Sobel-Feldman operator) is a discrete differentiation operator. It was co-developed by Irwin Sobel and Gary Delman at the Stanford Artificial Intelligence Laboratory in 1968. The idea was presented as an “Isotropic 3x3 Image Gradient Operator” (Sobel 2014). This operator is based on convolving the image with a filter in both the horizontal and vertical planes. Although this method is computationally efficient, the results produced might not be as accurate. Nevertheless, it depends on the intention and requirements in obtaining the edges; if the application is to identify the outline of the buildings for comparison purpose, this might be a possible solution.

b. Canny Method

John Canny developed the Canny edge detection method in 1986 utilizing a multi-stage algorithm that he developed to detect the edges in imagery. As stated, after the application of the Gaussian filter to first smoothe the image and remove the noise, the gradient magnitude and orientation using the finite difference approximation of the partial differentiation are computed. This is an important step to ensure that the noise is filtered to reduce false detection of edges due to the noise. In addition, the non-maximum values are suppressed to check if the pixel is a local maximum along the gradient direction. Hysteresis thresholding is also completed on the edges to link them together by using a high

threshold at the start of curves and a low threshold to join them. The Canny algorithm is useful in different environments as it allows the parameters to be tailored for the identification of edges based on the application requirements.

c. Comparison of Results

Based on the different methods, the edges were evaluated in operations using the two techniques in MATLAB. Based on the Sobel method, the images generated tend to several areas of discontinuity and the edges are not smooth. Unlike in the results obtained by the Canny method, the lines are distinctly generated. The roads of the area are nicely mapped out and the lines are connected within the area of operations. Moreover, the possibility of tuning the threshold for the Canny edge detection gives it more flexibility. It was observed that both methods are very sensitive to noise and this might affect the edge detection results.

Nevertheless, these edge detection techniques are useful in object-based image analysis. Figure 27 shows the detection of infrastructure using edge techniques. A rectangle fit as a means for comparison is an ideal shape to use for analysis of damage to a building. This can be obtained by comparing the area of the building and obtaining the fraction of the changes. A threshold of greater than 50% of the changes constitutes a building that is likely to be damaged. This is an area where there is a need to collate the database and utilize machine learning to analyze the large set of samples to know what is the threshold to classify this area of interest

$$Rectangle\ Fit = \frac{A_O - A_D}{A_O} \qquad \text{Equation 12}$$

where A_O is the area of the original object and A_D is the area of the building of interest.

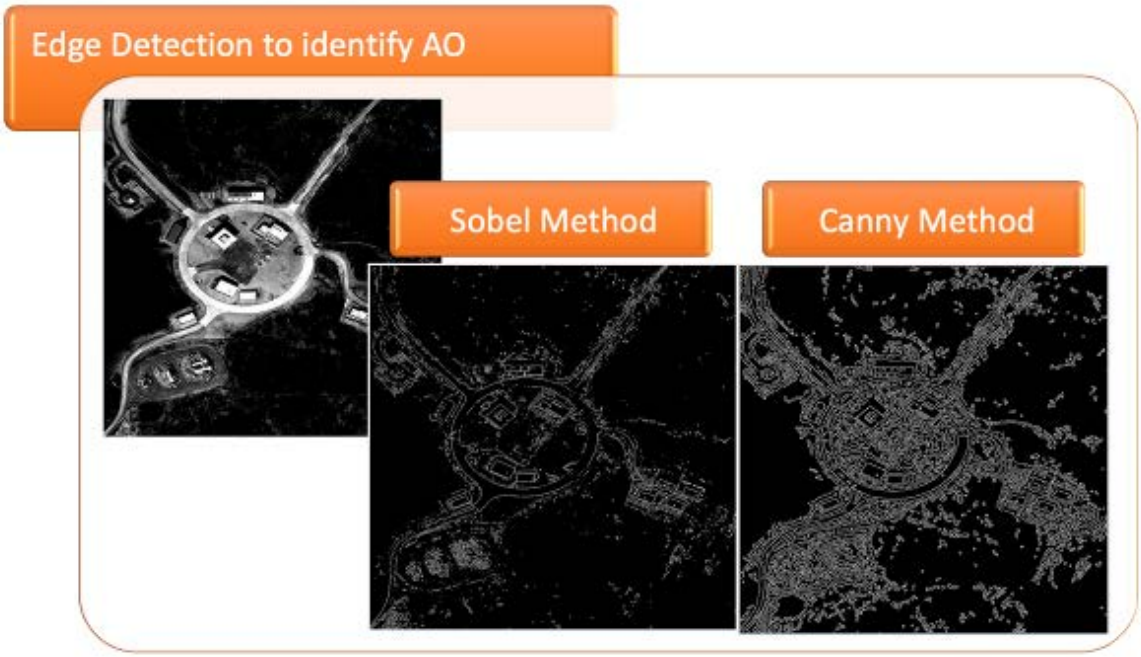


Figure 27. Detection of infrastructure using edge techniques

By utilizing simple methods, areas of interest can be identified for search operations. Depending on the environment where the disaster occurs, this technique can be used to obtain the necessary information. Thus, utilizing remote sensing imagery as a means for damage assessment has huge potential. With a large database extracted from past experiences in the various types of natural disasters, it is possible to use them in a neutral network and develop machine learning algorithms to detect damage caused by natural forces. With the availability of computer resources, it is possible to transit from the computer-based pixel-to-pixel or object-to-object comparison to a deep learning neural network like how humans recognize images.

E. DEVELOPMENT OF 3-D MAPS OF THE OPERATIONAL AREA

The techniques utilized in the previous section to first develop mission bubbles from the area of operation and identify high probability areas of survival are completed based on two-dimensional overview maps obtained from aerial platforms. To get a clearer picture of the situation in the post-disaster

environment, however, it is necessary to develop further visualization tools to capture the essence of the environment in the form of models, as shown in Figure 28. The world, after all, exists in three dimensions, not only in terms of elevation but also the complex infrastructure that evolves in every city. In this section, a three-dimensional environment is created based on the data obtained from imagery obtained from the various resources. The environment will be used as a visualization tool for the commander to plan and have a better situational awareness of the ground. This model subsequently will be used as a baseline for reconstruction effort of the city.

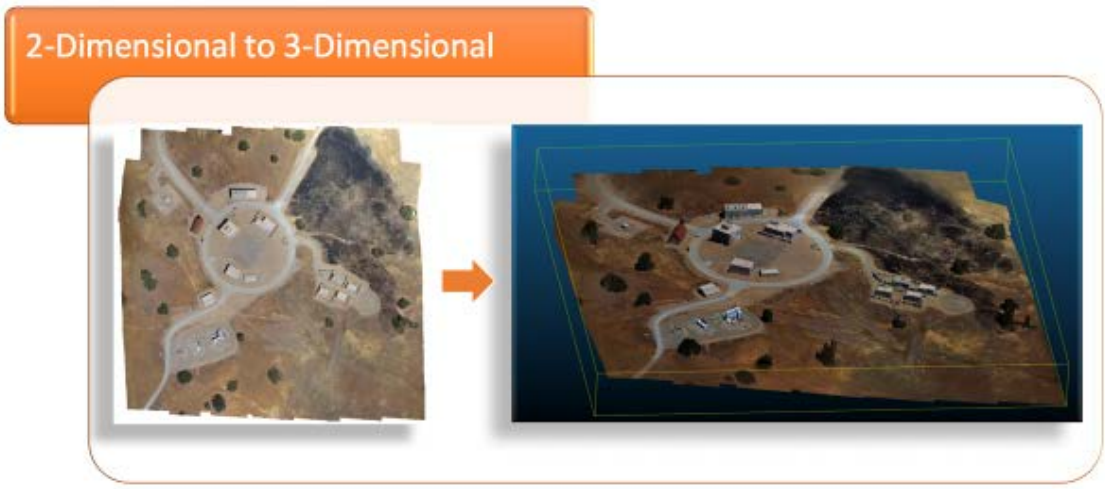


Figure 28. Conversion of two-dimensional to three-dimensional environment

The two-dimensional overview situational map is a good tool for understanding the situation at the strategic level; it gives an initial indication of the environment (e.g., number of buildings that are damaged) through comparison with pre-disaster imagery, or by identifying possible routes through edge detection as shown in the previous section. The Fire Administration SOP stated, however, that a commander is still needed on the ground to assess the situation and identify possible areas of ingress or egress at the site. This itself is challenging not only in terms of situational awareness but also the stress induced by the chaotic environment. Due to the limited visual purview of the area of

operations, there will be a tendency to miss critical elements that are hidden in the blind spots of the commander, which might lead to unnecessary risk. This ill-informed decision might trigger a sequence of unfortunate events.

The intended application of the three-dimensional maps will drive the resolution of the environment that will be built. For our scenario, it is not the resolution of the images that we are targeting; instead, it is spatial analysis that is important. The models showing the shapes of the buildings, as shown in Figure 29 give a good perspective of the environment describing the type of buildings that the rescuers need to tackle. These maps, even when partially completed, will provide more information than a two-dimensional image—as the saying goes, “an image paints a thousand words,” while a model describing the details of the world probably represents a million words.

Figure 29. Outline of buildings shapes

To obtain the model and gain a clearer understanding of the environment, the collation of images of the environment can be pieced together to form a three-dimensional environment. This tool can be used as a visualization aid for planning and provide a better situational awareness for the commander on the ground. The challenges in this conversion of the two-dimensional images to a three-dimensional environment come in the form of understanding the element of depth in the picture and converting the object in the image to a three-dimensional element in the environment. To extract the rich information of the buildings, it is

necessary to obtain high-resolution remote sensing data from DigitalGlobe as well as images at different views from the ground. These images define the building's height, volume and location as pieces in a three-dimensional world, as shown in Figure 30.

Figure 30. Development of point cloud based on multiple images from various orientations

The state of the environment (i.e., damage to the buildings) is the focus in the initial phase of the search. Thus, the resolution of the three-dimensional maps focuses on the outlook, as shown in Figure 31. The facet of each side of the buildings gives the commander a better understanding of the key buildings to focus on. As the team makes their way to the area of interest based on the path generated (which will be described in the next chapter), this three-dimensional map allows the commander to start the initial assessment of the destruction in the environment, saving time and providing a better sense of the environment to shorten the decision process. As the commander is at the command center and has all the resources on hand, he or she can decide on the resources to be

deployed to the area of operations. Moreover, upon the detection of abnormalities in the environment (i.e., potential danger areas or tasks that require more equipment), resources can be activated instantly instead of waiting for feedback, as occurred in the past. For example, when it is detected that access to a building is blocked, but there is a need to rescue a survivor on the second level, the commander can direct a vehicle that is nearby to the actual site to aid the rescuers. This map will be constantly updated as more imagery is obtained throughout the rescue mission, which eventually is a useful tool for the reconstruction phase of the affected area.

Figure 31. Representation of buildings in three-dimensional model

The first step in the development of such three-dimensional maps is to overlay the environment with the terrain elevation map, which is widely available. This terrain map defines the topography, contours and elevation of the environment and is typically used by the aviation industry to determine the height above ground level in their flight path planning to avoid collision with natural features like mountains. This map forms the baseline of the ground condition, and additional information obtained of the infrastructure is placed on top of the ground at the various elevations, as shown in Figure 32. The additional information obtained from the ground, aerial or satellite photography captured at both nadir or oblique are used to build an accurate and informative environment. Due to the large volume of data to be analyzed in comparing the time of image

being captured and computing the height of each building based on the projection, however, this form of reconstruction might be time consuming.

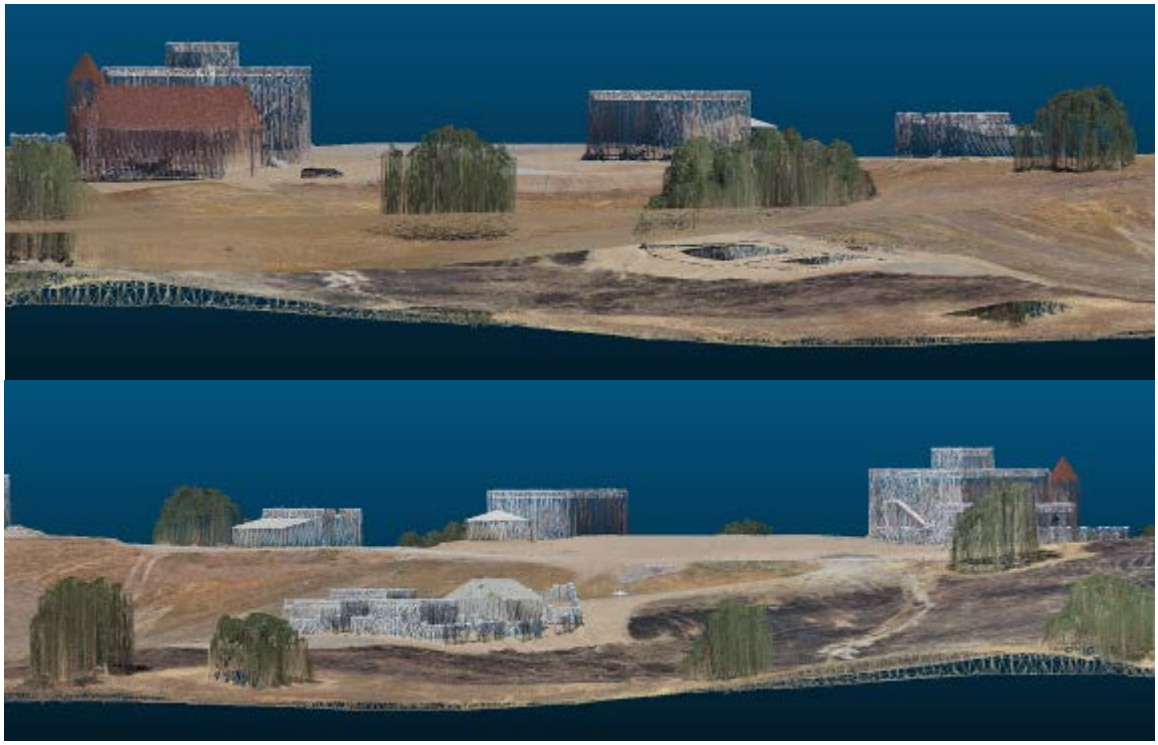


Figure 32. Infrastructure being built on top of the elevation model

As stated, the requirements and intention of the maps dictate the resolution of the map. Based on the illustration, additional details like trees were added as they are required for navigation for the unmanned ground vehicle. They are represented as blocks instead of actual trees, however, so the areas under the branches should be empty. The aim of this model is to distinguish the various features of the environment; a sample portion of the road and tree were extracted and are shown in Figure 33. The map and the trees are clearly indicated and segregated and represented as blocks.

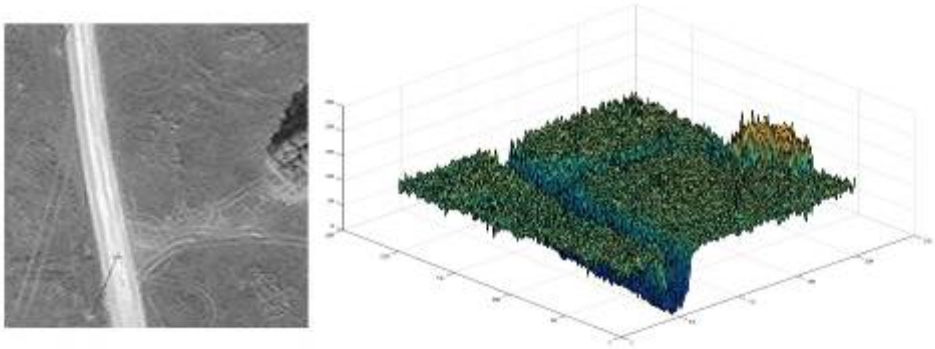


Figure 33. Distinction between the various features of the environment

As the three-dimensional map is built in layers, the details of each feature can be added when more information is obtained of the environment. This will assist the people in charge for the recovery phase after the natural disaster. Moreover, it can be used as a tool to understand potential issues and develop a mitigation plan. An example of such scenario planning is utilizing the three-dimensional map to simulate a flood; the planners can identify hot spots and potential areas of concern—especially the low-lying areas—and derive strategies to mitigate loss of lives when such disaster occurs. This model is a useful tool for simulating what-if scenarios and the impact of various types of natural disaster, which allows for better contingency planning and, thus, more efficient allocation of the appropriate resources.

In the context of our defined search mission, the challenge is to obtain the three-dimensional environment quicker. As the key objective is to evaluate the infrastructure and identify specifically the location of the damage to buildings, a localized model will suffice. A localized scan of the area of interest from different perspectives reduces the information data set, which allows quicker development of the three-dimensional environment. This was completed by taking images from drones and meshing them into a single map. These images of the area of interest were taken by Jeremy Metcalf, Associate Researcher from the Physics Department in NPS, with a DJI Inspire drone. The drone was programmed to fly

a specific route and capture images at the specific time step. With the time step and location of the drones known, the data could be extracted to develop the three-dimensional environment. These images were stitched together and re-constructed by Jeremy into a three-dimensional map by geo-referencing the various locations in the image and piecing them together in Agrisoft.

The elevation model as shown in Figure 34 is a useful tool for both manned ground and aerial systems to navigate in the environment. This concept is no different from how larger aircraft navigate in the world today. The aircrafts utilize the digital elevation of the terrain to avoid natural obstacles like mountains. As the unmanned systems are required to navigate through the infrastructure (e.g., buildings and roads filled with obstacles), such maps will aid in the development of a collision-free trajectory for the unmanned systems. The unmanned ground vehicles (UGV) can utilize this map to avoid obstacles on the ground while the drones will require this data of the environment to avoid colliding with the buildings. These three-dimensional maps will, therefore, be the main source to develop the trajectory to navigate to the mission bubbles for the various unmanned systems in the next chapter.

Figure 34. Elevation model after the incorporation of images

As the areas become denser (i.e., in a city), the resolution and accuracy of the model plays a higher role in ensuring that the obstacles can be avoided. With the development of the mission bubbles and the construction of the three-dimensional map completed, we will now shift the focus to the development of trajectory to the area of interest and deriving an optimal search pattern to ensure that the survivors can be found in the shortest possible time.

THIS PAGE INTENTIONALLY LEFT BLANK

IV. PATH GENERATION AND SEARCH PATTERN

The optimal path to the key areas of interest must be obtained from the maps developed at the strategic and tactical level. Subsequently, an optimal search pattern for that area of interest must be generated. In this chapter, the development of the path based on the mission bubbles will first be developed prior to the search pattern to optimally search that area being completed. In the planning phase of the search mission, there are two main tasks required to generate the two main plans: (1) a trajectory plan to get to the key area of interest and (2) an optimal search plan to cover all the key features identified as potential rescue sites. This process is shown in Figure 35.

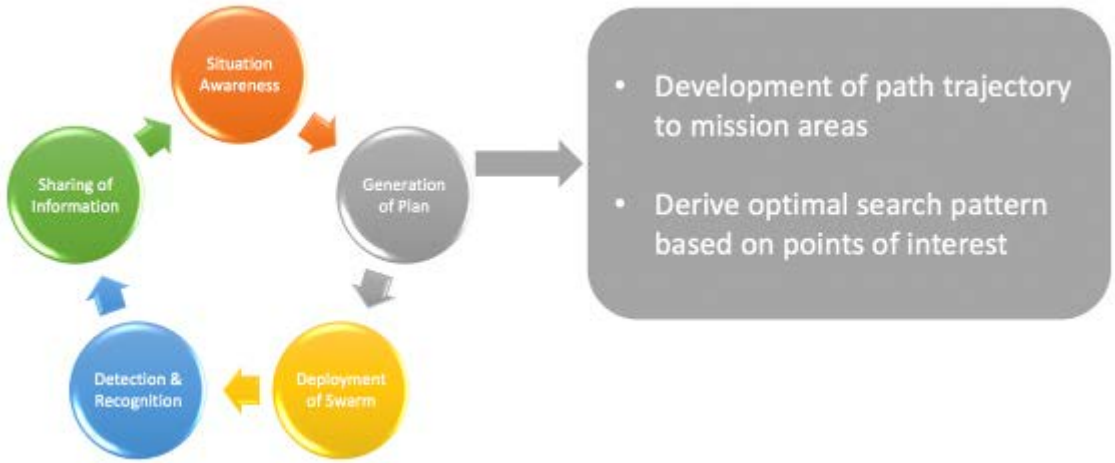


Figure 35. Phase 2 - Generation of Plan

A. PROBABILISTIC ROADMAP

The objective of the trajectory plan is to get the heterogeneous swarm of unmanned systems to the identified mission bubble in the shortest time. There is a trade-off between the time to develop a plan and the optimal solution, however. The most optimal plan will require all the information about the operational area,

which means all possible points on the map and their associated paths must be analyzed, including those that do not provide a solution. As the overarching objective is still to find the shortest possible time to identify the survivors' location and rescue them, this trade-off study allows a balance between providing the near optimal solution in the shortest time.

This trajectory planning problem is solved based on a defined configuration space, which is an area on the map that the robots can maneuver in. This configuration space, based on the information obtained, is split into two distinct types: (1) forbidden areas $C_{forbidden}$ and (2) obstacle-free zones C_{free}. Those areas that have obstacles are marked as forbidden zones, while obstacle-free zones are areas where the robots can operate freely within the configuration space. In the dynamic environment, the segregation of the space is based on information received from the various sensors. The configuration space of the area of operations obtained from the satellite is shown in Figure 36; the areas marked in black are forbidden zones and the white indicates areas where the drones can be maneuvered. This specific configuration space that was used seeks to determine the trajectory for unmanned ground vehicles.

Figure 36. A configuration space generated for the operational area

A probabilistic roadmap planner (PRM) will be utilized to generate the trajectory of the unmanned system. The PRM is efficient in terms of computation resources, easy to implement based on established concepts, and versatile for different types of applications. The path that is identified for the robots will correspond to the configuration space that connects the defined start point of the robots to the desired end for the search mission. This trajectory is collision-free based on the conditions that all points generated and the path connecting each point are not within or do not cross the forbidden zones. The global idea of the probabilistic roadmap planner is to sample the free space C_{free} to identify points or nodes of a graph $G = (V, E)$. A graph G consists of two elements: a vertex set V whose elements are all the points or nodes on the graph and the edge set E connecting the pairs of the nodes. Each edge $e \in E$ is associated with a pair of nodes within the configuration space. The useful pairs of points are chosen and used to connect these points by a local planner. If the paths are collision free (i.e., do not pass through the forbidden area), then an edge is added to the graph. The graph generated will consist of all possible connections within the chosen configuration space. The pseudocode for the construction of the graph is shown in Figure 37. Out of all these possible edges, a search algorithm is used to optimally obtain the path from start to end to generate the optimal trajectory desired.

```
Algorithm 1: Construct Roadmap
Let: Vertices V ← ∅; Edges E ← ∅
while |V| < n where n is the number of vertices required
    Find useful random points, a where
        c ← a within configuration space
        until all point is collision-free in configuration space C
        select points as vertices V ← V ∪ {c}
    for all c ∈ V in order of increasing distance from c do
        If c' and c are not connected then
            If the local planner finds a path between c' and c then
                Add the edge c'c to E
```

Figure 37. Pseudocode for the construction of the PRMRoadmap

Thus, it can be seen that the PRM approaches the problem in three distinct phases: (1) sample configuration space is examined to obtain possible points in which the robots can move and (2) the pairs of points are connected to evaluate the feasibility of the paths based on specific criterion before (3) completing a tree search to obtain the most feasible path from the sets of paths generated in the configuration space. There is no best technique for the respective phases as the computation is dependent on the environment and requirements of the area of operations. Thus, a comparison between the different techniques based on the computational time as well as probability of obtaining a solution are evaluated in this section. This comparison gives an insight of the merits of the various techniques and the rationale in selecting the method for the different phases. A set of optimal waypoints for the robots to navigate through will be generated by this PRM.

1. Generation of Sample Points within the Configuration Space

There are several methods to sample the configuration space for motion planning. The most commonly used method is to sample the entire space randomly or pseudorandomly. In this method, the points are obtained by using a distribution within the sample space and randomly identifying points on the map. Non-uniform probabilistic sampling is useful in scenarios in areas of operation along a narrow pathway. Tan et al. (2017) successfully explored the utilization of

a normal distribution instead of a uniform distribution in generating the waypoints more optimally for the Kingfisher unmanned surface vehicle (USV) in Monterey's Lake El Estero, in motion planning for the probabilistic roadmap.

The points are randomly generated based on the applied statistical distribution by a random number generator. An algorithm is used by a computer program to generate the random numbers systematically. The terms systematic and random contradict themselves, however; to be programmable, a systematic method is required to generate the algorithm. Based on this requirement, a computer scientist uses a seed, which defines the start point of the generated numbers, to compute random numbers. This will mean that the numbers generated will follow the same sequence whenever the same set of seeds is used, however. Although it follows a specific sequence, due to the computational speed and power, it can process a large set of data computation and thus produce a set of random numbers in a data set. This is called pseudorandom number generators. MATLAB utilizes the widely used general-purpose Mersenne Twister algorithm to produce pseudorandom numbers. The name of the algorithm was derived from the fact that its period length was chosen to be a Mersenne prime. If a truly random number is required, however, the generator seed can be shuffled based on implementing the following command prior to the calling of the respective random number generator in *MATLAB-Rng('shuffle').* This command uses the current time from your computer as a seed, which makes it extraordinarily unlikely to obtain identical results.

From the trade-off study completed in the simulation by Tan et al. (2017b), we found that the computational time can be reduced utilizing a normal distribution for the sampling strategy, although the distribution chosen is dependent on the type of map. As the bulk of the computation time is dependent on the number of connections required, however, the simulation will focus on the connection strategy and the search method instead.

2. Variation of Connection Strategy

The time to complete the connection is dependent on the number of points and the criteria in selecting each connection. Thus, a connection strategy is required to evaluate the different edges based on (1) sampling requirements and (2) the length or distance between each of the nodes to evaluate whether or not it meets the criterion of being collision-free. The extremes in sampling the points are comparisons for all points in the configuration space versus sampling points that are closest to each point's connection strategy. By sampling all points, the most optimal solution might be obtained, but it is not as practical, as there are obstacles within the space that mean unnecessary selection and verification. Similarly, by lowering the connection distance, you can limit the number of connections to be evaluated and thus reduce computational time. If the distance was set too small, however, there will be insufficient edges to obtain a solution.

For optimality in computational resources, connecting to K-Nearest Neighbors instead of to all the points was explored. The K-dimensional (K-d) graph converted to the binary tree is shown in Figure 38 as obtained from de Berg et al. (1998). This method searches for the nearest points based on the defined K value. The most efficient method to determine the K's nearest neighbors utilized the K-d tree data. A K-d tree is a space-partitioning data structure and is used in organizing points into a K-dimensional space to construct a binary tree that decomposes space into cells such that no cell contains too many points.

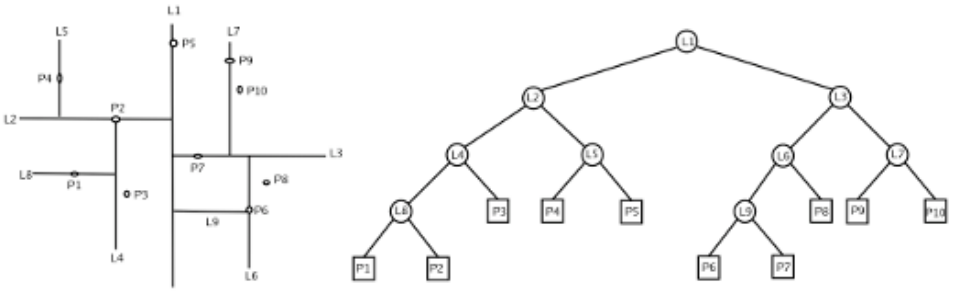


Figure 38. K-d and binary tree. Source: de Berg (1998).

The K-d graph search was implemented in MATLAB utilizing the *KDTreeSearcher* function. This model stores results of a nearest neighbor search using the K-d tree algorithm. Utilizing the *knnsearch* function, the K-nearest neighbors using K-d tree is completed and compiled into an index. As the data set will flag out the own location, the nearest neighbors are taken from the second column onwards. The nodes can be generated after the completion of the search.

a. Sampling Requirements

The first analysis was completed by varying the number of neighbors to connect. The analysis was completed based on the assessment of the global parameters to verify if a solution is obtained at every simulation and a trade-off between the shortest distance as well as the computing resources required to complete the tasks. The shortest distance is selected due to the limited energy available from the platform; the shorter the distance, the less the consumption of battery power, and thus the more efficient the mission. The rationale on understanding the computing resources is mainly due to the relation of the size of the computer in proportion to the computational requirements. The larger the computational requirements, the bigger the computer and thus the heavier the system to be placed on board, which indirectly will reduce the efficiency of the drones.

In each simulation, 20 runs were completed with the same parameters to evaluate if an optimal solution can be achieved at every instance. A study on varying the k values from 5 to 30 in six steps was completed and compared against the extreme case where all points are connected. As observed in Figure 39, a solution is unlikely to be obtained when we connect the nearest five neighbors, especially in an environment where there are many obstacles or when the free space is along a curvature like a road. When more points can be connected, the probability to connect across the configuration space increases.

The configuration is almost filled out by the multiple cyan lines when 30 nearest neighbors were connected in the configuration space.

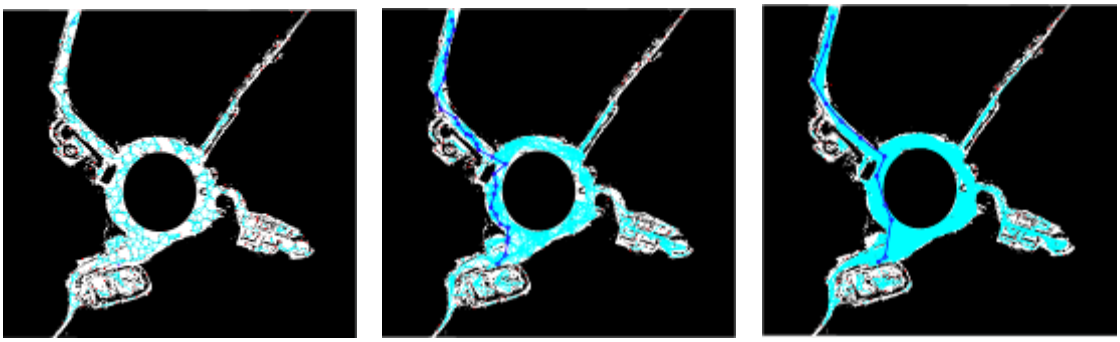


Figure 39. Variation of K-values in the C-Space variation

A summary of the data obtained from the simulation run is tabulated in Table 2. When the K-value increases, the number of edges to be connected increases. To connect all 500 points, 125,751 edges were investigated, compared to fewer than 10,000 edges when the evaluation was completed for 20 neighbors. Although the number of edges investigated for all points is so large, only 7,837 of them are valid, meaning they do not cross the forbidden configuration space. It was observed that the ratio of the edges investigated to number of good edges flattens out in the middle region before exponentially increasing.

Table 2. Summary of data for variation of K-values

Evaluation Criteria						
K	**10**	**30**	**50**	**100**	**200**	**300**
Total Samples	500	500	500	500	500	500
Edges Investigated	9538	9538	9538	9538	9538	9538
Edge Requirement	10	30	50	100	200	300
Overall Solution						
Probability of no Solution	0.95	0.00	0.00	0.00	0.00	0.00
Probability of Solution	0.05	1.00	1.00	1.00	1.00	1.00
Min Total distance	315.5	289.7	290.9	288.3	290.2	291.1
Average distance	315.5	302.5	300.5	303.7	303.9	303.7
Min Time	29.2	55.1	56.9	60.3	54.9	60.8
Sampling						
Min Sample Time	0.205	0.200	0.181	0.188	0.188	0.193
No of Nodes	3219	3280	3163	3175	3187	3228
Connect						
Min Connect Time	10.692	34.478	33.458	35.044	31.038	34.441
No of Good Edges	2664	4871	4979	5007	5159	4946
Search						
Min Search Time	12.482	18.788	20.806	22.602	21.667	22.545

We plotted a graph in Figure 40 to evaluate and understand which solution provides the shortest distance and computational time. The orange line, which depicts the computational time, obviously increases with the K-value; this is mainly due to the larger number of connections to be investigated. The minimal distance does not significantly improve even when we evaluate all the connection points, however. In the local minimum, where the minimal distance extracted from the 20-simulation run reduces by approximately eight meters, the average among the 20 runs did not improve the situation as significantly as the increase in time to obtain the solution. Thus, based on the optimization frontier, a K-value between 15 and 25 will suffice in obtaining a solution with the given increase in computational time. It is evident that the small decrease in distance does not warrant the usage of the computational resources. Therefore, the K-value of 20 was chosen as the baseline value in the development of the probabilistic road map for the area of operations.

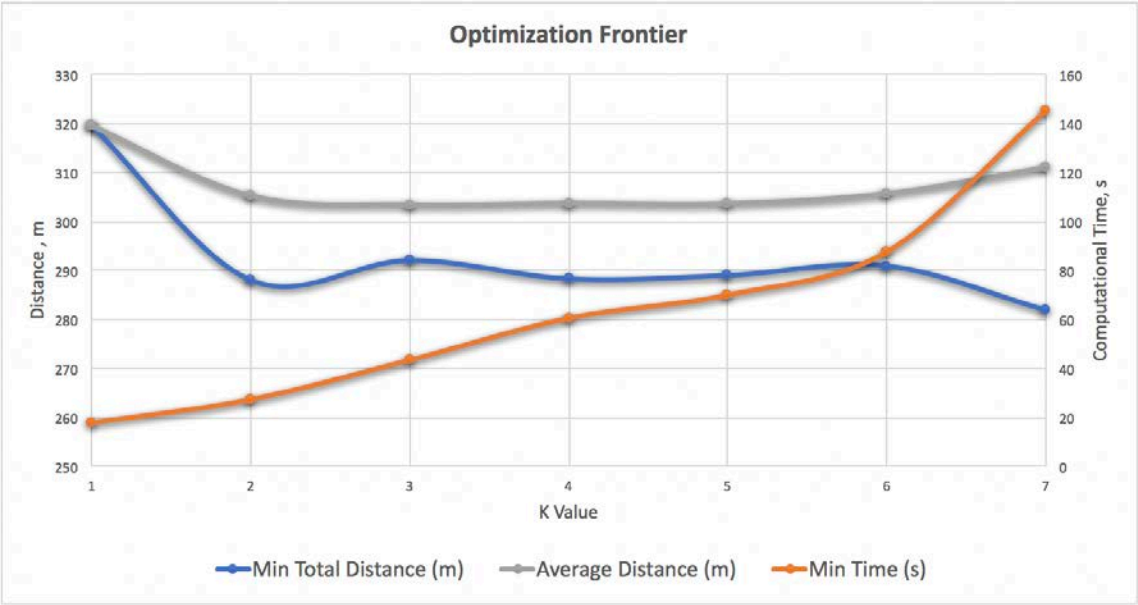


Figure 40. Plots of K-values against computational resources and distance

b. Connection Length Variations

With the K-values determined, the length of connection was varied to evaluate the impact on the distances and computational time. As shown in Figure 41, a shorter connection will result in a similar scenario with the lower K-value where a solution might not be obtained due to its inability to connect the cluster of points. With the increase in length, more points are selected and a solution is obtained for every simulation run. We plotted a graph as shown in Figure 42 based on the data obtained from Table 3. It was clear that there is no significant improvement even though the length increases; moreover, the computational time saturates, so the length of 100m was selected as the baseline value for the PRM.

Figure 41. Variation of length of connection in the C-Space variation

Table 3. Summary of data for variation of length of connection

Evaluation Criteria						
K	**10**	**30**	**50**	**100**	**200**	**300**
Total Samples	500	500	500	500	500	500
Edges Investigated	9538	9538	9538	9538	9538	9538
Edge Requirement	10	30	50	100	200	300
Overall Solution						
Probability of no Solution	0.95	0.00	0.00	0.00	0.00	0.00
Probability of Solution	0.05	1.00	1.00	1.00	1.00	1.00
Min Total distance	315.5	289.7	290.9	288.3	290.2	291.1
Average distance	315.5	302.5	300.5	303.7	303.9	303.7
Min Time	29.2	55.1	56.9	60.3	54.9	60.8
Sampling						
Min Sample Time	0.205	0.200	0.181	0.188	0.188	0.193
No of Nodes	3219	3280	3163	3175	3187	3228
Connect						
Min Connect Time	10.692	34.478	33.458	35.044	31.038	34.441
No of Good Edges	2664	4871	4979	5007	5159	4946
Search						
Min Search Time	12.482	18.788	20.806	22.602	21.667	22.545

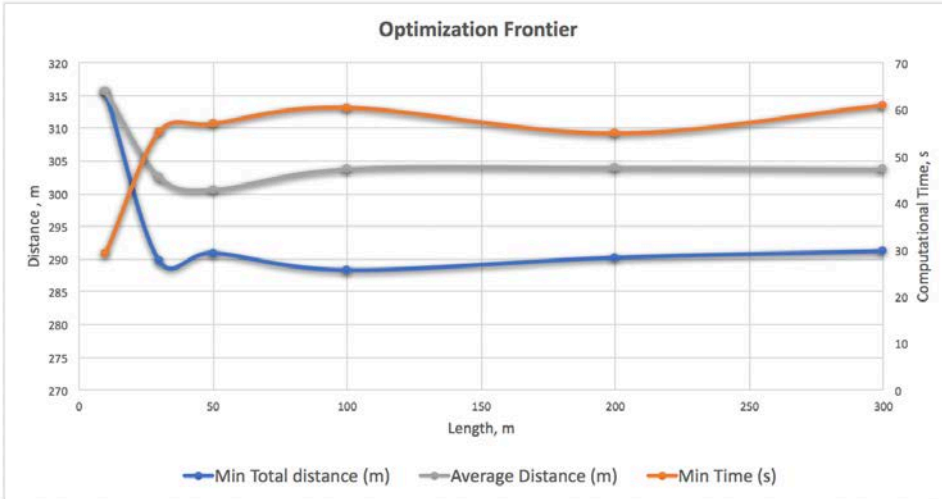


Figure 42. Plots of varying length against computational resources and distance

3. Variation of A* Heuristic Function

A* search is the best-first-search technique that solves the problem by searching the edges via the "greedy" manner that finds the optimal solution based on the algorithm shown in Figure 43. It evaluates each path based on the sum of the cost from start $g(n)$ and cost-to-go to the goal $h(n)$ as shown,

$$f(n) = g(n) + h(n) \qquad \text{Equation 13}$$

Algorithm 2: A* Algorithm

```
while Not reached goal do
    read current state from queue;
    If current state is goal then
        break;
    for next state in neighbor of current state do
        new-cost = cost-from(start) + cost-to-go(goal);
        if next state not unique of new-cost less than old-cost then
            old-cost = new-cost;
            priority = new-cost + heuristic (new State to goal);
        if next state not in collision then
            put next state, priority in queue;
        parent(next State) = current State;
```

Figure 43. The A* search algorithm

The heuristic function used to compute a cost-to-go estimate in the A* search algorithm must be an admissible heuristic. To get an admissible heuristic, we depict three edges (A, B and C), as shown in Figure 44. A is a simple cost-to-go function based on the straight-line distance from the point of interest to the goal. The metric is admissible as the straight-line distance never overestimates the cost or distance to reach the goal. The straight-line distance is always the shortest distance connecting any two points in the two-dimensional environment. C is always less than or equal to the sum of A and B; thus, it never overestimates. The Euclidean distance, which is used when the movement is possible at any angle, was used as the measurement of the heuristic function. It is computed based on the following equation:

$$h(n) = \sqrt{\left(x_{point}\text{-}x_{goal}\right)^2 + \left(y_{point}\text{-}y_{goal}\right)^2} \qquad \text{Equation 14}$$

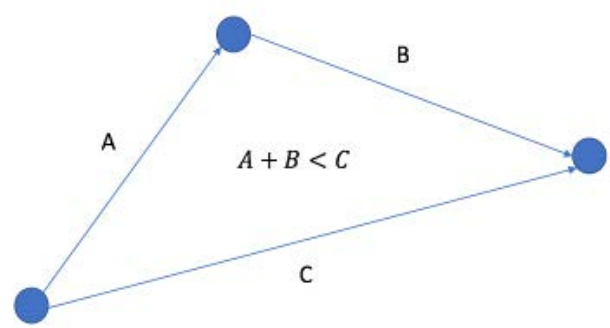


Figure 44. Shortest distance heuristics

a. Shortest Distance

The heuristic score is a computational estimate of the distance between each node and the goal. At one extreme, $h(n) = 0$, $g(n)$is the only function to determine the score, and the A* search in fact is the Dijkstra's algorithm, which guarantees the shortest distance for the selected path. If the heuristic $h(n)$ is

always lower than the total cost of getting from the nth location to the goal, however, then the A* search is guaranteed to find the shortest path but at the expense of time. The A* search will behave perfectly given perfect information (i.e., $h(n)$ is exactly the cost of moving n to the goal). The A* search flexibility to vary its computational behavior based on the heuristic and its cost function allows the trade-off for computational speed versus optimal solution. The weighted heuristics allow speeding up the A* search by decreasing the cost functions.

b. Weighted Heuristics

In the weighted form, a factor ε can be included in the computation of the heuristic. The lower the factor, the more likely to find a best path, while a higher factor will reduce computational resources. Based on the same heuristic function as the Euclidean distance but with the factor included, the cost function was modified to

$$f(n) = g(n) + \varepsilon h(n) \qquad \text{Equation 15}$$

The choice of heuristic for the A* search will determine the time to complete a search for a solution; it is a trade-off between obtaining an optimal solution where the distance is the smallest against computational time. We concluded that by choosing the right parameters, it is possible to obtain a solution consistently, but the tradeoff will be dependent on application. A sensitivity study was completed to understand the impact of the computational time against the variation of the factor ε.

c. Sensitivity Analysis

The sensitivity analysis was conducted by varying the factor ε from 0 to 2 in five steps. The solution for three of the PRMs generated is shown in Figure 45.

When the factor was set to zero (i.e., $\varepsilon = 0$), the solution gave the shortest possible distance and the most optimal solution in terms of distances. This computation requires the most computational resources. We plotted a graph as shown in Figure 46 based on the data obtained from the simulation run summarized in Table 4. It was clear that as the factor decreases the computation time to compute the solution decreases. We could reduce the computational resources by almost half if the factor $\varepsilon = 1.5$ was selected. In this scenario, the reduction was approximately 60s. The selected area of operations is required to be scaled for different scenarios, as the $\varepsilon = 1.5$ is still able to provide consistent results; thus, this factor was selected as heuristic function for the PRM.

.

Figure 45. Variation of weighted heuristic in the C-Space variation

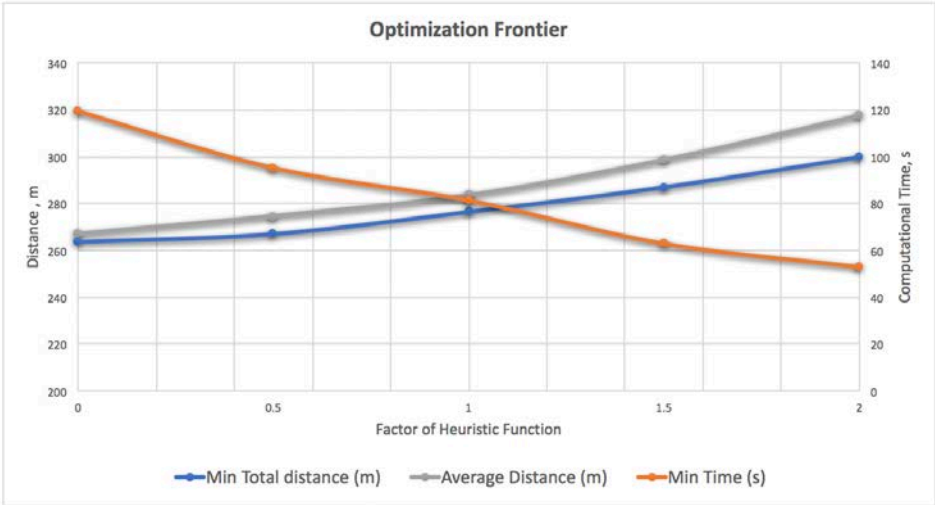


Figure 46. Plots of varying length against computational resources and distance

Table 4. Summary of data for variation of heuristics

Evaluation Criteria					
K	**0**	**0.5**	**1**	**1.5**	**2**
Total Samples	500	500	500	500	500
Edges Investigated	9538	9538	9538	9538	9538
Edge Requirement	100	100	100	100	100
Overall Solution					
Probability of no Solution	0.00	0.05	0.00	0.05	0.00
Probability of Solution	1.00	0.95	1.00	0.95	1.00
Min Total distance	263.6	267.0	276.3	286.8	299.4
Average distance	267.0	274.5	283.5	298.5	317.3
Min Time	119.1	95.1	81.3	63.0	53.1
Sampling					
Min Sample Time	0.187	0.190	0.181	0.194	0.181
No of Nodes	3209	3309	3204	2984	3158
Connect					
Min Connect Time	32.646	34.110	34.432	36.010	32.038
No of Good Edges	5177	4928	5222	5190	5126
Search					
Min Search Time	81.349	59.649	46.118	21.195	16.123

In this section, the probabilistic roadmap develops the path that the ground vehicles should use to maneuver to the area of interest based on the shortest path identified in the configuration space. This can be used for unmanned aerial vehicles by representing the area as blocks and ignoring the altitude of all the building (i.e., assuming that the buildings are of constant height). Alternatively, this can be scaled into a three-dimensional probabilistic

map that can used for drones if they are required to navigate in an environment where the buildings have different heights, for example in downtown San Francisco. The trade-off is the extensive resources required to obtain a solution for the probabilistic road map.

B. SEARCH PATTERN

The probabilistic roadmap to the areas of interest is only the first part of the solution. The next task is to identify the optimal means to search the areas of interest that have possible survivors in them. As the layout of the operational area will differ from site to site, and depending on the search requirement, the points identified might not be in defined shape to execute the typical search pattern. Thus, in this section, a flexible means was developed to create a pattern to conduct the search optimally based on the points of interest identified as key areas to cover by the commander.

To begin with, we will need to evaluate the typical search patterns that have been used universally. There are several search strategies and techniques that are established internationally for different types of scenarios. The International Aeronautical and Maritime Search and Rescue (IAMSAR) manual, which defines search patterns used by aerial and marine assets, recognized the following general search patterns applied in the various situations (MOC/ICAO 2010). They are the (1) parallel or creeping line search for a big area, (2) expanding square search for a specific area, and (3) contour search in a mountainous environment.

Both the parallel or creeping line search as illustrated in Figure 47 are based on sweeping the search area by maintaining parallel tracks throughout the search. The only difference between the two search patterns is the orientation of the search leg. For a manned platform, as the search area might be huge and the camera have a large field of view, the turns might not be a critical factor. Unlike unmanned platforms, this turn will consume energy and thus reduce the already low endurance of the unmanned systems. Both UGV and UAS will be

affected, and minimizing the turns will allow the battery power otherwise drawn by the propulsion system to be used for other purpose. This type of search is typically used when the area of search is huge and requires the area to be searched uniformly (i.e., when the target location is unknown and has equal probability of being anywhere in the area). In our context, this search pattern will probably be the most effective in searching for a survivor in the aftermath of a disaster. This search pattern was probably used by USAF pilots during the search for survivors after Hurricane Katrina.

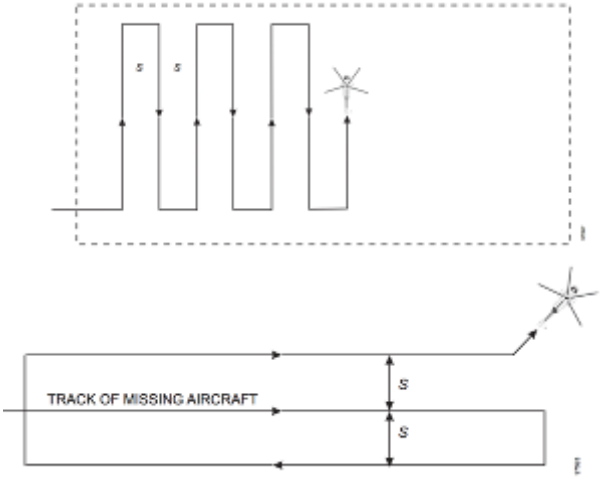


Figure 47. Creeping line and parallel track search

On the other hand, the expanding square pattern is usually used when the predicted location of the target is centered at a specific position (i.e., the target is expected to be in the center but might have drifted away due to the currents of the sea or wandered off from a crashed aircraft). This type of search, as illustrated in Figure 48, is typically used during the search for survivors after an accident where the accident location is known. The search area is characterized by a smaller environment or when a concentrated search strategy is required, like the search for USS Scorpion (SSN-589). The shape can also be in the form of a circle and not necessarily be limited to a square as defined. The main

objective is to start the search from a known point where the probability of finding the survivor is the highest and expand outwards. Finally, a specialist type of search method called the contour search, as shown in Figure 49, is typically used in mountains or valleys where the survivors are likely to be injured or trapped along the tracks that hug the edges of the mountains. This requires the search vehicle to scan the area of interest following the path and increase or decrease the elevation as they scan the area of operations.

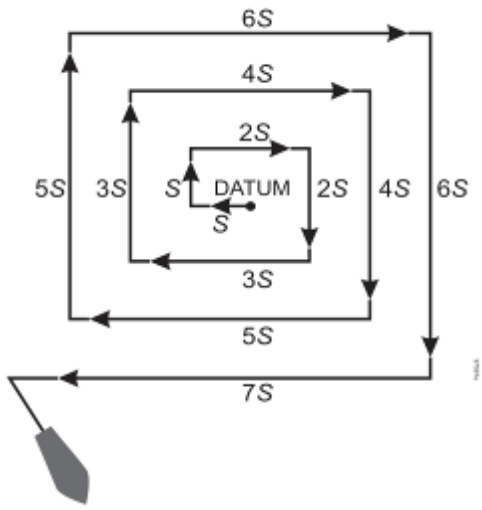


Figure 48. Expanding square search pattern

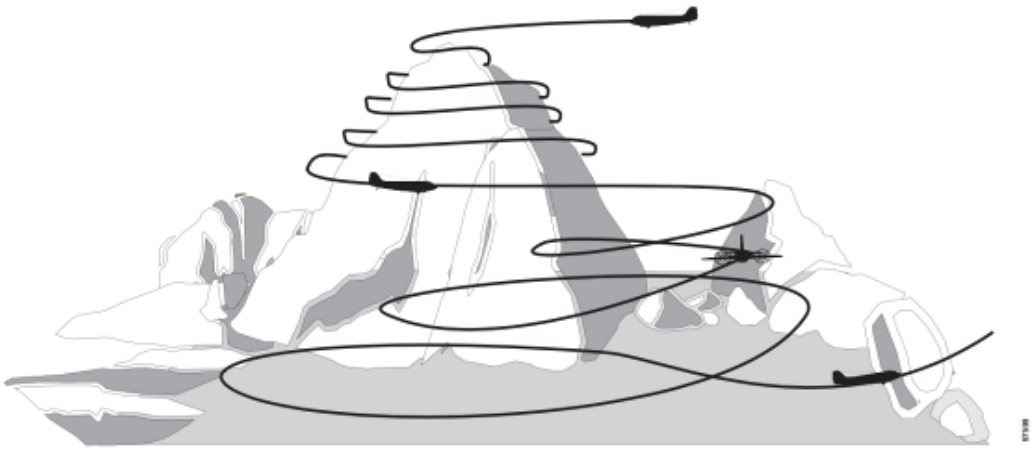


Figure 49. Contour search

Drones can be used in place of the manned platform to effectively search the area of interest and obtain the aerial images that can be used to both locate survivors and reconstruct the three-dimensional environment. In the event the area is free of obstacles, ground vehicles can be used but with limited search area. Thus, for the development of search, drones will be used. With a wide area of search to be completed, it is likely that the creeping line or the parallel track search method will be used for the operations. As stated, however, due to the limitation of drones, it is ideal to reduce the number of turns, so the search pattern must be set up like the parallel track search. The drone performance is governed by the altitude or speed that it flies; the higher the altitude, the less likely the searcher can identify the target correctly, and the faster it flies, the lower the probability of detecting a survivor even though the drone covers a large area. This challenge was tackled in the works of Ergezer (2014), where he explored the problem of planning routes for multiple UAS with the objective to collect data from a designated region. The information is obtained from the sensors on board the UAS and the quality of the information is dependent on the altitude and speed of the drones. Thus, to tackle this coverage path planning problem, a holistic approach considering the various factors must be accomplished systematically.

Coverage path planning is the task in the robotics domain that determines a path that requires the robot to cover all the specific areas defined by the user. The simplest form of such a requirement is the home-based vacuum cleaner, where the robot is required to cover the floor area and clean it thoroughly. A general method utilizes the belief map, which maps the highest probability area of survivors to move itself in that space until all the cells identified are covered. In this method, the only optimization required is to determine the method whereby the grid must be searched before all the required cells are covered. This can be in the form of greedy heuristics whereby the UAS will move to the highest belief grid among the neighboring grids in which it can maneuver. This is effective if the belief map is well defined with varying probabilities. If it is a uniform environment, this method has no additional advantage. Alternatively, a potential field method can be used based on applying repulsive force on the visited cell and instead searching areas that have not been explored. In this form, the search pattern tends towards looking at areas not visited; the downfall is if the survivor is near a cell that was searched before, there is a chance that he or she will be missed or be found at a later stage.

By utilizing multiple platforms, the search time will be reduced as the task is divided among the various resources. Moreover, it introduces redundancy for mission completion as it allows drones to collaborate and cover each other if a failure has occurred to any of them. The other UASs can be used to cover the region that was allocated to the failed drone and thus do not compromise the overall mission requirements. A common approach to such a coverage problem can be tackled like the vehicle routing problem, whereby a set of routes that have been identified are split optimally amongst the available resources. This is the generalized form of the traveling salesman problem typically discussed in operational research or computer science. The routes identified must fulfill all the customers' requirements (i.e., to deliver a product), which in this case is to be searched by the drones based on the limited energy capacity that they have. The transformation of a coverage problem into the vehicle routing problem requires

the mapping of all the points that are required to be covered up to a set of edges of a graph. Once the graph has been visited, it is assumed that the robot has completed the search of that specific area and fulfilled the necessary requirements.

This dynamic vehicle routing problem aims to converge spatial (a distributed area) and temporal coverage of the area of interest. The temporal convergence is governed by the existence of the time constraints to reach the survivors as quickly as possible. Thus, the objective is to minimize the distance travelled and thus optimize the usage of drones to maximize the requirements to search the assigned points of interest and minimize the number of drones to be deployed so that they can be used in other areas of interest. Thus, the solution to the coverage problem is governed by the following conditions in this sequence: (1) to specify the optimal search pattern given the specific area of interest and (2) to determine the optimal number of drones required to complete the mission.

1. Development of Search Pattern

The area of operations must first be identified by determining all the points of interest that the commander wants to explore. The development of the search pattern was based on the methodology that was derived by Huang (2001), who stated that the number of turns directly affects the time required to complete the search. The coverage strategy will depend on the platform that is used. To reduce the number of turns (which typically consume more energy), it is necessary to align the route carefully; thus, the sweep direction will be completed parallel to the smallest linear dimension of the area. It is commonly understood in the aviation world that the route length and duration of flight can be significantly reduced if the number of turns is optimized. Thus, for a given search area, the parallel track search pattern is more optimal in terms of energy consumed than the creeping line search pattern.

Since the shape of the search pattern, which is governed by the points of interest, is unlikely to be in the form of a rectangle in our type of scenario, it is

essential to analyze the selected points. All the points identified are connected based on the similar method defined in the probabilistic roadmap method. They are all connected to each other to evaluate the distances between them based on the Euclidean distance. From the pool of points defined, the four extreme points are identified to determine the direction of search, which will be parallel to the length of the smallest distance governing the boundary. To have the most optimal usage of the chosen platform, the strategy developed must generate the search path that searches parallel to the longest dimension of the set of points.

A sets of arbitrary sample points was selected to test the algorithm in generating the search pattern; from the results obtained, as shown in Figure 50 where a longitudinal search pattern (x-direction) was generated and Figure 51 where a lateral search pattern (y-direction) was selected, the optimal search pattern was generated correctly based on the points selected, as indicated by the blue crosses in the image.

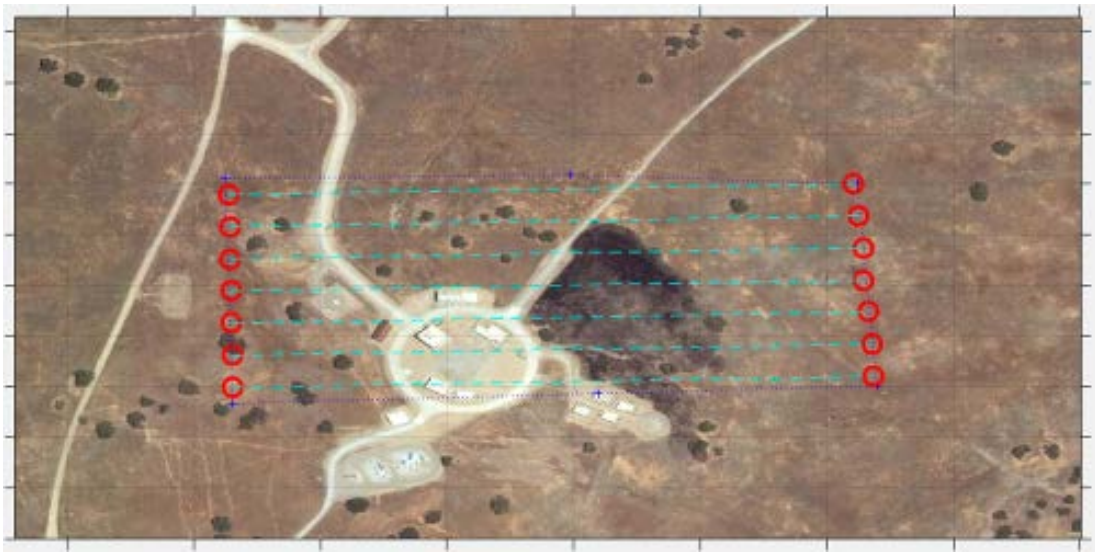


Figure 50. Search pattern based on the longitudinal direction

Figure 51. Search pattern based on the latitudinal direction

From the area of interest obtained in the previous chapter, the commander will identify all locations of interest where the probability of survivors is higher. This will be at the areas where there are buildings and, thus, the commander will select the points of interest as shown in Figure 52. All the buildings in the environment will be selected by clicking on the user interface. Upon the identification of the points of interest, the search pattern will be generated to ensure all the points of interest are covered and the optimal pattern is derived. This is shown in Figure 53, where the blue crosses are areas that the commander has identified as key points of interest, while the red circles are the boundaries for the search pattern with the cyan lines as the optimal orientation of the search pattern.

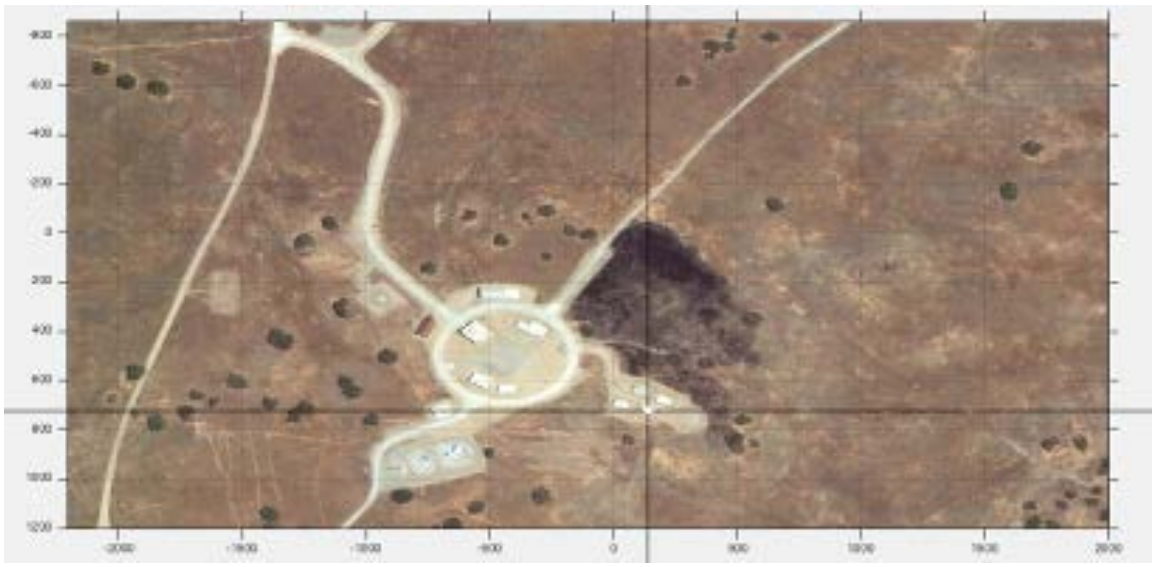


Figure 52. Selection of area of interest

Figure 53. Search pattern for the area of operations

2. Routing Strategy for Search

The coverage problem can be posed as a vehicle routing problem, which requires a set of vehicles to visit several customers. In the context of the research problem, intuitively the customers might be assumed to be the points of interest where there is a possibility of a survivor. As we are mapping a coverage

problem, however, this assumption will not provide an optimal solution. Instead the customers will be defined as the extreme points on the coverage row, as indicated by the red circles in the search pattern. The rationale revolves around the fact that all the points of interest have been mapped onto a search pattern that has been clearly defined and requires the servicing vehicle to cover the area; thus, to avoid missing any points of interest, the extreme points of the coverage rows must be covered. The points will be serviced by the available unmanned systems, who need to overfly or scan the region to observe if the survivor is present in that specific point of interest. The number of unmanned systems is dependent on the availability and thus a variable in the problem. The objective is to minimize mission time with the resources available for disposal, and constraints must be added to ensure that all the points are covered sufficiently but practically.

The starting point to the routing strategy is to define the requirements; coverage rows have been defined based on the search pattern. The cyan lines are paths that the unmanned system must take, while the red circles indicate the boundaries that the vehicles must cover to ensure that all the points of interest have been covered. Thus, the unmanned systems must be forced onto the cyan lines as part of their routes and they must visit all the customers in the form of the red circles to ensure that the coverage problem is resolved. Effectively, the mission time is dependent on several components: the distance S_{ij} from customer i to j, the velocity of the unmanned system V_{ij} when flying from customer i to j, and the preparation time of the kth unmanned system L_k.This function L_k is dependent on the number of drones and number of operators available to set up a single UAS in time t_s. Each UAS will also have an endurance limitation E_k, which is dependent on the platform. A binary variable

$X_{ij}^{k} \in \{0,1\}$ was used to indicate if the kth unmanned system was used to cover the specific path on the route. This is to ensure all the paths are covered and at the same time no duplication of resources was used. The scenario will be based on the usage of drones as they are the most effective unmanned system in covering a wider area of search.

$$T_{mission} = \sum_{i=1}^{N} \sum_{j=1}^{N} \frac{S_{ij}}{V_{ij}} X_{ij}^{k} + L_{k} \qquad \text{Equation 16}$$

This is to be accomplished by U number of drones where $U \in \mathbb{N}$, operated by O number of operators where $O \in \mathbb{N}$ over a specified N number of customers in the search pattern where $u \in \mathbb{N}$. The main objective is to minimize mission time; this can be achieved by minimizing the time taken for the longest distance required to be covered ξ.

$$\min(\xi) \qquad \text{Equation 17}$$

subject to

$$\sum_{i=1}^{N} \sum_{j=1}^{N} \frac{S_{ij}}{V_{ij}} X_{ij}^{k} + L_{k} \leq \xi, k = 1, \dots, U \qquad \text{Equation 18}$$

$$t_{s}\left(\frac{k}{O}\right) \sum_{j=1}^{N} X_{ij}^{k} = d_{k}\ , k = 1, \dots, U \qquad \text{Equation 19}$$

In this problem, each constraint serves a different purpose. In equation 18, the individual time for each drone is accounted for and, defining it with the objective function, it will form a min-max linear problem. The second constraint in equation 19 handles the resources available to launch multiple UAS; if there is a

single operator, the constraint will be on the operator to set up and launch the UAS. Thus, there is a lag time in the utilization of the platform (i.e., when the operator is working on the first drone, there is no action on the second drone). This might result in the ineffectiveness of having more drones if the area to be searched is small (i.e., if the search area requires only ten minutes to be searched, and the preparation time of a single UAS is ten minutes, before the second drone can be launched the search might be completed and thus render the second drone useless). This of course will change if more operators are used and the results will differ, assuming there are two drones and two operators. Effectively, the flight time not including the launch time can be halved.

As each UAS has an endurance limitation, however, an additional constraint must be added and it is governed by equation 20. This constraint will thus limit the area that the set of drones can operate in (i.e., if the search area is too large, the only way is to have more drones to cover the whole area). Moreover, if the launch point is too far for the drones to complete any meaningful search (i.e., the time to fly to the site is equivalent to its endurance), there will not be a feasible solution. Thus, it is necessary to tie in with the initial planning phase as described in Chapter III, where the mission bubbles must be allocated based on the capabilities of the platforms available. The size of each mission bubble should be allocated appropriately for the effectiveness of the system.

$$\sum_{i=1}^{N}\sum_{j=1}^{N}\frac{S_{ij}}{V_{ij}}X_{ij}^{k} \leq E_k\,, k = 1, \dots, U \qquad \text{Equation 20}$$

To ensure that the sets of drones visit each node, the following constraints were added: Equation 21 enforces that all the nodes are visited except for node one, which is the launch node, while equation 22 states that a drone will leave from the node to which it arrived to avoid discontinuity in the solution.

$$\sum_{k=1}^{U}\sum_{i=1}^{N} X_{ij}^{k} = 1\,, j = 2,3 \ldots, N \qquad \text{Equation 21}$$

$$\sum_{i=1}^{N} X_{ip}^{k} - \sum_{j=1}^{N} X_{pj}^{k} = 0\,, \qquad p = 1, 2 \ldots, N, k = 1, 2, \ldots, U \qquad \text{Equation 22}$$

This equation ensures that the UAS returns to its original node and there are no internal cycles based on the standard sub-tour elimination constraint by Christofides (1981).

$$u_i - u_j + N \sum_{k=1}^{U} X_{ij}^{k} \leq N - 1\,, i, j = 2, 3 \ldots, N \qquad \text{Equation 23}$$

where $u_i \in \mathrm{Z},\ i = 2,3, \ldots N$

Finally, the number of UAS used in the mission cannot be the maximum number of drones available, and this is defined as the following constraint in equation 24.

$$\sum_{k=1}^{U}\sum_{j=1}^{N} X_{1j}^{k} = u\,, u \leq U \qquad \text{Equation 24}$$

By solving the objective function in equation 17 with the following constraints defined from equations 18 to 24, the minimum number of drones required to cover the search area will be defined. Based on a search pattern as shown in Figure 54, for a single UAS with an operator, the time for the mission to search the location was approximately 26.5 minutes and the total mission time was 30.5 minutes where four minutes was set as the launch time for the drone. When two drones $U = 2$ are similarly operated by a single operator (Figure 55) with the same setup time of four minutes to launch each drone, however, the total time required to complete the mission was 21 minutes, with the first drone

flying for 17 minutes and the second drone for 13 minutes. If we add an additional drone for the same mission (Figure 56), the savings will only be 1 minute with the three drones' operation time at 19, 18 and 20 minutes, respectively. Thus, a trade-off is required to determine if the additional resources should be used here or at other locations.

Figure 54. Single UAS search pattern

Figure 55. Two UAS search pattern

Figure 56. Three UAS search pattern

Based on the tools developed in Chapters III and IV, mission bubbles are developed to obtain trajectory for the unmanned systems to navigate to the search area. In addition, an optimal search pattern was generated to complete the search at the points of interest. A simple experimentation was completed in the next chapter, and tied in with another research in detection of moving targets completed by CPT Ang Wee Kiong.

THIS PAGE INTENTIONALLY LEFT BLANK

V. FIELD TRIALS

With the development of the initial framework in identifying mission bubbles, obtaining trajectories and search patterns for points of interest, an experimentation was conducted at Camp Roberts in conjunction with the research on the feasibility of using visual sensors onboard an unmanned aerial system (UAS) to autonomously detect and track moving targets in real-time operation. The key goal of the experimentation was to understand the limitations on the task completed thus far and identify potential areas of improvements that should be explored to enhance the capabilities, which will be covered in the next chapter.

A. OPERATIONAL SCENARIO

The scenario for the field experimentation is bounded to the area surrounding the McMillan Airstrip at Camp Roberts, California, as depicted in Figure 57. The scenario is that a hurricane has swept through these areas and the team from the California Fire Department was tasked to locate possible survivors around the vicinity.

Figure 57. Operational area for field experimentations

The UAS platform was used during the flight trial flown by CPT Ang Wee Kiong was the Matrice 100 shown in Figure 58 from the Da Jiang Innovations (DJI) Science and Technology Company Ltd. The 3.6-kilogram UAS is capable of up to 22 minutes of flight and is equipped with a camera that can be customized for various research and development uses. The technical specifications are shown in Table 5.

Figure 58. Overview of Matrice 100

Table 5. Key performance of Matrice 100 UAV. Source: DJI (2017)

Parameter	Specification
Battery TB47D Voltage/Capacity	22.2V/4500 mAh
Maximum Takeoff Weight	3600 g
Maximum Wind Resistance	10 m/s
Maximum Speed w/o payload & wind	22 m/s
Hovering Time w/o payload & wind	22 mins
Transmission Range (LOS, no interference)	5 Km

B. PHASES OF EXPERIMENTATION

The various phases of the search as developed throughout the thesis were put to the test during the field experimentation. This was based on the techniques developed in Chapters III and IV to determine the mission bubbles in the operational area and allocate the required unmanned system to the various areas through the most optimal trajectory as well as the idealized search pattern to maximize energy and at the same time minimize time. The flow charts of the task and information used for these tasks are based on the five key phases identified, while the information flow is illustrated in Figure 59.

Figure 59. Field experimentation flow chart

1. Development of Mission Bubbles

In the first phase, the mission bubbles must be developed at the area of interest. The overview of the area of McMillan Airstrip obtained from DigiGlobe on July 12, 2017 was obtained for the initial analysis. Upon further study of the area, it was found that the key area of interest was identified at the southeastern portion of the area, as shown in Figure 60 and indicated by the white pixels in the image. These white pixels indicate the built-up area and, thus, are the likely points where there are potential survivors. This point of interest must be investigated further to obtain more information; thus, a set of unmanned systems

must be sent to the area. In addition, the airstrip is another area of interest and should be evaluated. The rationale to evaluate the runway is that it is a key entry point for supplies to be delivered. The runways should be evaluated for damage to see its functionality and allow the commander to evaluate if it is a potential resource that can be utilized during the whole operation. Thus, apart from focusing on the search mission, this tool gives the commander a better situational awareness to not only search for survivors but also to plan for further operations. The flexibly of the system gives the commander the latitude to determine points of interest for different objectives, not only in search operations but also to identify access routes and infrastructure that can be used for other purposes throughout the operations.

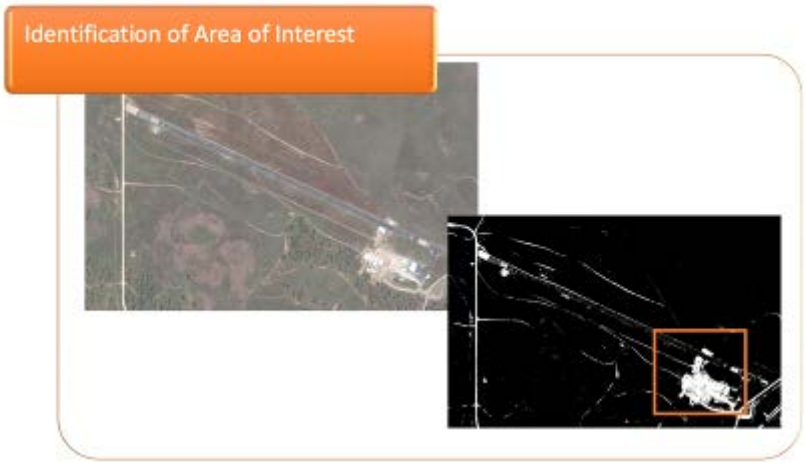


Figure 60. Operational area for field experimentations

2. Search Pattern

Utilizing the same tool developed in Chapter IV, the points of interest near the built-up area and at the end of the runway were selected. The algorithm based on the capability of the sensors' field of view will determine the point to which the drone is required to fly to develop the search pattern. The derived search pattern does not go to the end of the indicated points; instead, the search

pattern is derived optimally to the maximum point at which the sensor can cover the point of interest. The search pattern and the proposed trajectory for a single UAS is shown in Figure 61. The search pattern similarly was developed based on the points. The operational time for a single UAS is 19.2 minutes with a flight time of 15.2 minutes based on the specifications of the UAS.

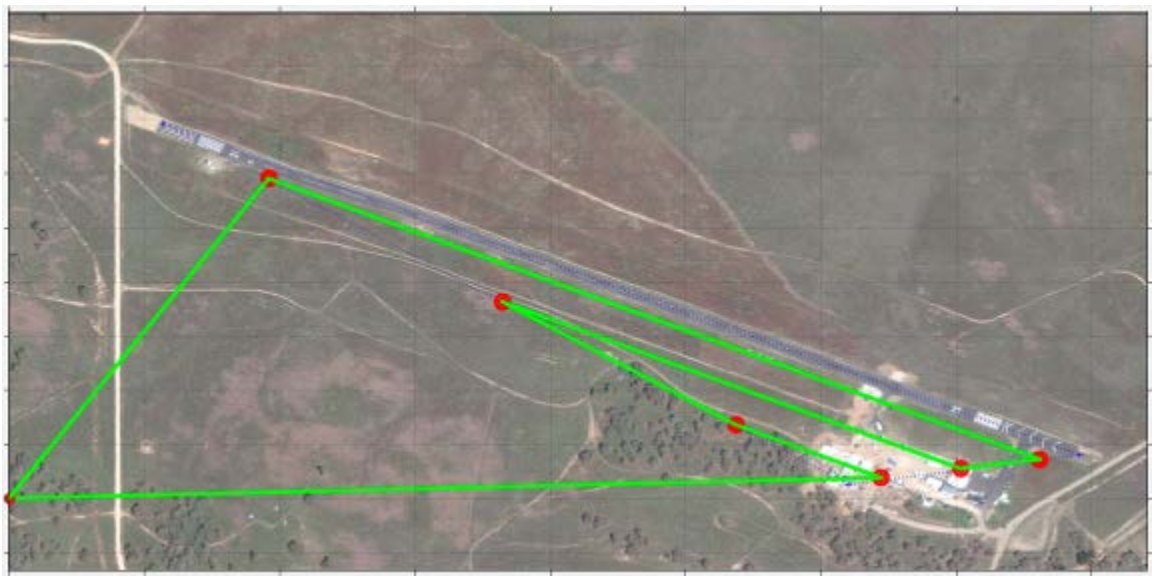


Figure 61. Search pattern for the area of operations

The tool was used to evaluate the optimal number of UASs for the operations. From the simulation run, it was observed that for this specific scenario, two UASs will suffice, as shown in Figure 62. The two UASs will complete the mission within 17.3 minutes, with one UAS flying for 9.3 minutes and the other for 11.6 minutes. The third UAS can only be ready to be launched at the 12-minute mark as there is only one operator; moreover, due to the launch location, it is not optimal to launch the third UAS, so it was not deployed. It can thus be seen that the number of UASs to be deployed for an optimal search not only depends on the preparation time but also the distance where it is launched from. This tool was used effectively and has the latitude to change parameters for different types of operations, not limiting to a search mission. For example,

this can be used in the military context if a requirement is to identify threats or to deliver a payload to a specific location; by tuning the parameters, we can quickly identify the number of resources to be utilized optimally for any type of mission.

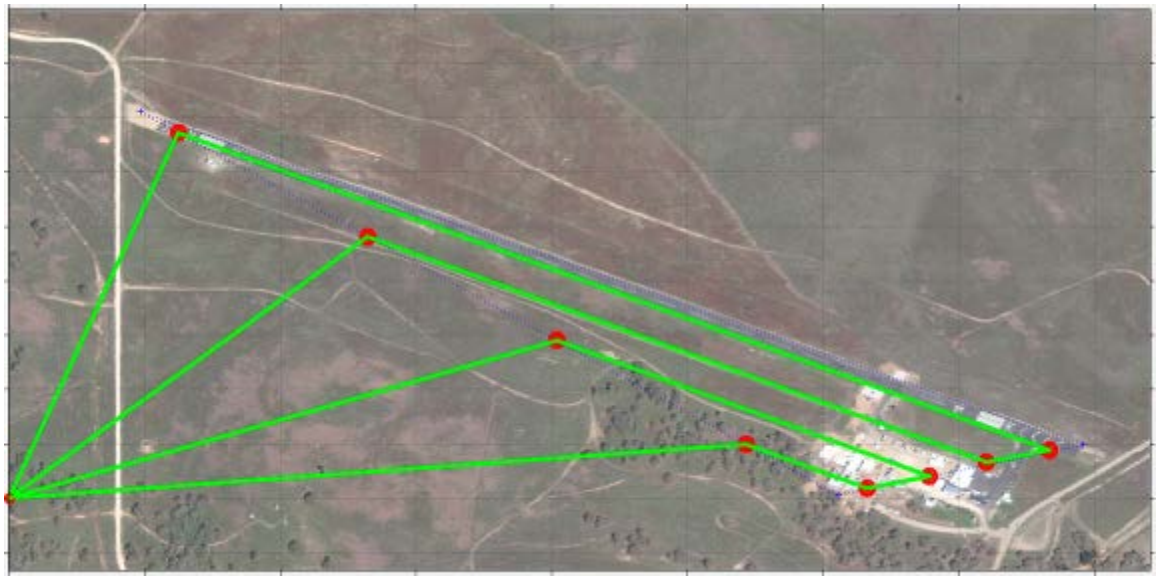


Figure 62. Two UAS search pattern

C. DETECTION AND RECOGNITION

The key focus of the thesis was mainly on the assessment of the situation and the development of mission bubbles and subsequently the trajectory to the location and the development of the search pattern. The search pattern as shown above is the tool to navigate the drones to the location; the next phase as described in the phases of a search operation is the detection of targets. The detection of targets, which is another important element of a search mission, was undertaken by Ang (2017) as part of his thesis in assessment of onboard electro-optic sensors to enable detection and sensing capability in a cluttered operating environment (Figure 63). This is phase four of the five phases for a search mission that can leverage technological advancement, as highlighted in Chapter II, to aid search operations. Although the focus of his research was the systems

engineering approach, the application aspects of his works and possible integration to the search application tools were explored here.

Figure 63. Imagery obtained during trials. Source: Ang (2017).

The algorithm that was developed in his thesis autonomously detects and tracks moving objects, which is a good fit in searching for survivors in a rescue mission. The algorithm processes the video inputs to isolate the moving targets from the background. The target acquisition process can be tuned based on the angular variance and point density threshold. Upon identification, these moving targets are highlighted by a bounding box in the ground control station autonomously without a need for operator input, thus allowing an operator to control multiple platforms at one time, as shown in Figure 64. From the test conducted by Ang (2017), by varying the algorithm parameters it was observed that higher resolution video feed provides a wider field of view with better clarity. Due to the increased encoded data and network limitations, however, high-resolution video may result in increased latency. Thus, there is a trade-off in terms of resolution and transfer of information.

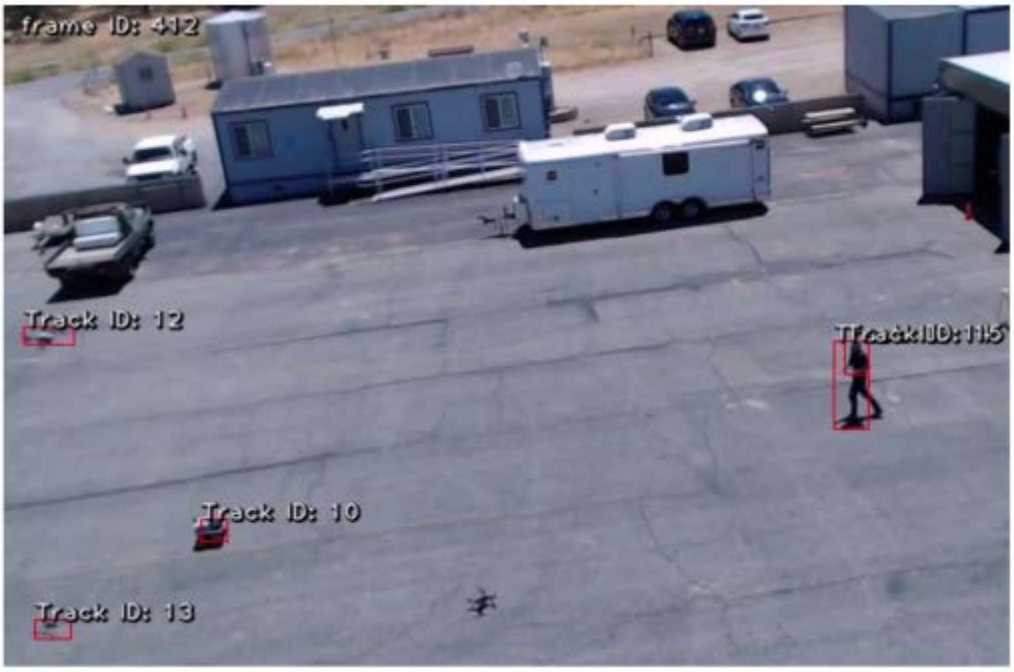


Figure 64. Identification of targets completed by Ang (2017).

VI. CONCLUSION AND RECOMMENDATIONS

The five key phases in the search mission were derived in Chapter II are clearly defined and recapped in Figure 65. Methods were used to enhance and shorten the process to give the commander a quicker means to identify survivors in the operational area. In fact, the tools used fused the observe, orientate and decision part of the observe, orientate, decide and action (OODA) loop. This chapter concludes the findings, identifies gaps and proposes future works to enhance this mission planning capability.

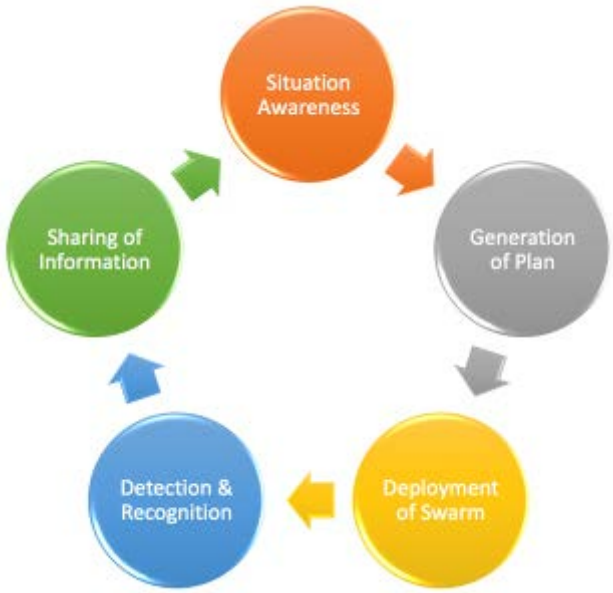


Figure 65. Proposed approach to search and rescue operations

A. CONCLUDING REMARKS

This research proved that by utilizing the technologies that are available and fusing them with the right techniques, it is possible to leverage them and transform simple innovation into a capability that is useful in many applications. In this thesis, a search mission was optimized by utilizing image processing techniques to consolidate information from various sources into a single map that

the commander could use to enhance situational awareness. Technologies were used to collect, store, and share essential information among the various stakeholders, which allows the commander in chief to allocate the right resources for various applications. This is necessary not only to provide emergency responders with an update on the natural environment, but also to inform them of the state of the infrastructure around the area of operations. In this thesis, the focus was to collate the information for a search mission; it can be expanded to include, for example, the status of the power grid or water supplies to serve those living in the environment. As the tool was completed modularly, the methods discussed can be expanded for this purpose. By utilizing the damage assessment tools, the status of the power grid can be evaluated, while constantly updating the three-dimensional maps allows plans to be developed for the recovery phase.

In addition, with the advent of computational power and miniaturization of computers, the unmanned system can develop the optimal trajectory within minutes based on the configuration space identified. This automated sequence can be done without any human intervention, which frees them to complete tasks that require their focus. The probabilistic road map can be used to find the best path available to reach the search area, and the search pattern can be easily defined based on the commanders' input. In the future, the points of interest can be computed autonomously by applying data analytics methodology embedded with machine learning in which the computer can learn from patterns to crunch large data sets and transform them to necessary information for the commanders. This helps to fuse the OODA loop and cut down on reaction time for commanders. Similarly, this tool is not necessarily fixed to a single application, and it can be customized for different purposes including military applications especially when we are shifting to network-centric operations where information is constantly shared and exchanged to accomplish a common goal.

B. THESIS CONTRIBUTION

The research establishes a mission planning tool with a set of heterogeneous unmanned systems to execute a search mission optimally. Although this was applied to a search mission in a post-disaster environment, it can be extended to network-centric missions in the military context. The ability to retrieve and compare various images to determine changes and convert them to a three-dimensional environment allows a common picture to be painted and can be utilized for the computation of optimal path and search plans. This is by no means a product, however; as technology advances further, more tools can be used effectively to enhance this capability. The study on data analytics in the financial world, where patterns are analyzed to optimize profits, or on autonomous machine learning are possible avenues of further expansion. The importance is the ability to change and adapt to the ever-growing environment. Otherwise, if the potential is not tapped, the efforts of our forefathers in the development of technologies will be wasted. Technologies should not be exploited—they should be harnessed, and humans should work in tandem with and not suppress them in fear of being taken over.

C. RECOMMENDATIONS FOR FUTURE WORK

As stated, the avenue for further work is boundless. For this thesis, specific areas where more work can be done in the five key phases are discussed here. This list is by no means complete, and it should evolve as technology develops.

1. Generation of 3-dimensional Search Plan

The probabilistic road map developed was demonstrated in a two-dimensional environment for an unmanned ground vehicle. Since the computational power is so advanced, however, a three-dimensional probabilistic road map can be explored, as shown in Figure 66. This is especially effective for

operations in an urban environment where drones will be required to fly past buildings and obstacles in a dense environment.

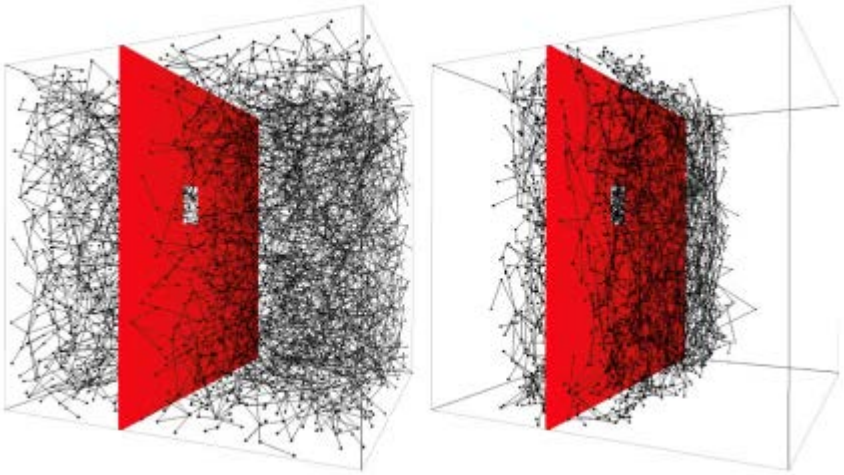


Figure 66. Three-dimensional probabilistic roadmaps

2. Sharing of Information

This is one area that the thesis barely touched on, but it is key in the sharing of information. The means to share information among the various platforms and the optimal means to exchange information must be studied intensively. The hardening of the network environment is also an area that the computer network gurus should consider, as search operations will occur in a cluttered environment. If the system was expanded to military operations, then the constant sharing of information might lead to a potential weak link in the capabilities. Thus, this discipline is something that must be addressed if the system is to be robust and effective.

APPENDIX. PROBABILISTIC ROAD MAP DATA

Figures 67 to 69 are the probabilistic roadmap plots that are obtained for the various simulation studies completed as part of the thesis.

(a) K = 5

(b) K =10

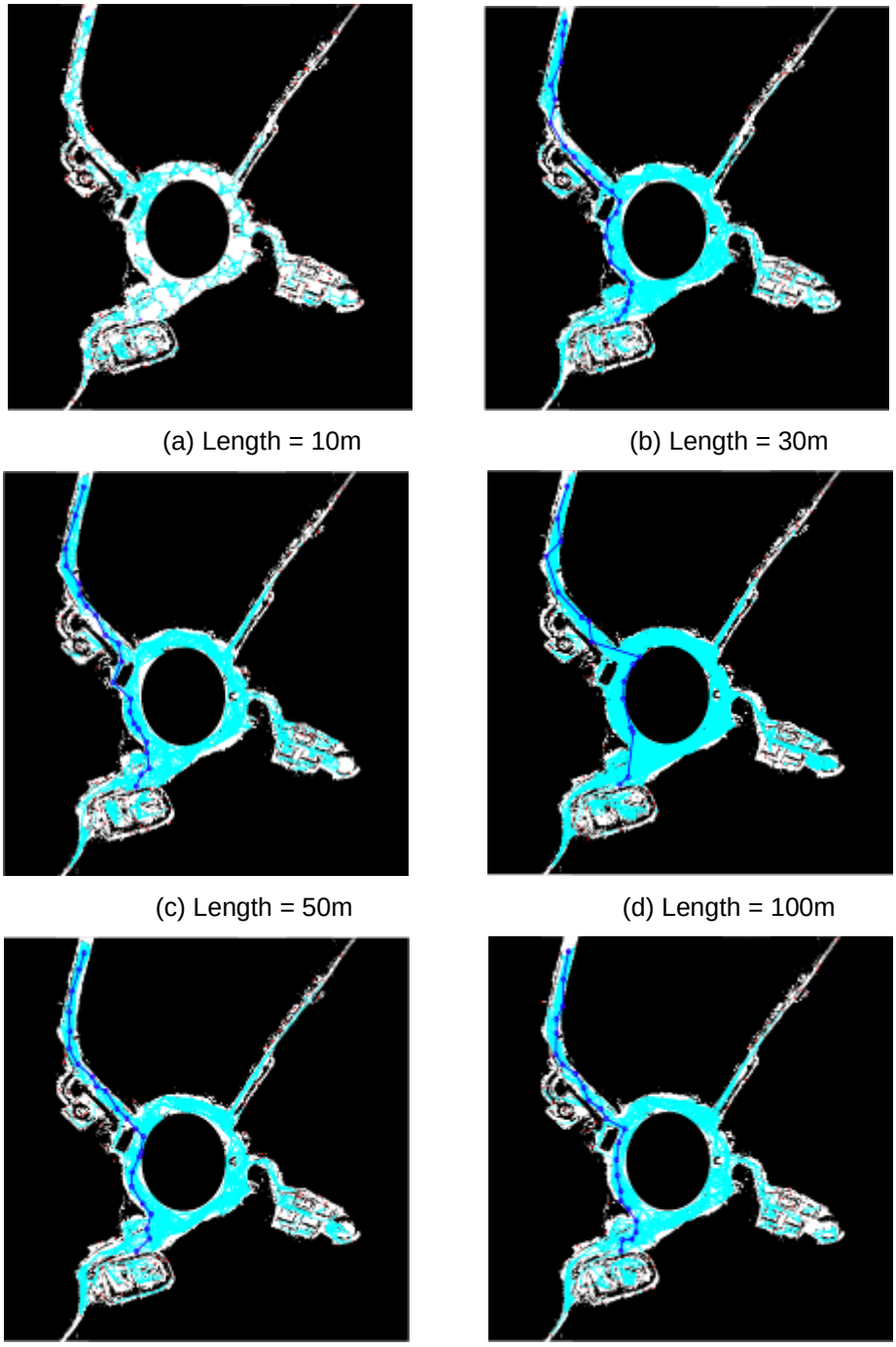
(c) K = 15

(d) K = 20

(e) K = 25

(f) K = 30

Figure 67. Uniform distribution of 500 samples with 100 m edge length



(a) Length = 10m (b) Length = 30m

(c) Length = 50m (d) Length = 100m

(e) Length = 200m (f) Length = 300m

Figure 68. Uniform distribution of 500 samples with 100 m edge length

(a) Dijkstra's Algo $\varepsilon = 0$

(b) $\varepsilon = 0.5$

(c) $\varepsilon = 1.0$

(d) $\varepsilon = 1.5$

(e) $\varepsilon = 2.0$

Figure 69. Normal dist. of 500 samples with 200 m edge length – Varying K values for weighted heuristics

THIS PAGE INTENTIONALLY LEFT BLANK

LIST OF REFERENCES

Ang, Wee Kiong. 2017. “Assessment of On-board Electro-optic Sensor to Enable Detect and Sense Capability in a Cluttered Operation Environment.” Master’s thesis, Naval Postgraduate School.

Arquilla, John and David Ronfeldt. 2000 “Swarming and the Future of Conflict.” RAND National Defense Research Institute.

Brimley, Shawn, Ben Fitzgerald, Sayler Kelley, and Peter W. Singer. 2013. “Game Changers Disruptive Technology and U.S. Defense Strategy.” Center for a New American Security.

Brumitt, B. and A. Stentz. 1996. “Dynamic Mission Planning for Multiple Mobile Robots.” In *Proceedings of IEEE International Conference on Robotics and Automation* 3: 2396–2401. Minneapolis, MN

Cao, Z., M. Tan, L. Li, N. Gu, and S. Wang. 2006. “Cooperative Hunting by Distributed Mobile Robots Based on Local Interaction.” In *Proceedings of IEEE Transactions on Robotics* 22(2): 403–407.

Chan Y.M., S. Wong, M. C. Foo, and R. Teo. 2004. “Engineering Intuition for Designing Multi-Robot Search and Rescue Solutions.” In *Proceedings of IEEE International Conference on Cybernetics and Intelligent Systems* 2: 1238–1242. Singapore

Christofides, N., A. Mingozzi, and P. Toth. 1981. “Exact Algorithms for the Vehicle Routing Problem, Based on Spanning Tree and Shortest Path Relaxations.” *Mathematical Programming* 20(1): 255–82.

Chung, T. and J. Burdick. 2007. “A Decision-Making Framework for Control Strategies in Probabilistic Search.” In *Proceedings of IEEE International Conference in Robotics and Automation*: 4386–4393.

Cortez, R. A., R. Fierro, and J. E. Wood. 2009. “Prioritized Sensor Detection via Dynamic Voronoi-Based Navigation.” In *Proceedings of IEEE/RSJ International Conference on Intelligent Robots and Systems*: 5815–5820. St. Louis, MO.

De Berg, M., M. van Kreveld, M. Overmars, and O. Schwarzkopf. 1998. *Computational Geometry (Algorithms and Applications)*. Springer Verlag Berlin Heidelberg.

DigitalGlobe. 2015. “The DigitalGlobe.” Last modified December 4. https://www.digitalglobe.com.

Elfes, A. 1989. “Using Occupancy Grids for Mobile Robot Perception and Navigation.” *Computer* 22(6): 46–57.

Ergezer, Halit and Kemal Leblebicioglu. 2014. “3D Path Planning for Multiple UAVs for Maximum Information Collection.” *Journal of Intelligent Robotic Systems* 73(1): 737–62.

Fierro R., C. Branca, and J. R. Spletzer. 2005. “On-line Optimization-based Coordination of Multi Unmanned Vehicles.” In *Proceedings of IEEE International Conference on Networking, Sensing and Control*: 716–721, Tucson, AZ.

Hope Hodge Seck. 2016. “Navy to Demo Swarming Drones at Sea in July.” *Militray.com*. http://www.military.com/daily-news/2016/06/24/navy-to-demo-swarming-drones-at-sea-in-july.html

Huang, W. 2001. “Optimal Line-Sweep-Based Decompositions for Coverage Algorithms.” In *Proceedings of the IEEE International Conference on Robotics and Automation*: 27–32. Seoul, Korea.

Hussain, Ejaz, Serkan Ural, Kyohyouk Kim, Chiung-shiuan Fu, and Jie Shan. 2011. “Building Extraction and Rubble Mapping for City Port-Au-Prince Post-2010 Earthquake with GeoEye-1 Imagery and Lidar Data.” *Photogrammetric Engineering and Remote Sensing* 77(10): 1011–23.

International Maritime Organization/International Civil Aviation Organization (IMO/ICAO). 2010. *International Aeronautical and Maritime Search and Rescue Manual* 3: 121–129. United Kingdom International Maritime Organization/International Civil Aviation Organization.

Jin Z., T. Shima, and C. J. Schumacher. 2006. “Optimal Scheduling for Refueling Multiple Autonomous Aerial Vehicles.” *IEEE Transactions on Robotics* 22(4): 682–693.

Karimoddini A., H. Lin, B. M. Chen, and T. H. Lee. 2011. “Hybrid Formation Control of the Unmanned Aerial Vehicles.” *Mechatronics* 21(5): 886–898.

Macwan, Ashish. 2013. “A Multi-Robot Coordination Methodology for Wilderness Search and Rescue.” Doctoral thesis, University of Toronto.

Murphy, Robin R., Satoshi Tadokoro, Daniele Nardi, Adam Jacoff, Paolo Fiorini, Choset Howie, and Aydan M. Erkmen. 2008. “Search and Rescue Robotics.” In *Springer Handbook of Robotics*, chapter 50, 1151-1173. Berlin: Springer-Verlag.

Parker, Lynne E. 2008. “Distributed Intelligence: Overview of the Field and Its Application in Multi-Robot Systems.” *Journal of Physical Agents* 2(1): 5–14.

Richardson, Henry R. and Lawrence D. Stone. 1971. “Operations Analysis during the Underwater Search for Scorpion.” *Naval Research Logistics* 18(863): 141–57.

Scharre, Paul. 2014. “Robotics on the Battlefield Part II - The Coming Swarm.” Center for a New American Security.

Schwab, James C. 2014. “Planning for Post-Disaster Recovery: Next Generation.” American Planning Association.

Sobel, Irwin. 2014. “An Isotropic 3x3 Image Gradient Operator.” Presentation at Stanford A.I. Project 1968.

Symington, Andrew, Sonia Waharte, Simon Julier, and Niki Trigoni. 2010. “Probabilistic Target Detection by Camera-Equipped UAVs.” In *Proceedings of the IEEE International Conference on Robotics and Automation*. Anchorage, AK.

Tan Choon Seng, Leon. 2017. “The Coming Age of Autonomous Systems – Reality or Science Fiction?” NS3021 Defense Capability Development Assignment, Naval Postgraduate School.

Tan Choon Seng, Leon, Ang Wee Kiong, Lai Wee Leong, See Hongze Alex, and Toh Ying Jie Benjemin. 2017a. “Detect to Engage Robotics Challenge.” ME4823 Cooperative Control of Multiple Autonomous Vehicles Project Report, Naval Postgraduate School.

Tan Choon Seng, Leon, Phang Chun Chieh, Preston Tilus, and Tan Yi Ling. 2017b. “Motion Planning with Probabilistic Roadmaps.” ME 3720 Introduction to Unmanned Systems Lab Report, Naval Postgraduate School.

Thrun, Sebastian, Wolfram Burgard, and Dieter Fox. 2005. *Probabilistic Robotics (Intelligent Robotics and Autonomous Agents).* Cambridge, MA: The MIT Press.

U.S. Fire Administration. 1996. *Technical Rescue Program Development Manual* (FA-159, 2/96). Emmitsburg, MD: Federal Emergency Management Agency, U.S. Fire Administration.

Wagner G., M. Kang, and H. Choset. 2012. “Probabilistic Path Planning for Multiple Robots with Subdimensional Expansion.” In *Proceedings of the IEEE International Conference on Robotics and Automation*: 2886–2892.

THIS PAGE INTENTIONALLY LEFT BLANK

INITIAL DISTRIBUTION LIST

1. Defense Technical Information Center
   Ft. Belvoir, Virginia

2. Dudley Knox Library
   Naval Postgraduate School
   Monterey, California