MULTI-ROBOT COORDINATION CONTROL METHODOLOGY FOR SEARCH AND RESCUE OPERATIONS

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submitted by **SEBAHATTİN TOPAL** in partial fulfillment of the requirements for the degree of
Doctor of Philosophy in Electrical and Electronics Engineering Department, Middle East Technical University by,

Prof. Dr. Canan Özgen
Dean, Graduate School of **Natural and Applied Sciences** _______________

Prof. Dr. İsmet Erkmen
Head of Department, **Electrical and Electronics Engineering** _______________

Prof. Dr. İsmet Erkmen
Supervisor, **Electrical and Electronics Eng. Dept., METU** _______________

Prof. Dr. Aydan M. Erkmen
Co-supervisor, **Electrical and Electronics Eng. Dept., METU** _______________

Examining Committee Members:

Prof. Dr. Erol Kocaoğlan
Electrical and Electronics Engineering Dept., METU _______________

Prof. Dr. İsmet Erkmen
Electrical and Electronics Engineering Dept., METU _______________

Prof. Dr. Veysel Gazi
Electrical and Electronics Engineering Dept.,IKBU _______________

Assist. Prof. Dr. Duygun Erol Barkana
Electrical and Electronics Engineering Dept., YTEU _______________

Asisst. Prof. Dr. Yiğit Yazıcıoğlu
Mechanical Engineering Dept., METU _______________

Date: _______________

I hereby declare that all information in this document has been obtained and presented in accordance with academic rules and ethical conduct. I also declare that, as required by these rules and conduct, I have fully cited and referenced all material and results that are not original to this work.

Name, Last Name: SEBAHATTİN TOPAL

Signature :

ABSTRACT

MULTI-ROBOT COORDINATION CONTROL METHODOLOGY FOR SEARCH AND RESCUE OPERATIONS

Topal, Sebahattin
Ph.D., Department of Electrical and Electronics Engineering
Supervisor : Prof. Dr. İsmet Erkmen
Co-Supervisor : Prof. Dr. Aydan M. Erkmen

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This dissertation presents a novel multi-robot coordination control algorithm for search and rescue (SAR) operations. Continuous and rapid coverage of the unstructured and complex disaster areas in search of possible buried survivors is a time critical operation where prior information about the environment is either not available or very limited. Human navigation of such areas is definitely dangerous due to the nature of the debris. Hence, exploration of unknown disaster environments with a team of robots is gaining importance day by day to increase the efficiency of SAR operations. Localization of possible survivors necessitates uninterrupted navigation of robotic aiding devices within the rubbles without getting trapped into dead ends. In this work, a novel goal oriented prioritized exploration and map merging methodologies are proposed to generate efficient multi-robot coordination control strategy. These two methodologies are merged to make the proposed methodology more realistic for real world applications.

Prioritized exploration of an environment is the first important task of the efficient co-

ordination control algorithm for multi-robots. A goal oriented and prioritized exploration approach based on a percolation model for victim search operation in unknown environments is presented in this work. The percolation model is used to describe the behavior of liquid in random media. In our approach robots start prioritized exploration beginning from regions of the highest likelihood of finding victims using percolation model inspired controller.

A novel map merging algorithm is presented to increase the performance of the SAR operation in the sense of time and energy. The problem of merging partial occupancy grid environment maps which are extracted independently by individual robot units during search and rescue (SAR) operations is solved for complex disaster environments. Moreover, these maps are combined using intensity and area based features without knowing the initial position and orientation of the robots. The proposed approach handles the limitation of existing works in the literature such as; limited overlapped area between partial maps of robots is sufficient for good merging performance and unstructured partial environment maps can be merged efficiently. These abilities allow multi-robot teams to efficiently generate the occupancy grid map of catastrophe areas and localize buried victim in the debris efficiently.

Keywords: Multi-robot, search and rescue, simultaneous localization and mapping, map merging, percolation theory, particle filter

ÖZ

ARAMA VE KURTARMA GÖREVLERİ İÇİN ÇOKLU ROBOT
KOORDİNASYON KONTROL METODU

Topal, Sebahattin
Doktora, Elektrik ve Elektronik Mühendisliği Bölümü
Tez Yöneticisi : Prof. Dr. İsmet Erkmen
Ortak Tez Yöneticisi : Prof. Dr. Aydan M. Erkmen

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Bu tez, arama ve kurtarma (AVK) görevleri için yeni bir çoklu robot koordinasyon kontrol algoritması sunmaktadır. Önceden herhangi bir bilgi sahibi olmadığımız karmaşık ve yapısal olarak düzenli olmayan felaket alanlarının hızlı ve devamlı olarak taranmasında zaman çok önemlidir. Göçüklerin doğası nedeniyle insanların bu alanda çalışmaları tehlikelidir. Bu yüzden, arama ve kurtarma görevlerinde çoklu robot kullanılarak felaket alanlarının keşfi gün geçtikçe önem kazanmaktadır. Hayatta kalanların konumlandırılması için robotların molozlar arasında kesintisiz ve kör noktalara sıkışmadan hareket etmesi gerekmektedir. Bu çalışmada, çoklu robotların koordinasyon ve kontrolü için hedefe yönelik öncelikli arama ve harita birleştirme yöntemleri önerilmiştir.

Ortamın ilk önce önemli bölgelerinin aranması etkili bir robot koordinasyonu için en önemli görevdir. Bu çalışmada, yaralının bulunması için sızma modeli tabanlı amaca yönelik öncelikli arama yöntemi önerilmiştir. Sızma modeli rastgele bir ortamda sıvının hareketini tanımlamak için kullanılmıştır. Bizim yaklaşımımızda, robotlar

sızma modeli ilhamlı kontrol mekanizması sayesinde yaralıyı bulma olasılığının en çok olduğu bölgeden başlayarak en az olduğu bölgeye doğru arama görevini devam etmektedir.

Enerji ve zaman yönünden arama ve kurtarma görevinin performansını arttırmak için yeni bir harita birleştirme yöntemi önerilmiştir. Harita birleştirme problemi, ızgara şeklindeki hücrelerin doluluğu şeklindeki haritaların tamamen birbirinden bağımsız hareket eden robotlar tarafında felaket alanından elde edildikten sonra birleştirilmesi olarak düşünülmüştür. Robotlar tarafından üretilen haritalar yoğunluk ve alan temelli özellikler kullanılarak ve robotların birbirlerine göre olan ilk konum ve yön bilgisi olmadan birleştirilmiştir. Önerdiğimiz yöntem literatürdeki şu eksiklikleri gidermektedir; robotlar arasındaki sınırlı miktarda örtüşen harita alanı verimli bir harita birleştirme için yeterlidir ve yapısal olmayan ve karmaşık çalışma alanlarının haritaları önerdiğimiz yöntemle birleştirilebilir. Bu kabiliyetler, çoklu robot takımlarına mümkün olan en kısa zamanda felaket ortamının haritasını çıkarma ve yaralıyı bulma olanağı sağlamaktadır.

Anahtar Kelimeler: Çoklu robotlar, arama kurtarma, aynı zamanda konumlama ve haritalama, harita birleştirme, sızma teorisi, parçacık filtresi.

to my family

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CHAPTER 1

INTRODUCTION

1.1 Motivation

Different natural or man made disasters yield catastrophe areas with many different characteristics such as variability of disaster from earthquakes, fires or terrorist attacks. Among these various characteristics, a common characteristic is that all disaster areas are highly complex, uncertain, vast in comparison to shortness of exploration time, and hardly measurable for search and reconnaissance tasks. There is no information about the internal structure of the disaster area and possible locations of buried victim. During search and rescue among rubbles of a disaster area, the location of survivor must be determined as quickly as possible and the environmental conditions for reaching victims must be determined as completely as possible so that rescuers can then enter the disaster area to reach and save the life of the located survivor. These requirements render the search and rescue operation more difficult.

Search and rescue operations can be hostile to human beings or trained dogs working within catastrophe areas due to unstable structures and/or leakage of dangerous gas or nuclear fumes which are the general characteristics of urban area disasters. Moreover human fatigue and even exhaustion are very common adversary to time critical search and rescue operations. Hence, robot usage, instead of human beings and trained dogs, becomes a must in these dangerous missions in disaster work spaces, thus, reducing the probability of human rescuers to be injured and increasing the efficiency of the task execution in time critical endeavor. The number of buildings which are affected by catastrophe can be very huge so that rescue teams, consisting solely of human beings, can be insufficient.

Recent technological developments on robotic hardware, software, control and communication abilities caused an increase in the use of autonomous robot usage in search and rescue operations, although they remain still highly inefficient in real world applications. Hence, in the last decade, a huge number of researchers have focused on the development of efficient multi-robot systems equipped with powerful sensors, actuators, computation abilities and control algorithms to help search and rescue teams which consists of human beings and trained dogs. Especially, robots with high navigation capabilities can penetrate through small debris volumes and rescue teams can generate the map of surroundings to give information about the internal characteristics of disaster area and the condition of survivor. Then, powerful robots can assist human beings to rescue buried victim from trapped position among obstacles.

However, some characteristics of the disaster areas and robot limitations (hardware and software) make the multi-robot search and rescue operation inefficient or unsuccessful in the sense of time and energy. First of all, disaster environments are highly uncertain, unstructured and there is no initial information about the location of the obstacles, victims and overall structural inventory of the catastrophe area being searched. Hence, multi-robot system has to navigate in the disaster area intelligently to localize buried victim without traversing complete mission area and get trapped into narrow holes.

Other challenging problems are the uncertainties of robots and environments such as limited and noisy sensor measurements, unpredictable and hard environmental conditions, mechanical failures of robots and some uncertainties caused by algorithmic approximations. These limitations and uncertainties make search and rescue operation difficult using multi-robot systems and they have to be solved to obtain an efficient and successful multi-robot search and rescue operations.

1.2 Objective

Te main objective of this dissertation is to develop a prioritized goal oriented multi-robot coordination control mechanism for search and rescue operations to localize buried victims as quickly as possible in a disaster area. In this solution, robots enter the vast disaster region from different parts bearing different initial orientations and position and they will start their individual exploration mission by generating their own occupancy grid environment maps of traversed regions and estimating their position. This task is time critical, so robots have to avoid redundant exploration. Hence, each robot will need a prioritized coordination control strategy to find safe navigation path throughout obstacles.

To increase the efficiency of the decentralized exploration task in the sense of time and energy, robots have to exchange their partial maps extracted from different parts of the work area, with the ground station where those maps are merged toward the formation of a globally consistent environment map. This ability provides extra information about other part of the disaster area. Main goals about victim search operation are described in Section 1.3 in detail.

1.2.1 Problem Characteristics

The most important distinguishing features of disaster environments are about internal structure where a lot of different shaped and sized obstacles are scattered randomly. There can be small voids, obstacle crowded areas and dead ends which are very dangerous for robot units. Robots can be trapped into there while they are passing throughout them.

Generally, there is no initial information about the location of the obstacles, buried victims and overall structural inventory of the area being searched. These environmental uncertainties make task execution more difficult.

Another characteristic of multi-robot search and rescue operation is about the uncertainties in robots distance measurements and encoder reading errors. During the exploration operation, some sensor may crash or their noise bounds may vary according to time and location. Communication signals are generally scattered within rubbles and may easily be obstructed. Moreover, the ground station has to merge partial occupancy grid maps under the different sensor models and noise bounds of different robots. Hence, simultaneous localization and mapping of robot units can be very difficult using noisy distance measurements and wrong encoder readings.

On the other hand, in order to increase the efficiency of the overall multi-robot system, robots have to enter disaster area from different parts and they have to generate their own environment map independently from each other, i.e., each robot have its own mapping reference frame. During the search and operation, robots can notice each other using communication ability and they exchange generated partial occupancy grid map of traversed region to obtain a global and consistent environment map. However, robots do not have initial position and orientation information of other robot units at the beginning of the exploration. Hence, robots have to estimate their initial position and orientation in the disaster area to obtain global environment map.

1.3 Goals

In this section, three main problems that have to be solved for efficient multi-robot search and rescue operations are described, namely; simultaneous localization and mapping, intelligent coordination control of robot team units and decision making on navigation path of each robot, and finally merging partial occupancy grid map of traversed regions.

1.3.1 Simultaneous Localization and Mapping

Autonomous disaster environment map generation and the estimation of robot location are two important tasks for real world search and rescue applications where global positioning data (GPS) is not available, such as semi-collapsed buildings. In Simultaneous Localization and Mapping (SLAM) problem, robots try to answer simultaneously the questions of *"What does the mission environment look like?"*, and *"Where am I in the disaster area?"* by using noisy range sensor measurements obtained from completely unknown environments and noisy traveled distance measurements coming from sensors. Simultaneous localization and mapping problem is a kind of chicken-and-egg problem, which makes the problem very difficult to solve. Because each robot needs a correct environment map to localize itself accurately in the work space, however robots also need their exact position and orientation informations to generate an accurate environment model representation.

During the simultaneous localization and mapping operation, robots have to deal with some source of uncertainties: 1) sensors have physical limitations such as range and resolution. They are subject to noise because of hard environmental conditions. 2) Second source is about actuators of the robots; mechanical failures or wear-and-tear noises can lead to noise into motion model of the robot system. 3) Finally algorithmic approximations, model errors and computational complexities are other source of uncertainties. Hence, robots can not estimate easily their position and environment map.

1.3.2 Intelligent Coordination Control of Robot Team Units for Buried Victim Localization

In order o localize buried victim as soon as possible, each robot team unit has to cooperatively navigate in the mission space using generated occupancy grid environment map of the disaster area. Hence, robots have to answer the question of *"Where do I have to navigate next to localize and rescue buried victim"*. In order to avoid multiple area coverage, each robot path has to be different as much as possible. Exploration of the same disaster region by multiple robot reduces the efficiency of the overall multi-robot search and rescue system in the sense of time and energy. To find buried victim as soon as possible, each robot primarily explores the big and connected free voids of the mission space. The possibility of finding living beings in these areas is higher than obstacle crowded spaces. Since robots can be trapped into obstacle crowded regions, task execution can be failed completely. The proposed system needs prioritized exploration strategy which force robots to explore big, free and connected voids. Since robots can only traverse a region if connected passages are available within the unstructured labyrinth of the rubbles.

1.3.3 Occupancy Grid Map Merging

Efficiency of the proposed system comes from the coordination and cooperation between robot units leading to the integration of partial maps which are generated by robot team members operating in different parts of the same mission area which leads to highly disparate maps when catastrophe areas are large. Each robot enters the disaster area from totally separate regions and independently explores and extracts the maps of different parts of the environment. When such robots exchange their partial occupancy maps of their exploration surroundings, it becomes extremely difficult to merge them, since, initial position and orientation of each robot is not known by other robots, i.e., each robot's reference frames for mapping are completely different. Hence, map merging problem in these situations are attempted after a preprocessing through translation and rotation that tries to align the robots local mapping frames. The preprocessing steps generally include first the detection of possible common features in each maps to be merged; then the computation of the translational and rotational difference between robot maps followed by the map of one robot being rotated and translated with respect to another robot's map taken as first priority.

1.4 Methodology

The objectives of the efficient multi-robot SAR methodology for complex and unknown disaster areas are given in Section 1.3, Particle filter (PF) based SLAM algorithm is used to generate environment map and estimate the position of the robots. Particle filter, as a popular nonparametric filter, relies on the approximation of robot state by predetermined number of particles to work on multi model form of posteriors and it handles the limitation of other SLAM methodologies such as :Gaussian noise assumption, the amount of uncertainty should be small; otherwise there occur huge errors because of linearization.

In our multi-robot exploration strategy, we use the occupancy grid map model to represent the internal structure of the disaster area. Environment is divided into grid cells in occupancy grid mapping methodology and occupancy of each grid cell is estimated independently from other cells. This discretization allows robots to extract environment map without using any features like corners, walls and predefined landmarks. Another advantage of occupancy grid mapping is the possibility of modeling unknown space of the environment. This ability is very important for exploration of unknown and complex environments where feature extraction is very hard or impossible due to physical constraints and huge number of uncertainties. This is because feature extraction may not be possible in disaster areas due to environmental and robotic uncertainties. Occupancy of a grid is a numerical value representing the posterior probability of a grid cell being occupied. Every grid has three states: occupied 1, free 0 and unknown 0.5. This provides a simple spatial representation of the mission environment.

The main idea of coordinated multi-robot exploration is to create possible moves for each robot according to connected free upcoming cells. Then, each robot selects the best one for itself to explore altogether cooperatively the mission area as much as possible and localize buried victim as soon as possible.

Percolation model inspired navigation control strategy is used to explore mission space in the presented methodology. In the literature percolation theory is used to model water flow in a porous medium. In this approach, if we consider victim search environment as a large and disordered porous medium, each robot try to find connected and free clusters with good porosity to reach a possible buried survivor. Robots can change their exploration direction when the obstacle density exceed predetermined threshold value toward another part of the disaster area. The motion of the robot in a collapsed building can be interpreted as the propagation of water in a porous medium. Robot exploration direction has to be guided into connected voids and safely spaces, because the likelihood of finding any survivor around such searchable regions is higher than small voided area. The presented approach is motivated by a prioritized exploration that is required when searching is done within rubbles with the aim of maximum possible coverage without getting trapped to the dead ends based on the structural characteristics of the disaster area.

The methodology for the last goal is about the partial occupancy grid environment map fusion to obtain global more complete map representation of disaster areas. The proposed map merging methodology is based on extracting invariant substructures called key-points in the each robot's occupancy grid map of disaster area. Key-points which are invariant to rotation, translation, even when generated maps contain significant amount of noise, have to be located in each robot map. These points which posses valuable asset for merging maps due to their invariance are used as a virtual landmark to find rigid transformation between individual robot maps. Robot maps can be merged easily by alignment of them using calculated transformation and addition operation based on these key-points.

We introduce two distinct key-point localization and matching approach, namely intensity and area based. Intensity based key-point localization give good performance especially for robots which have same distance measurement devices. However, robots can have different sensing abilities, for example, some distance measurement sensors can crush during the task execution or noise margin of sensors may be different from that of other robots. Hence, maps of same environments can be different and intensity based feature extraction can be limited in these cases, so area based key-point localization methodology is proposed to overcome these limitations. Some important features of disaster area obstacle properties such as area, orientation and center of mass are used to merge partial robot maps.

Our proposed approach handles the limitation of existing works in the literature such as; limited overlapped area between local map of robots is enough for good merging performance and unstructured and complex partial environment maps can be merged efficiently and successfully. These abilities allow multi-robot teams to efficiently generate the occupancy grid map of catastrophe areas and localize buried victim in the debris as soon as possible.

1.5 Main Contributions of the Thesis

The major contributions of this dissertation can be summarized as follows:

- A novel multi-robot coordination control methodology is developed for complex, unstructured and completely unknown disaster environments to localize buried victim in the debris efficiently. Robots can cooperatively extract the internal structure of the catastrophe area using prioritized exploration strategy and they can localize buried victim without traversing entire area. Existing works in the literature have focused on only the coverage of structured environments in a minimum time. However, maximum area coverage is not primary issue in the introduced strategy.

- Percolation model and entropy based hybrid navigation controller is presented for the navigation control of each robot for search and rescue operations. Percolation generates quick penetration of the robot units into unexplored free part of the disaster area. Thus, in this prioritized exploration, coverage does not become a primary issue. There, the optimality of both time and spatial exploration is achieved using guidance through prediction of upcoming voids. The proposed method guides robots navigation toward the biggest cluster of connected voids in the disaster area using a percolation model based controller.

- A new intensity and area based hybrid map merging algorithm is proposed for merging partial occupancy grid maps of each robot unit. Our proposed approach handles the limitation of existing works in the literature such as; limited overlapped area between partial maps of robots is enough for good merging performance and unstructured and complex partial environment maps can be merged efficiently. These abilities allow multi-robot teams to efficiently generate the occupancy grid map of catastrophe areas and localize buried victim in the debris.

1.6 Organization of the Thesis

This thesis is organized as follows:

Chapter 2 summarizes related work on search and rescue robotic field to show requirement of goal oriented multi-robot exploration algorithm development by giving detailed literature survey on search and rescue robotics, simultaneous localization and mapping, intelligent exploration of the task space by multi robots, coordination control, occupancy grid map merging and communication types between robot units.

Mathematical background about Particle filter, motion and measurement model of robot's sensors, and occupancy grid mapping methodology are presented in Chapter

3. These mathematical tools and algorithms are used frequently in the remaining parts of the thesis.

Chapter 4 develops the proposed percolation inspired prioritized multi-robot victim search and rescue methodology and the partial occupancy grid map fusion strategy in detail.

Chapter 5 provides and discusses simulation experiments to evaluate the performance of the proposed percolation inspired multi-robot exploration strategy to localize buried victim in the wide and unstructured disaster area, considering different catastrophes scenarios. Different number of robots is used in simulations and sensitivity analysis of the presented algorithm is provided in detail.

Finally, Chapter 6 concludes the thesis and gives the main contributions of the dissertation in summary. Future works that this thesis may lead to, is presented in this part.

CHAPTER 2

RELATED WORKS

Mobile multi-robot networks are relatively young and a challenging area of robotic research. Their primary aim is to collect and communicate environmental data for cooperatively monitoring and controlling their physical surroundings. Cooperation between networked mobile robots as well as cooperation of nodes within a network are becoming more robust, fault tolerant and enable adaptation of the networks to changing environment conditions. Many applications have emerged in a variety of fields such as [1]:

- *Surveillance*: In the last years, security of the borders gaining importance in the world. Hence, autonomous multi-robot usage in the surveillance of terrorist attacks is a hot topic in robotic field.

- *Military applications*: Smart and high navigation capable robot development and coordination of them is very important in military applications.

- *Space explorations*: To obtain information about life and structural characteristics of other planets, usage of robots is increasing. However, rapid temperature changes, the lack of gravity and uncertainties about the work space makes this usage harder.

- *Search and Rescue*: There occurs a huge amount of man made or natural disaster in the world where human beings can be insufficient to overcome all of them. In those dangerous situations, robot usage can be very efficient for victim search and rescue in wide disaster areas.

One of the main application areas of mobile robot teams is about search and rescue operations in disaster environments such as collapsed building after an earthquake or terrorist attack. Figure 2.1 shows the number of SCI indexed search and rescue robotic related publications which is obtained from Web of Science between the years 2000 and 2010. The popularity of this topic is increasing year by year. As different kinds of catastrophe occur in nature such as earthquakes, landslides and fires, usage of networked robot systems gaining great importance for these disaster situations [2].

Robots consistently can help humans in dangerous and complex tasks, providing information about areas that cannot be directly reached by the humans and trained dogs, especially in disaster areas, which are typically highly unstructured and uncertain. Search and rescue teams made of living beings such as human, dogs, have the main disadvantage of tiredness from continuous and tedious long hours of works, so robotic aids are increasingly being considered day by day in buried victim search and rescue tasks.

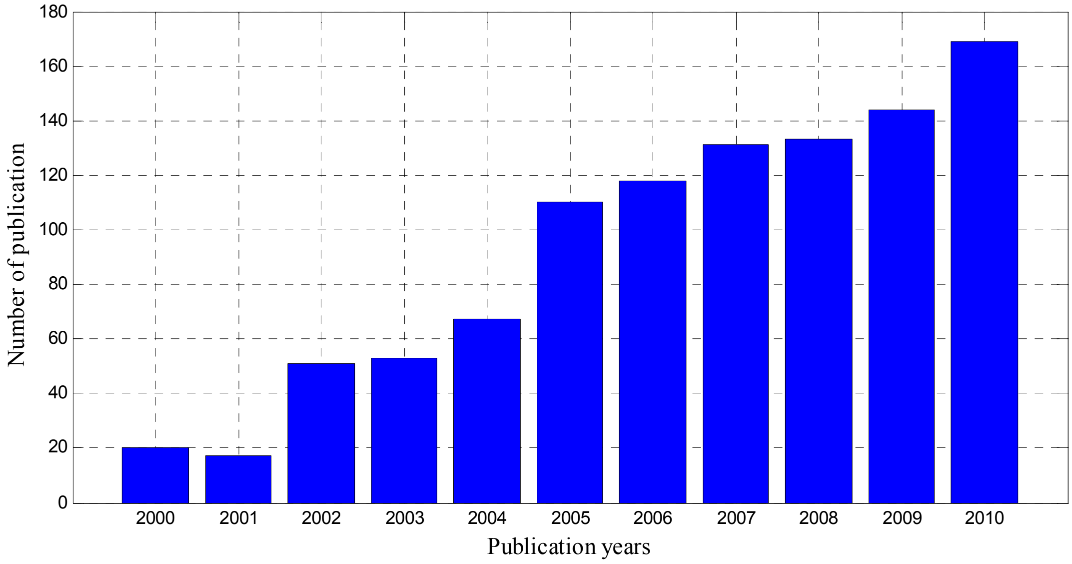


Figure 2.1: The number of SCI indexed publications on search and rescue robotic research in the Web of Science from 2000 to 2010.

The most important search and rescue task for networked robot teams in a disaster environment is the localization of buried victims within the disaster rubbles, so as to provide information about the condition of detected possible survivors in the disaster areas not easily reachable by human beings. Heterogeneous networked robot teams were constructed by Sato *et al.* [3] to control each robot unit to find survivors. They have mainly focused on mechanical construction of robot team units. Presented heterogeneous rescue teams are composed of three kinds of search and rescue robots, each of them equipped with different abilities: MA-I is a track type inspired from tanks and is remotely controlled by an operator over a radio signal, IGA is a track type with flippers, which gives the ability of navigation in rough terrain, and KOHGA is a snake-like robot which penetrate into small voids in the debris and can search for survivors with high navigation ability. Differently structured robots (MA-I, IGA, KOHGA) are used to improve mobility with the help of the robot's flippers, snake-like motion and the capability of physical support. For example, when a robot is trapped into the rough terrain by obstacles and cannot recover its mobility, other robot team members can give physical support to the trapped robot during its escape from its failed position. This improved robustness in mobility has promising capabilities for safe navigation in challenging unstructured environments.

Any system that is not affected by a single point failure (either in communication or in robot coordination control by failure of some units) is called a fault tolerant system, which is a very crucial property especially for decentralized systems such as networked mobile robots undertaking strategic and complicated tasks. Homogeneous centralized systems composed of robots with the same capabilities, both hardware and software wise, are more fault tolerant then heterogeneous ones since the failure of a robot member can be easily compensated by other network members that are identical to the failed one. However, homogeneous robotic systems cannot adapt themselves easily to complex and high level tasks where cooperation of different skills is required. This is the primary motivation behind the emergence of heterogeneous robot networks.

Parker [4] introduced a pioneering work on fault tolerant multi-robot coordination control method in heterogeneous robot networks. In their system, each robot has overlapping capabilities with other team members and adapts its actions using sensory feedback from the execution tasks related with each robots internal state and environmental conditions. Motivational behaviors are used to monitor task progress level and new tasks are dynamically distributed according to the state of the task accomplishment. Another fault tolerant multi-robot coordination system which is called *ALLIANCE* has been developed by Parker [5] for different multi-robot applications like box pushing and target tracking. The validity and fault tolerant capability of the introduced methodology is demonstrated using simulation and real world robotic applications.

Another problem for search and rescue teams is the mechanical development of robot platforms, since some of the robots need to be small and have high mobility while others need to be powerful and robust. Simple small devices are used for debris exploration making use of their high maneuvering capabilities and powerful robotic devices are used for treating heavy debris, opening passages and carrying victims out of collapsed buildings. There are various types of rescue robots, being either autonomous or human operated [6, 7, 8]. The Helios VII arm-equipped tracked vehicle is a simple yet robust robot developed by Guarnieri *et al.* [6] to explore debris. It has a mounted arm that assists the motion of the robot and can also be used for manipulation. The robot navigates through very harsh environments with the help of its tracks. For example, turned upside down, it is able to flip over using the mounted arm. In [7], Tanaka *et al.* reported a high power search and rescue robot to move big and heavy obstacles and to carry a victim out of debris as soon as possible using a high-pressure hydraulic actuator. After the localization of victims by a small robot with a high capability for maneuver, powerful robots carry the survivor out of the debris or helps human beings in the transportation of heavy obstacles. However, very limited work exists in the robotic literature about coordination of these mechanically constructed robot units for victim search and rescue operations in hard disaster areas.

Existing works about Search and Rescue (SAR) robotics is summarized in the above part of the thesis. In this work, we focus on software prototyping of search and rescue robot team coordination control algorithm to explore disaster area efficiently in the sense of time and localize buried victim. Hence, literature survey about problems that multi-robot search and rescue team have to solve during the SAR operation is presented in the upcoming parts of the thesis. Simultaneous localization and Mapping, intelligent exploration of the task space, coordination control, occupancy grid map merging and communication types between robot units which are the main goals of our proposed methodology as well are surveyed in detail.

2.1 Simultaneous Localization Mapping and Exploration

In Simultaneous Localization and Mapping (SLAM) problem, robots try to answer simultaneously the questions of "What does the mission environment look like?", and "Where am I in the disaster area?" by using noisy range sensor measurements obtained from completely unknown environments and noisy traveled distance measurements coming from encoders of the robot wheels.

Smith *et al.* [9] proposed an Extended Kalman Filter (EKF) based SLAM method for estimating the posterior distribution over robot position along with the positions of landmarks in the disaster environment. It is an initial work that established the fact that there is a statistical relationship between each predetermined landmark location and observation. Assumptions made by a Kalman Filter (KF) are that noise in the system is Gaussian distributed with zero mean and the process of the system is linear. These are quite error prone considerations for complex real world search and rescue robotic applications. Since, search and rescue robot systems are highly nonlinear and the noise models involved in the KF can be multi model, and not only Gaussian.

Linearity constraint is overcome by the extended version of KF, namely the Extended Kalman Filter (EKF), which is used considerably for the solution of SLAM problems in the literature [10, 11, 12]. Although EKF based SLAM methods are historically the earliest used approaches that work well for environments in which there should be limited number of features and landmarks, computational complexity increases with an increasing amount of features. Hence, computation burden and Gaussian assumption in the probability density function are the shortcomings of the EKF based SLAM algorithms [13, 14]. For initially unknown and complex environments, feature extraction can be very hard or may not be possible. Hence, in these environments, EKF based SLAM solutions may not be feasible.

An alternative Particle Filter (PF) based method for SLAM problem was introduced by Montemerlo *et al.* [13, 15]. Particle filter based approaches are approximations of Bayesian Filters such that probability distributions are approximately quantized by a finite set of particles [16]. Thus, arbitrary multi modal distributions can be approximated by using a sufficient amount of particles. The most advantageous characteristics of PF for SLAM problems are the ability of handling nonlinearities and non-Gaussian noise. However computational complexity increases with the number of particles, which makes the real-time implementation of PF difficult in complex and hard real world applications. Hence, the FastSLAM method, which is a modified version of PF, has been proposed to handle the computational burden in classical particle filter methods to successfully implement on real robots [13]. This proposed method utilizes a Rao-Blackwellized representation which integrates PF and KF representations. FastSLAM uses PF to estimate the robot navigation path and each particle runs EKF to estimate map feature locations. Since each particle generates an individual map representation of the work environment, the FastSLAM algorithm suffers from memory constraints. To improve the memory efficiency of the method, genetic algorithm based improved Rao-Blackwellized approaches are proposed by Feng *et al.* [17].

Due to advantages of Particle Filter described in detail above, Particle Filter based Simultaneous Localization and Mapping solution is developed in the proposed multi-robot victim search and rescue operation.

2.2 Exploration

In order o localize buried victim as soon as possible, each robot team unit has to cooperatively navigate in the mission space using generated environment map of the disaster area. Hence, another important task for networked multi-robot systems in the mission space is not only penetration of the new area ahead but mainly, exploration. Unfortunately, numerous researches are using single robot systems to simultaneously explore and create maps in an unknown environment such as search and rescue areas [18, 19, 20]. The most important disadvantage of single robot usage is that it takes much more time than networked robot systems. Time efficiency in the distributed system comes from task partitioning and coordination between robot units. Another disadvantage of the single robot is about the robustness of the system. Task execution is completely failed in the case of robot breakdown or when roots get trapped. Finally, single robot systems cannot overcome environment and sensor uncertainties. Coordinated multi-robot systems win over single robot approaches, dealing with limited communication range, map merging into a better global map of the workspace and better time constraints [21, 22].

To date, the major portion of coordinated search and rescue exploration works has focused upon coverage of an entire disaster area in minimum time [23, 24]. These techniques are based on the selection of the best next observation point for each robot in order to reduce the uncertainty of the environment map. Frontier cells, which are the cells on the borders between explored and unknown space, are taken as possible next observation points, because robots can obtain much more information by navigating toward unknown space [24]. Existing methodologies dwell on SLAM solutions that minimize only the cost of reaching the target observation point and expected information gain. Entropy based methodologies are geared toward optimal data acquisition for localization but with very limited exploration. These methods do not use any environmental structure and data as a control feedback to force robots toward buried victim who is trapped into obstacle crowded area [23]. There is no guidance on the exploration direction of SAR robots to execute given task.

Any additional information about the aim of the exploration, such as prior information about the work environment, can be a valuable guidance for the exploration. Preferred regions with the highest likelihood for finding victims can give a priority to the exploration, called prioritized exploration. A novel active exploration methodology is developed in this thesis based on percolation guidance, where a percolator estimates the existence of connected voids in the upcoming yet unexplored region ahead of the robot, so as to increase the efficiency of the reconnaissance operation by the superior ability of the percolator guidance for speedy coverage of the area [25]. However, in proposed prioritized exploration approach, coverage does not become a primary issue. There, space coverage and time optimization are mainly aimed through guidance, based on either prior knowledge, or on extra information reflecting the characteristics of the environments that lead to the estimation of connected voids by a percolator for the areas to be explored. These techniques have high map coverage accuracy, while being adversely affected by errors in robot localization that would be minimized if exploitation was done.

2.3 Coordination Control

Coordination between multi-robots means that they cooperate to achieve a given common goal. The usage of multiple robots has several advantages over single robot systems: cooperating robots have the potential to achieve a given task faster than a single robot by working in parallel [26]. Complex and high level tasks such as search and rescue operations cannot be accomplished efficiently by a single robot even if they have high sensing and actuation capabilities. Moreover, the overall performance of the solution for a single robot system cannot be improved, while for a network of robot unit's coordination and cooperation enhance the efficiency of the system performance in the sense of time, energy and data fusion [27, 28].

In the literature, multi robot systems are categorized according to their coordination level, as fully coordinated, weakly coordinated and not coordinated. Coordinated robot networks are classified into centralized and decentralized [29]. Many control tasks are based upon the partitioning of the mission into different subtasks, which are then assigned to individual robots by a central unit or leader [30, 31]. However, these systems do not handle the problem of distributing resources among robots. In centralized methods, a robot works as a "leader"and group members send their acquired information to the related unit. The leader, in turn, plans optimal actions for each of the group members. In this case, robot units act only according to the leader's commands. Although in such cases coordination control of robots can be perfect and all the important information can be used by the team members, these methods are computationally hard and have a heavy communication burden [32, 33]. An increase in complexity is drastically proportional to the number of robots and this makes the usage of these systems difficult in real-time application. Moreover, these systems are not robust in cases of single point failures, and if there is a problem with the leader's abilities such as communication errors or physical crash, the task cannot be completed by any of the remaining robots.

On the other hand, in decentralized systems such as in our proposed goal oriented exploration methodology, each robot unit is autonomous in the decision-making process as in works [34, 35] and executes a coordination protocol, while taking independent decisions. Since these systems are generally more robust to communication and group member failures, accomplishment of the task is not affected by a single point of failure, which gives the opportunity to use this architecture in real world applications [36]. However, disadvantages exist in distributed systems as well, such as integration of local task accomplishments toward a global aim. For example, partial environment maps, constructed by individual robot units, have to be merged to obtain global map. We developed coordinated and decentralized multi-robot systems due to robustness and efficiency properties.

2.4 Map Merging

Especially for SAR operations in wide, unstructured and hardly unknown catastrophe environments, mapping which is the process of incrementally extracting a map of the surrounding is a very crucial job to be undertaken during autonomous navigation of robots. SAR multi-robot systems are often suggested for mapping tasks due to many advantages such as energy and time efficiency over single robot systems [37, 38, 39]. Efficiency of the system comes from coordination and cooperation between robot units leading to the integration of partial environment maps which are generated by robot team members operating in different parts of the same mission area which leads to highly disparate maps. The necessity of map merging ability is increasing when catastrophe areas are large, complex and initially completely unknown. Robots can obtain an integrated information about the internal structure of other parts of the environment using merging environment map of other robots with their own individual map.

In multi–robot search and rescue operations, each robot enters the work space from totally separate regions and they independently explore and extract the maps of different parts of the environment. When such robots exchange their partial maps of their exploration surroundings, it becomes extremely difficult to merge them, since, initial position and orientation of each robot is not known by other robots, i.e., each robot's reference frames for mapping are completely different and independent. Hence, map merging problem in these situations are attempted after a preprocessing through translation and rotation that tries to align the robots' local mapping frames. The preprocessing steps generally include the detection of correspondence points that we call, key points, and the computation of translational and rotational difference between robots maps followed by the map of one robot being rotated and translated with respect to another robot's map taken as first priority. Map merging for a large SAR environment based a multi-robot system remains still a challenge and if such a merging could acquire high accuracy, which is still the focus of many nowadays works, then disaster area coverage would be achieved in a decentralized manner generating the inventory of the disaster leading to a faster localization of possible survivors.

Many researchers have worked on merging maps obtained by individual robots that start exploration from different parts of the same environment and extract the map of the surroundings independently with respect to their own reference frames [40, 48, 49, 50, 51]. Some simplifications are brought to the problem by basing the map merging on features such as doors, junctions, and corners [49, 50]. Although these works have demonstrated the success of feature based map merging methods for multi-robot systems, these approaches remain unfeasible for unstructured and complex work environments, because feature extraction is very hard to carry out in such unstructured areas where prior information does not exist. Moreover, predefined landmarks can be destroyed by the disaster and sensors cannot detect them due to environment and robot sensor measurement uncertainties.

Hence, some researchers have focused on occupancy grid based mapping approaches for modeling the disaster environment and merging the partial robots' maps [40, 48] in order to overcome the disadvantages of feature based mapping methodologies. Occupancy of each grid cell is a numerical value representing the posterior probability of the cell being occupied, estimated independently from the other cells. This provides a simple spatial representation of the environment. So far, several map merging methods have been proposed for occupancy grid maps generated by autonomous robots [40, 48, 51]. Carpin *et al.* [40], developed an iterative method to combine partial occupancy grid environment maps, in which the map of the second robot is translated and rotated in the space of possible rigid transformations on the map of the first robot, with the aim of maximizing overlapped region between robot maps using a similarity metric. This approach guarantees to find the optimal solution when the number of map merging iterations tends to infinity which is not feasible for real time and complex robotic applications like victim search and rescue operations where time is critical and extremely bounded.

In order to improve the efficiency of the proposed algorithm in the sense of time, Carpin [48] presented a new non-iterative and fast method using spectral information of generated occupancy grid maps. Hough transform is performed to detect the orientation of each occupancy grid map and translation information is obtained from two signals which are the projections along the x and y direction of the two maps. Although, this spectral information based technique is fast and accurate compared to the previous iteration based method [40], it still has also some limitations. In this method, it is essential that two partial occupancy grid maps being merged, exhibit a considerable amount of overlapping region in order to have successful map merging and moreover, the mapped environment has to be well structured which means that the mapping area consist of only straight walls and corridors, not only obstacles. So, these limitations and especially the second one make their proposed occupancy grid map merging methodology unfeasible for unstructured and complex search and rescue areas like collapsed building due to earthquake where walls and corridors are destroyed within rubbles.

Due to limitation of the existing disaster area map generation and map merging methodologies described above, a novel occupancy grid map merging strategy for multi-robot SAR systems is developed in this thesis to handle the above presented problems in the literature.

2.5 Communication

Communication between robot units in the network is essential for real world SAR robotic applications because of situational awareness of the overall system. In particular, cooperation and coordination in networked multi-robot systems requires a robust communication ability to accomplish a given mission accurately. Communication methods in networked robot systems are classified as implicit communication, also called stigmergy, and explicit communication. The effect of communication on the system performance is shown in a variety of works; non verbal communication efficiency in human robot teamwork [41], target search task performance evaluation with no communication, reflexive and deliberative communication [42], communication range effects on robot search task on two distinct search algorithms which are spiral search and informed random search [43].

Çayırpunar *et al.* [43], developed a cooperative search method in complex environments and showed the effect of communication in the target search mission on real experimental setups. In these experiments, e–puck robots try to find a hidden object via explicitly communicating with their local neighbors. They concluded that the system performance improves with increasing communication range, in terms of the task accomplishment time. Robots can exchange information about the other robots internal states and environmental conditions via explicit communication protocols, which also improves the system performance. Meanwhile, this yields a considerable computational burden to the robot team and these systems may not be robust to single point failures in centralized systems.

Explicit communication is achieved using special standard communication protocols. Environmental conditions are important for explicit communication especially in indoor applications such as search and rescue operations; reliability and robustness may be corrupted due to noisy or failed signals in explicit communication techniques as seen in some special cases of references [44]. For example, in a semicollapsed building, communication signal strength can be very strong only until one meter, whereas in outdoor environments, communication signals can generally easily cover 50 m with full bandwidth. Explicit communication approaches are also not suitable in the sense of scalability characteristics because of communication load and computational complexity [45].

In implicit communication techniques, information transmission is accomplished the environment or via the observation of robot behaviors. Implicit communication based approaches were first introduced by Balch *et al.* [46], who showed that there is no need for explicit communication in some task executions. Their communication strategy is inspired from biological systems such as social behavior of animals, and they proved that explicit communication is unnecessary in graze tasks. Although implicit communication is simple, it can suffer from limitations in robots sensing abilities.

Swarm robotic researchers have focused upon implicit communication to obtain emergent cooperation. This provides the opportunity for the colony's control algorithm to be scalable to large numbers. Anderson and Papanikolopoulos [47] presented an implicit cooperation methodology for networked robots search in unknown areas with a reactive, layered architecture composed of three behaviors; namely, obstacle avoidance, stall recovery, and search. Each robot selects its next search area in the border of a locally sensed area so the algorithm bases upon local experience rather than the collective experience. It is proved that selection of local search goals increases the system performance, because it reduces interference between robots.

CHAPTER 3

MATHEMATICAL BACKGROUND

This chapter overviews the mathematical background which it is used frequently throughout our proposed decentralized goal oriented multi-robot coordination control algorithm for victim search and rescue operations. First, Particle Filter which is a recursive Bayesian nonparametric filter for eliminating noise in measurement and motion of robots is introduced. Secondly, the general basic Simultaneous Localization and Mapping problem is formulated and its algorithm is given. Finally, occupancy grid environment mapping, motion model of the robot units and sensor models which are used in the SLAM algorithm are presented to generate environment model and estimate position of the robot in the search and rescue task space.

3.1 Particle Filter

Particle filter (PF) as a recursive state estimation technique of a dynamical system is a nonparametric implementation of the Bayes Filter. It is widely used for probabilistic robotic applications such as Simultaneous Localization And Mapping. Some source of environmental and robotic uncertainties like distance sensor measurement corruption, actuation errors of robots, and algorithmic approximations require a probabilistic estimation methodology such as PF. Distance measurements of robots and encoder reading of wheels can be corrupted by source of errors in especially hard and complex disaster environments.

The purpose of the Particle filter is to represent each robot state using predetermined number of particles such as in Equation 3.1 which is an approximate representation of robots' belief. Since it is a nonparametric representation, multi modal functions can be represented using PF such as in Figure 3.1 while other estimation techniques such as KF and EKF are restricted with Gaussian distribution assumption. This multi-model function representation ability is the main advantage of the PF. Another advantage of sample based representation of the PF is about the capability of modeling nonlinear transformations [37].

$$X = [\ \{x^i, w^i\}\ |\ i = 1, 2, 3, ..., N\ ] \tag{3.1}$$

The state representation of the robot units is done using set of weighted samples as in Equation 3.1, where x^i is about the state of the i^th particle and w^i is the corresponding importance weight which is a non zero factor. The summation of those weights is equal to one. This importance factor shows the importance degree of the corresponding particle x^i (state of the robot unit).

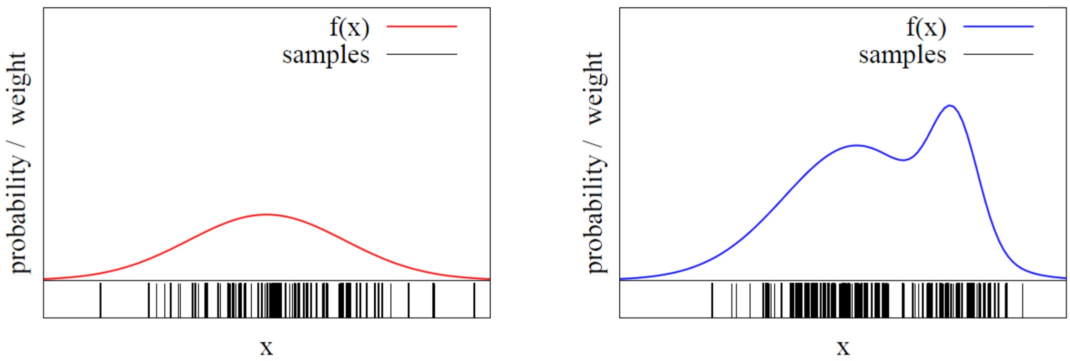


Figure 3.1: Particle based representation of two functions [37], Gaussian and multi-model functions, respectively.

The most general Particle Filter algorithm is given in the following Algorithm 3.1.1. There are three inputs for Particle Filter algorithm; previous state which is represented by set of particles X_{t-1}, most recent action u_t of the robot unit given by actuators and last distance sensor measurements z_t. The output of the PF is most recent state related particles.

There exist three main subparts in the particle filter algorithm; namely, sampling of the particles, importance factor and finally resampling of particle set.

1. *Sampling*: Generation of current state x_t using most previous state x_{t-1} and actuation signal of the robot u_t. This step is done by making sampling operation on state transition function of each robot $p(\ x_t \ | \ u_t, \ \ x_{t-1} \ )$.

2. *Importance Factor*: Importance of the particle represented by w is calculated using measurement probability $p(z_t|x_t)$.

3. *Resampling*: This step discard lower importance related particles to increase the performance of the state estimation.

Algorithm 3.1.1: PARTICLEFILTER(X_{t-1}, u_t, z_t)

$\widetilde{X}_t = X_t = \emptyset$

for $m \leftarrow 1$ **to** M

$\quad$ $sample\ \ x_t^{[m]} \approx p(\ x_t \ | \ u_t, \ \ x_{t-1}^{[m]} \ )$

$\quad$ $w_t^{[m]} = \ \ p(\ z_t \ | \ x_t^{[m]} \ )$

$\quad$ $\widetilde{X}_t = \widetilde{X}_t + \langle x_t^{[m]}, w_t^{[m]} \rangle$

$\quad$ $\widetilde{X}_t = \widetilde{X}_t + \langle x_t^{m}, m_t^{m}, w_t^{m} \rangle$

end

for $m \leftarrow 1$ **to** M

$\quad$ $draw\ \ i\ \ with\ \ probability\ \ w_t^i$

$\quad$ $add\ \ x_t^i\ \ m_t^i\ \ to\ \ X_t$

end

return (X_t)

3.2 Simultaneous Localization and Mapping

This subsection provides Particle Filter based Simultaneous Localization and Mapping algorithm for search and rescue robots. In the presented SLAM solution, probability distribution such as in Equation 3.2, has to be computed for each time step of the search and rescue task execution to obtain the internal structure of the work space and estimate the position of the robot using distance sensor measurements, actuation data and initial state of the robot.

$$P(\ x_k, m \mid Z_{0:k},\ \ U_{0:k},\ \ x_0\ ) \tag{3.2}$$

Where;

x_k= State of the robot at time k

m= Environment map representation

$Z_{0:k}$= Robot sensor measurements from 0 to k

$U_{0:k}$= Control inputs of the robot between time interval 0 and k

x_0= Initial state

Joint posterior probability density of robot poses x_k and map state m are calculated using the robot distance measurements Z, control inputs U and initial state of the robots x_0. The main idea in particle filter is to represent the above posterior probability approximately by a set of particles which represents possible states of the robot in the dynamic system. The particle based state representation of a robot is represented using set of weighted particle set as in Equation 3.1.

Graphical representation of the Simultaneous Localization and Mapping problem is given in Figure 3.2. This figure shows the main goal of SLAM which is to estimate a posterior over the current pose with the help of occupancy grid environmnet robot map.

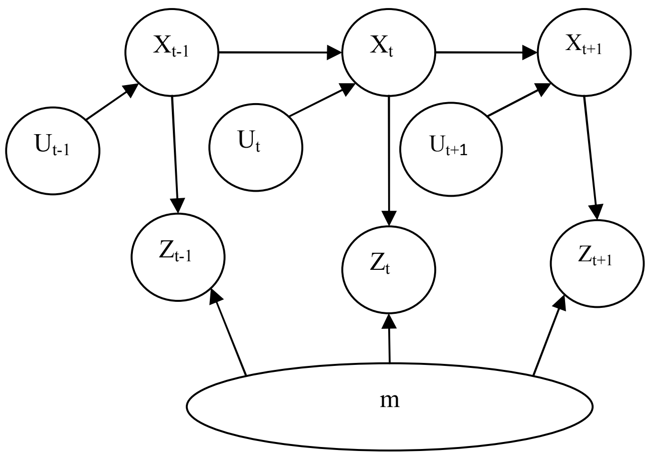


Figure 3.2: Graphical representation of the Simultaneous Localization and Mapping problem [38].

Algorithm 3.2.1: PARTICLEFILTERBASEDSLAM(X_{t-1}, u_t, z_t)

$\widetilde{X}_t = X_t = \emptyset$

for $k \leftarrow 1$ **to** M

1. $x_t^k = MotionModel(u_t, x_{t-1}^k)$
2. $w_t^k = MeasurementModel(z_t, x_t^k, m_{t-1}^k)$
3. $m_t^k = GenerateOccupancyGridMap(z_t, x_t^k, m_{t-1}^k)$
4. $\widetilde{X}_t = \widetilde{X}_t + \langle x_t^k, m_t^k, w_t^k \rangle$

end

for $k \leftarrow 1$ **to** M

5. *draw i with probability* w_t^i
6. *add* x_t^i m_t^i *to* X_t

end

return (X_t)

Particle Filter based simultaneous localization and mapping algorithm is given in the above Algorithm 3.2.1. The main phase of the given SLAM methodology; sampling, importance factor calculation for each particle and resampling can be summarized as follows:

Motion model related line of the algorithm, called sampling phase, generate next state x_t based on previous state x_{t-1} and recent control input u_t for each particle M using motion model of the robot unit. Importance weighting step in measurement model related line, is used to calculate a weight for each particle to incorporate the measurements z_t into particle set according to the sensor readings and finally, lines from 5 to 6 in the particle filter algorithm is about replacement M particles from the temporary particle set $\widetilde{X}$ using importance weight. Hence, particles with low probabilities are eliminated while high probability related states gather more particles to estimate the state with a small error. Finally, occupancy grid environment map of each particle is generated using estimated position and orientation information.

Motion model of the robot units, distance measurement model, occupancy grid mapping which are used in SLAM algorithm and their mathematical details are described in the following subsections of this chapter.

3.3 Motion Model

During the last decade, robotic researchers have mainly focused on deterministic robot kinematic models. However, these models cannot be valid when robot control and wheel encoder measurements have noise due to drift and slippage occurrence. This case is ordinary for multi-robot search and rescue operations due to hard environmental conditions especially for disaster work spaces. This part of the thesis describes motion model which is the essential part of the state estimation in probabilistic kinematic model for SLAM problem to obtain state transition probability $P(x_t \mid u_t, x_{t-1})$. In state transition equation, x_t and $x_{x_{t-1}}$ are the most recent and previous state of the robot respectively and u_t is the actuation input. Motion model gives the posterior probability of the robot state after u_t input command at x_{t-1}. Odometry motion model in which traveled distance and rotated angle of the robot is used to predict next position and orientation of the robotic system.

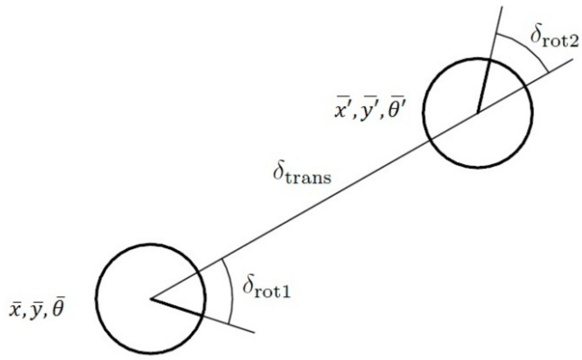


Figure 3.3: Three consecutive robot actions; rotation, translation, followed by another rotation for motion modeling.

Figure 3.3 represents three consecutive robot actions such as rotation, translation, followed by another rotation in the time interval between $t - 1$ and t. These three actions are used for odometry motion modeling which is more accurate than velocity motion model.

Probabilistic odometry based motion model algorithm as shown in Algorithm 3.3.1 is presented for consecutive translation, rotation and again rotation robot motion. Lines between 1 to 3 are the calculation of robot rotations and translation using noisy odometry readings. Then, true motion parameters are obtained by subtracting motion error from estimated translation and rotation parameters between the fourth and sixth steps of the given motion model algorithm. α_1 and α_4 are specific noise parameters for each robot and determined for each robot. The resultant true position of the robot is calculated in lines 7 to 9.

Algorithm 3.3.1: ODOMETRYMOTIONMODEL(u_t, x_{t-1})

1. $\delta_{rot1} = arctan2(\bar{y}' - \bar{y}, \bar{x}' - \bar{x}, \bar{\Theta})$
2. $\delta_{translate} = \sqrt{(\bar{y}' - \bar{y})^2 + (\bar{x}' - \bar{x})^2}$
3. $\delta_{rot2} = \bar{\Theta}' - \bar{\Theta} - \delta_{rot1}$

4. $\bar{\delta}_{rot1} = \delta_{rot1} - sample(\alpha_1|\delta_{rot1}| + \alpha_2|\delta_{trans})|$
5. $\bar{\delta}_{trans} = \delta_{trans} - sample(\alpha_3\delta_{trans} + \delta_4(|\delta_{rot1}| + |\delta_{rot2}|))$
6. $\bar{\delta}_{rot2} = \delta_{rot1} - sample(\alpha_1|\delta_{rot2}| + \alpha_2|\delta_{trans})|$

7. $x' = x + \bar{\delta}_{trans}cos(\Theta + \bar{\delta}_{rot1})$
8. $y' = y + \bar{\delta}_{trans}sin(\Theta + \bar{\delta}_{rot1})$
9. $\delta' = \delta + \bar{\delta}_{rot1} + \bar{\delta}_{rot2}$

return $(x_t = (x', y', \Theta))$

3.4 Occupancy Grid Mapping

Different variety of environment mapping methods exist in the robotic literature such as feature based, geometric and occupancy grid based methods. The usage of feature and geometry extractions cannot be efficient in hard disaster environments due to environment and robot uncertainties. Doors, corners and corridor like predetermined landmarks may be destroyed by the disaster. Besides there is no information about the internal structure of the search and rescue space. In such situations, the localization of landmarks cannot be possible. Hence, feature based and geometric environment mapping methods are not suitable for search and rescue operations in unstructured and complex disaster environments. In this thesis we model the mission environment with occupancy grid map algorithm developed by Moravec and Elfes [52, 53].

Occupancy grid map decomposes the high dimensional continuum mapping problem into a one dimensional problem, where the occupancy of each grid cell is estimated independently [54]. Occupancy of a grid is a numerical value representing the posterior probability of a grid cell being occupied. This provides a simple spatial representation of the environment. Each cell of the environment map m_i has an occupancy value which represents the possibility of an obstacle to exist in a related cell of the map. This value varies between zero and one; zero means that there is no obstacle and robot can navigate safely on these areas, one means that there is most probably an obstacle. Initially, occupancy value of each environment map cell is set to 0.5 which means that there is no knowledge about environment.

Occupancy grid mapping is represented by posterior distribution $p(m|z_{1:t}, x_{1:t})$, where, m is about environment map, distance measurements between 1 and t time interval is represented by $z_{1:t}$ and $x_{1:t}$ is the pose of robot unit. Occupancy environment maps consist of cells $m = m_i$. Resolution of the map increases with the number of occupancy grid cell numbers. Hence, environment map is represented as in Equation 3.3

$$P(m) = \prod_{m_i \epsilon m} p(m_i) \tag{3.3}$$

Occupancy grid environment map algorithm is presented in Algorithm 3.4.1.

Algorithm 3.4.1: OccupancyGridBasedEnvironmentMapping(l_{t-1}, x_t, z_t)

for *all environment grid cell* **do**
    if *grid cell is in sensing range*
        $l_t = l_{t-1} + l(p(m_i|x_t, z_t)) - l_0$
    else
        $l_t = l_{t-1}$
    end
end
return (l_t)

Where l_t is closed logarithmic representation of the occupancy grid cell given as in 3.4

$$l_t = log \frac{p(m_i|z_t, x_t)}{1 - p(m_i|z_t, x_t)} \tag{3.4}$$

This logarithmic representation is computationally efficient, because, truncation problems occurs near zero and one probability values, and log representation handles these problems. Final occupancy grid cell probability can also be obtained easily as given by Equation 3.5.

$$p(m_i|z_t, x_t) = 1 - \frac{1}{1 + \exp\{l_t\}} \tag{3.5}$$

Inverse sensor model is obtained using Equation 3.6.

$$l(p(m_i|z_t, x_t)) = log \frac{p(m_i|z_t, x_t)}{1 - p(m_i|z_t, x_t)} \tag{3.6}$$

In the following part of this chapter, we give detailed mathematical derivation of occupancy grid update formula. By using Bayes formula, Equation 3.7 is obtained as follows:

$$p(m_i|x_{1:t}, z_{1:t}) = \frac{p(z_t|m_i, x_{1:t}, z_{1:t-1}).p(m_i|x_{1:t}, z_{1:t-1})}{p(z_t|x_{1:t}, z_{1:t-1})} \tag{3.7}$$

if we assume that z_t is independent from $x_{1:t-1}$ and $z_{1:t-1}$,

$$p(m_i|x_{1:t}, z_{1:t}) = \frac{p(z_t|m_i, x_t).p(m_i|x_{1:t}, z_{1:t-1})}{p(z_t|x_{1:t}, z_{1:t-1})} \tag{3.8}$$

and

$$p(z_t|m_i, x_t) = \frac{p(m_i|x_t, z_t).p(z_t, x_t)}{p(m_i|z_t)} \tag{3.9}$$

We combine Equation 3.8 and Equation 3.9, so following Equation 3.10 is obtained.

$$p(m_i|x_{1:t}, z_{1:t}) = \frac{p(m_i|x_t, z_t).p(z_t|x_t).p(m_i|x_{1:t-1}, z_{1:t-1})}{p(m_i).p(z_t|x_{1:t}, z_{1:t-1})} \tag{3.10}$$

similarly

$$p(-m_i|x_{1:t}, z_{1:t}) = \frac{p(-m_i|x_t, z_t).p(z_t|x_t).p(-m_i|x_{1:t-1}, z_{1:t-1})}{p(-m_i).p(z_t|x_{1:t}, z_{1:t-1})} \tag{3.11}$$

and if we divide 3.10 and 3.11,

$$\frac{p(m_i|x_{1:t}, z_{1:t})}{p(-m_i|x_{1:t}, z_{1:t})} = \frac{p(m_i|x_t, z_t).p(-m_i).p(m_i|x_{1:t-1}, z_{1:t-1})}{p(-m_i|x_t, z_t).p(m_i).p(-m_i|x_{1:t-1}, z_{1:t-1})} \tag{3.12}$$

we use the fact that $p(-m_i) = 1 - p(m_i)$ and we obtain 3.12,

$$\frac{p(m_i|x_{1:t}, z_{1:t})}{1 - p(m_i|x_{1:t}, z_{1:t})} = \frac{p(m_i|x_t, z_t)}{1 - p(m_i|x_t, z_t)}.\frac{1 - p(m_i)}{p(m_i)}.\frac{p(z_t|x_{1:t}, z_{1:t-1})}{p(z_t|x_{1:t}, z_{1:t-1})} \tag{3.13}$$

and finally, logarithmic occupancy grid update formula is obtained as in 3.14

$$log\frac{p(m_i|x_{1:t}, z_{1:t})}{1 - p(m_i|x_{1:t}, z_{1:t})} = log\frac{p(m_i|x_t, z_t)}{1 - p(m_i|x_t, z_t)} + log^{-1}\frac{p(m_i)}{1 - p(m_i)} + log\frac{p(z_t|x_{1:t}, z_{1:t-1})}{p(z_t|x_{1:t}, z_{1:t-1})} \tag{3.14}$$

Occupancy probability of each grid cell $P(m_i|x_t, z_t)$, as in the map update Equation 3.14, is calculated using laser range scanner measurement model.

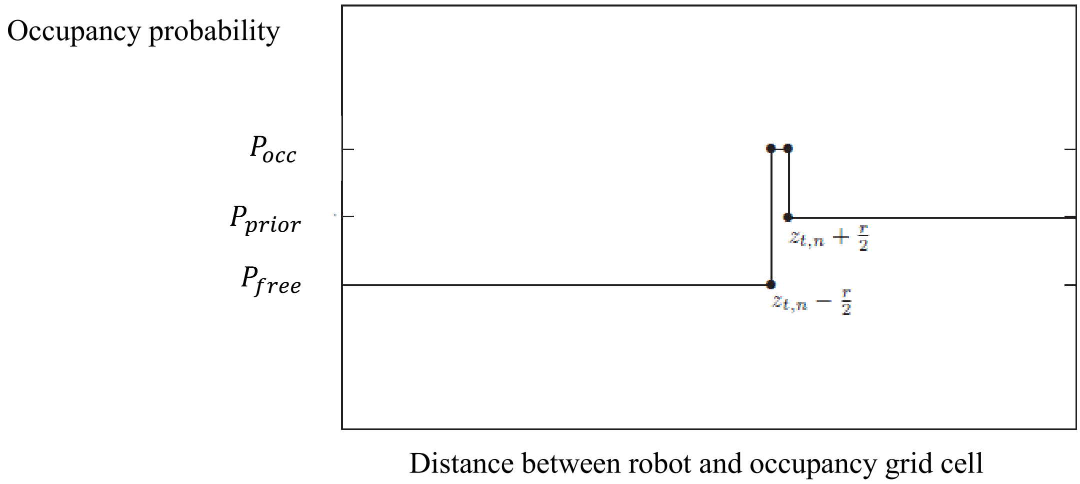


Figure 3.4: Laser sensor model of robot units.

3.5 Measurement Model

In this part of the thesis, probabilistic model of the distance sensor model is presented to model noise in sensor measurements. A large variety of sensors are used in robotic applications such as cameras, laser range finders, sonar and tactile sensors. Cameras cannot take high quality image or videos due to limited illumination conditions in the disaster area; hence, camera usage as a sensing device cannot be efficient for search and rescue operations. Sonar sensors can suffer from huge amount of reflection in disaster area. Hence, laser range scanner sensor is used in our simulations due to its accuracy in the disaster areas.

Measurement model such as in Figure 3.4 is used to calculate the occupancy probability $P(m_i|x_t, z_t)$ of each cell of the environment map using robot position and the range measurements and the formulation of it is given by Equation 3.15.

$$P(m_i|z_{t,n}, x_t) = \begin{cases} P_{prior} & \text{for} \quad z_{t,n} \quad is\ a\ maximum\ sensor\ range\ reading \\ P_{prior} & \text{for} \quad m_i\ is\ not\ covered\ by\ z_t, n \\ P_{free} & \text{for} \quad z_{t,n} \geq dist(x_t, m_i) \\ P_{occ} & \text{for} \quad |z_{t,n} - dist(x_t, m_i)| < r \end{cases} \tag{3.15}$$

Where $z_{t,n}$ represents the observation of n^{th} laser sensor, $dist(x_t, m_i)$ is about the distance between related map cell and robot position and resolution of the map is shown by r.

CHAPTER 4

METHODOLOGY

Main goal of this dissertation is to generate a novel prioritized goal oriented multi-robot coordination control strategy for search and rescue operations to localize buried victim efficiently in wide and complex disaster areas. In the proposed approach, each robot should enter the vast and unstructured disaster region from different parts bearing different initial orientations and position. Then, they start their individual exploration mission by generating their own occupancy grid environment maps of traversed regions and estimating their position. After the localization of buried victims by any robot unit, the mission of the robot team is completed successfully. This task is time critical, so robots have to cooperate with each other and avoid redundant area exploration. Hence, each robot needs prioritized coordination control strategy to find free and safe navigation paths among obstacles. Robots can also get rid of from trapped positions in obstacle crowded area with the help of this prioritized exploration strategy.

The presented multi-robot victim search and rescue strategy consists of four main subparts: fist one is about estimation of each robot position in the work space using noisy odometry data coming from robot encoders, second part is the extraction of occupancy grid map of traversed disaster environment with the help of distance measurements which are corrupted by environment and robot uncertainties. Prioritized and goal oriented multi-robot exploration toward the localization of a survivor in the optimal fashion, is the third part. Finally, merging generated partial occupancy grid environment map of each robot unit to obtain global and joint environment map. For efficient multi-robot victim search and rescue operation, all these tasks have to be executed simultaneously by using noisy distance sensor measurements and wheel encoder readings of each robot as in Figure 4.1.

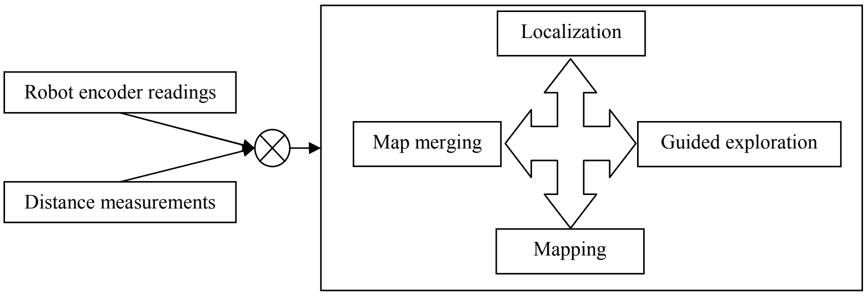


Figure 4.1: Tasks that have to be executed simultaneous for multi-robot victim search and rescue operation in catastrophe areas.

Particle Filter based Simultaneous Localization and Occupancy Grid environment Mapping modules of the methodology, described in the Mathematical background section of the thesis, are implemented to obtain information about the internal structure of the disaster environment and to estimate position of the robot units. The solution of these two modules of the proposed algorithm is not described in this methodology chapter to avoid repetition.

In this section, prioritized multi-robot exploration strategy and occupancy grid mission space map merging modules of the proposed approach are presented in detail. In the introduced solution, each robot unit is guided toward big, connected and free voids by percolation inspired multi-robot motion controller to increase the performance of the overall system. This controller also prevents redundant and repeated exploration. Repeated exploration means that any region of the environment is explored by more than one robot. Lastly, occupancy grid map merging module also increase the efficiency of the proposed victim search and rescue strategy, because, robot units can obtain information about other part of the work space without traversing on these areas by map combining different occupancy grid map of other robot units.

To understand the proposed buried victim search methodology for disaster areas using robot team, consider a wide and unstructured disaster environment occurred after a disaster such as an earthquake. Wideness and disorder properties are most common characteristics of catastrophe environments. There are a lot of different shaped and sized rubbles which are scattered on the surface of the disaster area randomly. There is no information about the location of the buried survivor and the internal structure of the task space.

Multi-robot search and rescue team enter the debris from different parts. Each robot unit starts to explore the mission environment using percolation theory inspired coordination control strategy giving priority to large, free and connected voids, since, the possibility of finding buried victim in these free and big spaces is higher than small and obstacle crowded areas. And also during the victim search and rescue task execution, each robot has to estimate its position and orientation in the environment and generate the map of traversed region, simultaneously.

It is firstly assumed that each robot has unlimited communication range. They can generate a joint occupancy grid map of the traversed region by sharing all their distance and odometry sensor measurements with the other team members. After introducing the occupancy map merging methodology in this section, unlimited communication range assumption is relaxed to make proposed solution more realistic for real world buried victim search and rescue robotic applications. Hence, robots do not have position and map information and sensor measurements about other robots due to limited communication range.

At a specific time, if any two robot notice each other using their communication ability, they merge their environment map with its neighbor robots to obtain global map information about other parts of the disaster areas which are not visited by different robots. Guidance on each robot's exploration direction provides efficient prioritized victim search strategy. Map merging ability also improves the efficiency of the overall system in the sense of time and energy.

Details of the Percolation inspired multi-robot exploration strategy and occupancy grid map merging methodology are presented in the following subsections in detail. The other two modules of our proposed victim search methodology (simultaneous localization and occupancy grid mapping) are described in Mathematical Background chapter of this thesis.

4.1 Percolator Guided Multi-Robot Exploration Strategy for Victim Search and Rescue Operations

4.1.1 Percolation Theory

John M. Hammersley and Simon R. Broadbent focused on the behavior of fluid through a random medium in 1957. They supposed the following problem; a large porous stone which is made up of occupied and empty holes, was immersed in a bucket of water. The critical question was *"Would the water reach the center of the pumice stone?"*, i.e., can the water *percolate* between free holes and can it reach the center of the rock. They showed that there is critical value of the density of porosity in the stone enabling a fluid to reach the pumice stone center [55, 57].

The idea behind percolation theory can be described as follows. Let Z^2 be a grid lattice of a two dimensional disordered medium such as in Figure 4.2 and p be a number varying between zero and one, each cell in Figure 4.2 is considered as free (white cells) with a probability p and occupied (black cells) with $(1-p)$ and the emptiness of each cell is completely independent from each others. Percolation theory try to estimate the possibility of large *percolated* and connected free cell cluster existence in the disordered and porous medium. Intuitively, there occurs large and free connected spaces for high values of the free void probabilities p. It would be difficult to occur giant cluster in low free concentration p. The main problem is about: *When the transition between these two phases occurs*, i.e., what is the critical threshold p_c for p.

Two types of percolation model have been developed and applied in the literature: bond and site [55] as in Figure 4.2. Site percolation considers lattices sites (vertices), in which the vertices are declared to be free with probability p and occupied with probability $1-p$. Bond percolation considers edges instead of vertices and they are asserted to be free with probability p or occupied with probability $1-p$. Bond percolation model is used in the modeling of computer or electric transmission networks. There exist a critical value of p which is called critical threshold p_c such that there exist a free and connected giant cluster between top of the lattice and its bottom

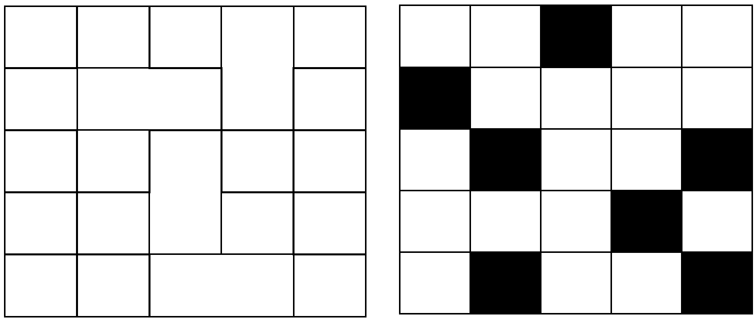


Figure 4.2: Bond and Site type environment modeling in percolation theory, respectively.

when $p>p_c$. Figure 4.3 shows the phase transition function of percolation occurrence according to the openness probability p of free holes.

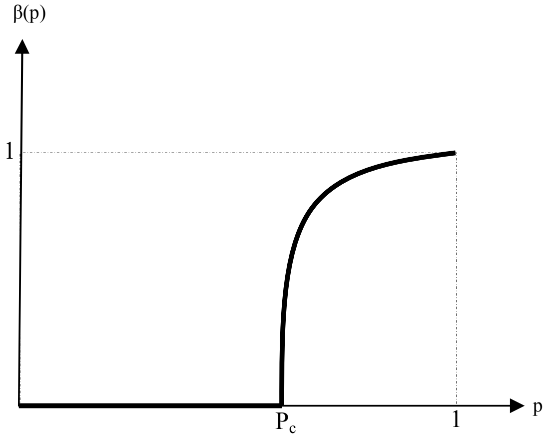


Figure 4.3: The probability of free connected cluster $\beta(p)$ occurrence according to p.

There are three phases in the Figure 4.3; subcritical, critical and supercritical, which are described as follows:

1. *Subcritical*: This case occurs if $p < p_c$ and it shows that the possibility of connected big free cluster (percolation) occurrence is nearly zero.

2. *Critical*: When the value of p begins to exceed the critical threshold p_c, the probability of percolation occurrence begins to increase from zero towards one.

3. *Supercritical*: If $p > p_c$, the probability of percolation occurrence is increasing with p.

$$P_c(p) = sup\{p : \beta(p) = 0\} \tag{4.1}$$

Critical threshold value p_c of the disordered medium can be defined as in Equation 4.1. If percolation theory is used to model a work space, the threshold determination p_c and emptiness probability p calculation are the most critical two issues. These values depend only on which kind of disordered medium grid model is used and what is the structural characteristics of the work space. Some example for the calculation of critical threshold values, in the literature [55], are given below.

The shape of Figure 4.3 varies according to the model which is used in percolation theory. A simple formula that can be used for critical threshold calculation in $p > p_c$ case, is as follows [55].

$$\beta(p) \approx (p - p_c)^{\gamma} \tag{4.2}$$

In the above expression, critical exponent γ, called power law, is only depends on the dimension of the model, the kind of lattice being used and p. Some computed p_c examples for different disordered mediums are given as follows:

$$p_c^{bond}(2D) = 0.5, \tag{4.3}$$

$$p_c^{site}(2D) = 0.59, \tag{4.4}$$

$$p_c^{bond}(triangularlattice) = 2Sin(\pi/18) \tag{4.5}$$

$$p_c^{bond}(hexagonallattice) = 1 - 2Sin(\pi/18) \tag{4.6}$$

In the literature, percolation theory is widely used in the solution of different real world problems. It was applied to describe the dynamical behavior of the epidemic spreadings and forest fires [58], air traffic control simulations [59], edge detection in image processing [60] and the determination of electrical resistance level of the disordered materials [56]. For example, in [56], Pajot models the structure of a semi conductor as in Figure 4.4 to decide the conductivity level of the electric components and to calculate effective resistance of the resistor. Black cells are about electrical conductors and insulators are represented with white colored squared cells in Figure 4.4. After application of the electrical voltage into system, electric current can only flow between nearest black cells (neighbor conductor). Hence, at low conductor concentration p, electric component works as an isolator, because there is no connected conductor cluster between two poles. If the concentration of conductor p cells is increased step by step, conduction paths between opposite edges exist at a specific threshold value p_c. At that critical value, there occurs a phase transition between insulator and conductivity and so hole system works as a conductor,

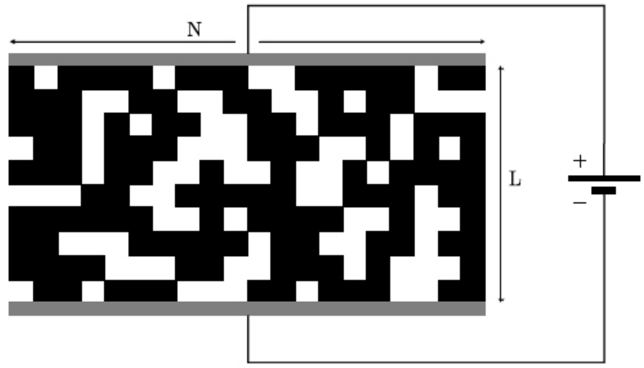


Figure 4.4: Conductivity representation for a random semiconductor [56].

In the following subsection, proposed percolation inspired unstructured disaster environment modeling is described. Critical values p and p_c, in the percolation theory, are introduced and their formula are also given.

4.1.2 Proposed Approach

In the proposed victim search and rescue approach, disaster environment is assumed as a large disordered porous medium such as in percolation theory. Each robot tries to find connected and large void (free) clusters with good porosity to reach and localize possible survivor. The motion of each robot in the collapsed building can be interpreted as the propagation of water in the porous medium. In percolation theory, water tries to reach the center of stone. In our problem, robots try to find safe and obstacle free navigation path from their starting position to location of the buried victim which is not known initially by robot units and humans. Hence, each robot exploration direction has to be guided into large and connected obstacle free voids and safe spaces, because the likelihood of finding any survivor around such searchable regions is higher than small and obstacle crowded areas. If the buried survivor is not found in big spaces, robots change their exploration direction toward small and obstacle crowded voids. This phase transition occurs, when the obstacle density of the work space exceeds a predetermined threshold value.

The proposed approach is completely motivated by a prioritized exploration that is required when survivor searching is based on the structural characteristics of the disaster area. Work space is divided into grid cells with predetermined resolution and occupancy grid mapping methodology is used to model a disaster area. It is very similar with site percolation model as seen in Figure 4.2. Occupancy probability of each cell in the map $p = p(m_i|x_{1:t})$ is very similar to p free cell probability in percolation model. This value is calculated as in Equation 4.7. The occupancy probability of each map cell is calculated independently from other cells.

The details and derivation of occupancy probability of any map cell p is given in the occupancy grid mapping section of the Mathematical Background chapter of the thesis. The derivation of this formula 4.7 is not given here again to avoid repetition.

$$log\frac{p(m_i|x_{1:t},z_{1:t})}{1-p(m_i|x_{1:t},z_{1:t})} = log\frac{p(m_i|x_t,z_t)}{1-p(m_i|x_t,z_t)} + log^{-1}\frac{p(m_i)}{1-p(m_i)} + log\frac{p(z_t|x_{1:t},z_{1:t-1})}{p(z_t|x_{1:t},z_{1:t-1})} \tag{4.7}$$

Now consider the disordered environment model given in Figure 4.5 which represents an artificial occupancy grid map of a work space and occupancy probabilities of each cell which is varying between zero and one. This model is used to show the relationship between our model and percolation model. Occupancy grid map is very similar with two dimensional disordered media model in percolation theory, site model. However, in our model, we have focused on occupancy probability instead of emptiness which is used in percolation model. And our percolator based controller tries to estimate large and connected clusters in the disaster area.

Figure 4.6 shows a occupancy grid map simulation result of a disaster work space after a victim search and rescue operation. The resolution of the cells is very high

1	1	0	1	1	0.5	0.5	0.5	0.5	05
1	1	0	0	0	1	1	0.5	0.5	0.5
1	0.1	0	0	0	0	0	1	0.4	0.5
1	1	0	0	0	0	0.3	0.3	0.4	0.5
1	0.9	0	0	0	0	0.3	0.3	0.4	0.5
1	1	0	0	0	0	0.3	0.3	0.4	0.5
0.9	0.9	0	1	0	0	0	1	1	1
0	0	0	1	0	0.1	0.9	1	1	1

Figure 4.5: Artificial occupancy grid map of an environment and occupancy probabilities of each cell.

(approximately 250x250), hence, environment occupancy grid cells cannot be observed separately. The occupancy probability value of black cells which is about obstacle related area is nearly one and the occupancy p value of white colored area is zero (free space area traversed by robot unit) and finally, gray color related cells with $p = 0.5$ represents unknown and not traversed regions by robot units.

Up to here, two important issue about proposed strategy is presented, p occupancy probability and how environment is modeled. Critical threshold p_c value of p as in percolation theory, is given at the end of this subsection in detail to avoid disrupting the flow of the algorithm.

Figure 4.6: Bond percolation type search and rescue environment map representation.

The flow chart of our proposed percolation inspired multi-robot prioritized exploration strategy is summarized in Figure 4.7. Details of each block are given in the following part of the thesis. The main idea of coordinated multi-robot exploration is to create possible moves for each robot and each robot has to select the best one to find survivor as quickly as possible using generated occupancy grid environment map of disaster area.

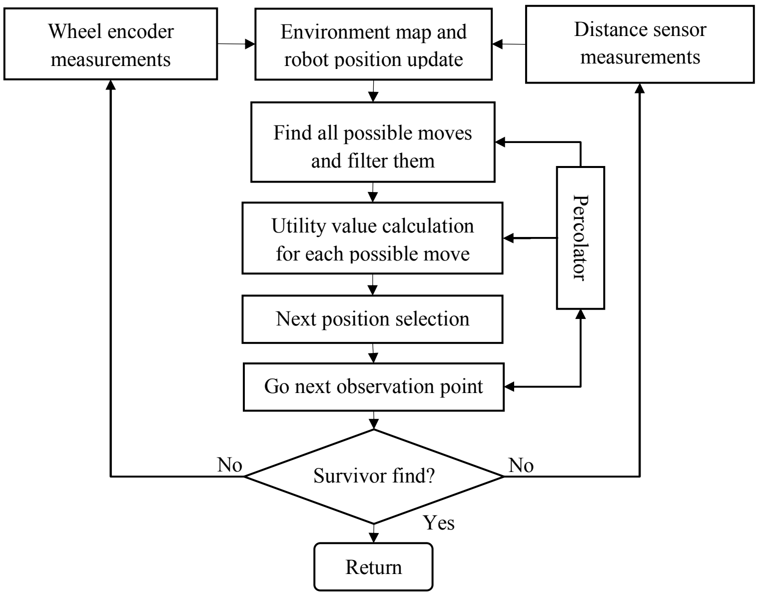


Figure 4.7: Flow chart of the percolation theory inspired multi-robot exploration algorithm for buried survivor search in catastrophe environments.

Algorithm starts with the deployment of each robot into the search and rescue space. Since there is no initial knowledge about the environment map, occupancy of each cell is exactly $p = 0.5$ at the beginning of work. Initial belief of each map cell is represented with gray color as in Figure 4.8. Each robot reads its wheel encoders and IR distance sensor measurements which can be corrupted by noise due to environmental and robotic uncertainties. Simultaneous position, orientation and occupancy grid map of each robot is calculated using PF based SLAM algorithm. Secondly, each robot finds all frontier cells (as blue cells in Figure 4.9) which represent the boundary between explored and unexplored areas in the common environment map. These frontier cells are the possible next position for each robot, because, frontier based exploration forces robots to the regions on the borders between explored and unknown spaces [61], [62]. Small length frontier borders through which a robot cannot pass are eliminated, because robots cannot pass throughout narrow spaces safely and they can be trapped. At this point each robot has to calculate utility values for each possible move (for each frontier cell) and navigates in the direction of maximizing the utility value of them. Utility values are calculated by using the utility function given by Equation (4.8).

Figure 4.8: Initial knowledge of robot units about the disaster environment.

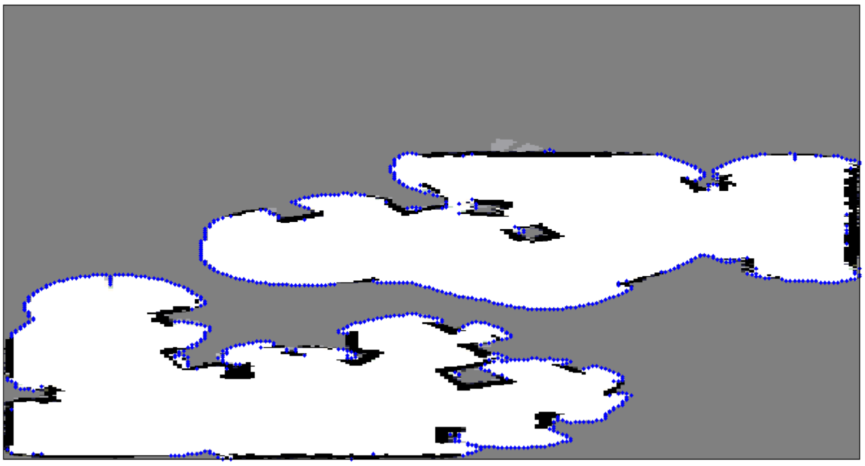


Figure 4.9: Occupancy grid environment map and frontier cell locations (Blue cells) at a specific time t.

$$U^i_{TOTAL} = U^i_I(m_i) - U^i_C \tag{4.8}$$

Utility function consists of two parts. First one is the amount of expected information gain Equation 4.9 available for each possible frontier cell and second part is the cost of reaching target frontier cell Equation 4.11. Robots calculate the expected information gain at m_i candidate frontier cell by using Equation 4.9.

$$U_I^i(m_i) = \sum_{p \in R^i} H(p) \tag{4.9}$$

Where R_i is the region around the frontier cell m_i. $H(p)$ is the entropy value for each cell p in the R_i region and is calculated as given by Equation 4.10. Figure 4.10 shows an occupancy grid map cell m example and related entropy and expected information calculations around them. There are three different map cell states, obstacle (black), free space (white) and unknown space (gray). and their occupancy probabilities are equal to 1, 0 and 0.5, respectively. Entropy of black and white colored cells is calculated using Equation 4.10 and it is exactly equal to zero, because, there is no uncertainty about these cells. Similarly, entropy of unknown area related occupancy grid environment cell is $p = 1$ which shows the highest uncertainty. Hence, in our map representations, entropies are varying between 0 and 1.

To understand expected information gain around a specific cell m, two square shaped map regions is presented in Figure 4.10. Expected information gain around map cell m_1, left hand side square area, is greater than right hand side squared map area of cell m_2. Because, on the right hand side area related cell m_2, there are some obstacle related grid cells and these cells decrease the expected information gain dramatically.

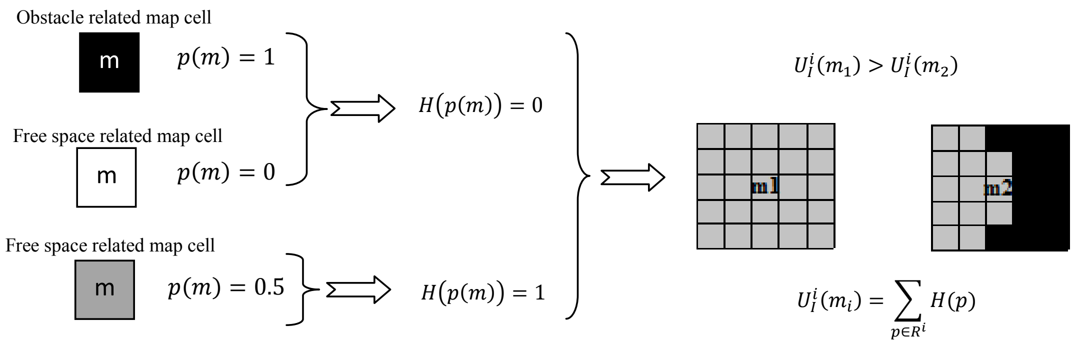


Figure 4.10: Visual example about expected information gain and entropy around a occupancy grid cell m.

$$H(p) = -plog_2(p) - (1-p)log_2(1-p) \quad (4.10)$$

Second term of the utility function is about cost. We use Manhattan Distance Equation 4.11 to calculate the cost of navigation from initial position to the next observation location of the robot. Other distance measures such as Euclidean distance are not applicable into obstacle crowded areas, because, generated paths can intersect obstacle related area and robots cannot reach target position safely.

$$U_i^c = |x_{initial} - x_{final}| + |y_{initial} - y_{final}| \quad (4.11)$$

After the calculation of utility, every robot chooses its next observation position from candidate frontier cells by maximizing its expected utility and navigates toward the next position. Multiple area coverage is handled by reducing utility of target locations whenever they are expected to be covered by another robot. This property increases the efficiency of the system in the sense of time, because each robot try to navigate on different disaster areas using different located frontier cell selection as a next observation point selection.

During the multi-robot exploration operation to localize buried victim, Percolator, as seen in Figure 4.11, checks the probability of finding any survivor in the local search area when robot navigates toward the next position. Each cell on occupancy grid is used as in site percolation model and each robot try to find the answer to the question of *"Is there any connected cluster between robot and buried victim"* using structural characteristic of local traversed region. Percolation model based search area controller, percolator, is used to guide the robot toward big and free connected clusters in the search and rescue environment.

P_{find} triggers the controller that toggles to other state according to the structural characteristic of the local area. If that likelihood decreases under the predefined threshold, robot navigates toward other part of the environment to gain more information about environment and survivor location, because robot decides that there is no free big connected cluster in the following navigation area. Equation 4.12 gives the probability of finding any victim P_{find} in the existing local region and is calculated approximately as 1 minus the ratio of obstacle area to the total swept area in Δt time interval as given by Equation 4.12.

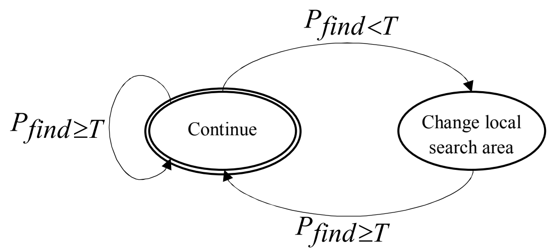


Figure 4.11: Percolation model inspired multi-robot victim search controller, percolator.

$$P_{find} = 1 - \frac{A_{obstacle}}{2v(r_{robot} + S_{max})\Delta t} \tag{4.12}$$

Where v is the robots average speed for the time interval Δt, S_{max} is the maximum sensing range of robots and r_{robot} is the radius of robot.

If P_{find} is smaller than threshold, robots decide that the likelihood of finding victim is low in the local search region and selects next observation point from other part of the work space by using only the expected information gain, not by using also cost value to reach frontier cell. The derivation of Equation 4.12 can be better explained using Figure 4.12. It represents the movement of robot between X_{t-1} (previous position) and X_t (current position) with the average speed v in the Δt time interval. Swept area between two positions is equals to $2v(r_{max}+S_{max})\Delta t$. The ratio of obstacle related area in the swept area to the total swept area is equal to the complement of probability of finding survivor in the local search environment.

After the calculation of P_{find} which is related with critical threshold p_c about the occurrence of giant connected cluster, percolation inspired multi-robot control algorithm is completed. Occupancy probability of each map cell p and environment modeling type are given at the beginning of this section.

A novel occupancy grid map merging methodology is introduced in the following section.

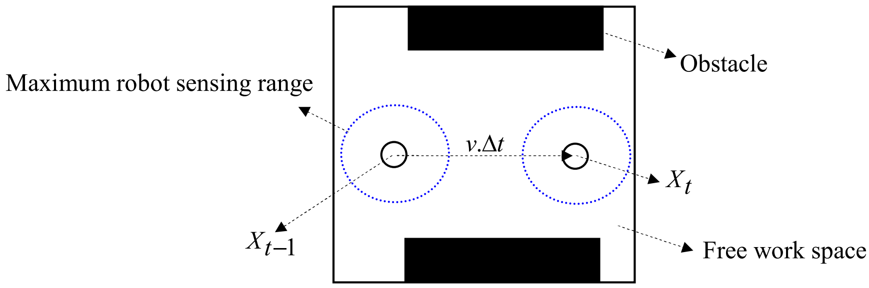


Figure 4.12: Movement representation of the search and rescue robot between X_{t-1} and X_t positions.

4.2 Map Merging

The most important distinguishing features of disaster environments are their internal structure. They have generally rubbled structure that renders them highly uncertain and unstructured. Generally, there is no initial information about the location and size of the obstacles, victims and overall structural inventory of the area being searched. A search and rescue mission primarily includes coverage and mapping of the mission area using multiple autonomous robots of different capabilities. Those robots enter the vast disaster region from different parts bearing different initial orientations and position and start their individual exploration mission generating their own occupancy grid environment maps based on their local reference frame. Hence, mapping reference frames of each robot is completely different compared to other members of the robot team, and rotational and translational differences occur between generated occupancy grid environment maps of robot units.

To increase the efficiency of the decentralized exploration task in the sense of time and energy, robots have to exchange their partial occupancy grid maps which are extracted from different parts of the work area. Then, these individual maps are fused by a ground station (or by robots) to obtain globally consistent and joint occupancy grid map of the disaster area. If SAR robots know their relative initial positions, orientations and their mapping reference frames, the alignment of the individual local maps would then be trivial. However, this assumption is not valid in real world applications such as search and rescue operation in disaster areas and so this assumption is relaxed in our proposed approach. Hence, rotational and translational differences between generated occupancy grid environment maps of robot units have to be computed and those maps are fused to obtain global disaster area map.

The problem of map merging using partial occupancy grid maps can be looked upon as the problem of fusing local map pairs without any information about robots' mapping reference frames. Each robot has a different reference frame which is assumed at their starting position and orientation. In the presented methodology, it is assumed that the relative position and rotation information between robots is not available which makes this algorithm more realistic for real world SAR applications. For a successful and efficient map merging, partial robot maps have to possess only limited overlapping regions, generated after the individual exploration of the same region by more than one robots.

Another difficulty of multi-robot SAR map merging operation is about the uncertainties about robots' distance sensor measurements. Since, during the exploration operation some sensor can crash or their noise bounds can vary according to time, communication or sensory signals are generally scattered within rubbles and can easily be lost. Hence, ground station or robot units have to merge partial occupancy grid maps under the different sensor models and noise bounds of different robots.

In the introduced multi-robot exploration for search and rescue operations, occupancy grid environment map model is used to represent the internal structure of the disaster area. Environment map is divided into grid cells with a predetermined number and occupancy of each grid cell is estimated independently using distance sensor measurements. It allows robots to extract environment map without using any features like corners, walls, doors and predefined artificial landmarks. Occupancy of a grid is a numerical value representing the posterior probability of a grid cell being occupied. Every grid has three states: occupied, free and unknown. This provides a simple spatial representation of the environment. Different cell states are represented by different colors. Black cells are related with obstacles and rubbles, gray ones show the unknown part of the environment which has not been visited by the robots yet and free space, where robots can navigate safely, are represented with white cells as in Figure 4.14.

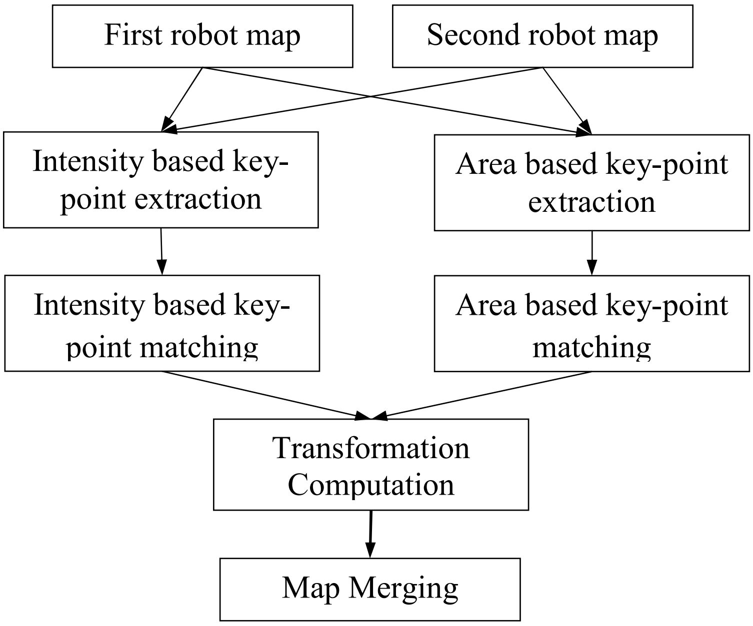


Figure 4.13: Flow chart of proposed occupancy grid map merging algorithm.

The proposed novel multi-robot occupancy grid map merging methodology proceeds as in Figure 4.13. It is based on extracting invariant substructures called key-points in the occupancy grid map of disaster area. Key-points are invariant to rotation, translation, even when generated maps contain significant amount of noise. They have to be located in each occupancy grid robot map and determines correspondence pairs between maps of robot units. These points which possess valuable asset for merging maps due to their invariance are used as virtual landmarks to find rigid transformation between individual robot maps.

Two distinct key-point localization and matching approaces are used, namely intensity and area based. Intensity based key-point localization give good performance especially for robots capable of same distance measurement or merging different map patches. However, robots can have different sensing abilities, for example, some distance measurement sensors can crush during the task execution or noise margin of sensors may be different from that of other robots. Hence, maps of same environments can be different and intensity based feature extraction can be limited in these cases, so area based key-point localization methodology is proposed to overcome these limitations.

Selected key-points are subsequently matched to label the same explored region between the maps of each robot. Correspondence key-points are thus found between maps during the matching process leading to detection of the sort: “this point in the first map is related that point into second environment map”. By using these correspondence points between maps, rotational and translational difference between maps are calculated and then maps are merged using an estimated transformation. Our proposed approach handles the limitation of existing works in the literature such as:

- Limited overlapped area between partial maps of robots is enough for good merging performance.
- Unstructured and complex partial occupancy grid environment maps can be merged efficiently.

These abilities allow multi-robot teams to efficiently generate the occupancy grid map of catastrophe areas and localize buried victim in the debris efficiently. Details of the all above steps of the proposed novel map merging process are explained in detail in the following subsections, demonstrated within the flow of a simple map fusion example.

4.2.1 Intensity Based Key-point Localization and Matching

In occupancy grid map merging problem, distinctive and stable key-points which are invariant to rotation, translation and noise have to be localized to find correspondence points between partial local environment maps of robots. In the literature, scale invariant feature transform algorithm, which is widely applicable in pattern recognition and computer vision [63], [64] has been proved to be a robust detector of invariant interest points especially for gray scale images [65]. Hence, it can be used as a powerful key-point extraction tool in the map merging task. In our approach, scale invariant feature transform is used to localize key-points for each occupancy grid maps to find correspondence points between partial robot environment maps. Key-point localization algorithm consists of important subparts; first one is about detection of key-points followed by their localization and the other ones are orientation assignment and descriptions of key-points. All these stages are explained in the following subsections in detail.

4.2.1.1 Scale Space Extreme Detection

This first step is the identification of potential distinctive interest points (key-points) that are invariant to orientation, translation and scaling using Difference of Gaussian (DoG) function and also these key-points have to be stable toward noise. Local extreme of Difference of Gaussian filters at different scales are used to identify potential interest points. These points are located at scale-space maxima and minima across different scales of a difference of Gaussian function. The formula of Difference of Gaussian $D(x, y, \sigma)$ of a occupancy grid robot environment map $M(x, y)$ is calculated as in (4.13).

$$D(x, y, \sigma) = (G(x, y, k\sigma) - G(x, y, \sigma)) * M(x, y) \tag{4.13}$$

$$D(x, y, \sigma) = (G(x, y, k\sigma) * M(x, y)) - (G(x, y, \sigma) * M(x, y)) \tag{4.14}$$

$$D(x, y, \sigma) = L(x, y, k\sigma) - L(x, y, \sigma) \tag{4.15}$$

Where $M(x, y)$ is the occupancy grid environment map generated by robot units and $L(x, y, k\sigma)$ is the scale space representation of it, x and y are the pixel coordinates in x and y direction of the map, respectively. Multiple factor represented as k is used for changing scale and $G(x, y, \sigma)$ the Gaussian Filter (GF) which is used for smoothing the map image and σ is the width of the filter. In order to detect the local maxima and minima of DoG filter $D(x, y)$, each sample point is compared to its eight neighbors in the current occupancy grid map and nine neighbors in the scale above and below. It is selected as a candidate key-point only if it is larger than all of these neighbors or smaller than all of them. This procedure provides to localize maxima points in the environment map. Some example key-points of an occupancy grid disaster environment map are shown with red stars as in Figure 4.14.

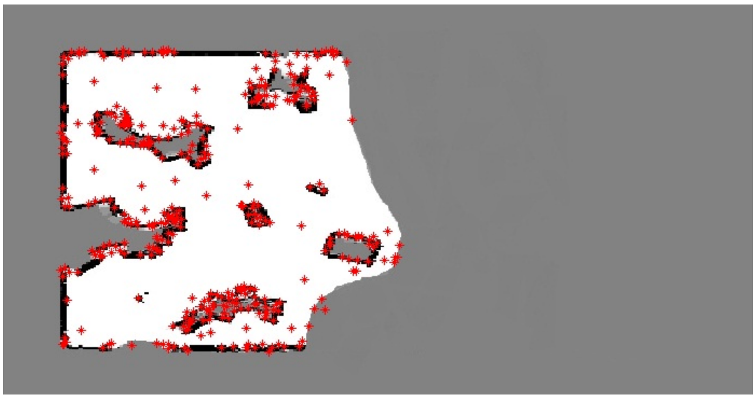


Figure 4.14: Occupancy grid environment map of mission space and estimated key-points locations labeled with red stars.

4.2.1.2 Key Point Localization, Orientation Assignment and Description

The basic idea in this part is about the rejection of key-points whose pixel is lower than a predetermined threshold value (0.02) due to their sensitivity to noise. After the extraction of candidate interest point locations, unreliable key-points whose intensities are very low are eliminated. According to this threshold applied to environment map presented in Figure 4.14, “strong”set of key-points remaining after the elimination procedure are shown in Figure 4.15. Key-point detection is very sensitive to noise and so performance of the map merging algorithm would be affected if noisy maps were considered without this thresholding.

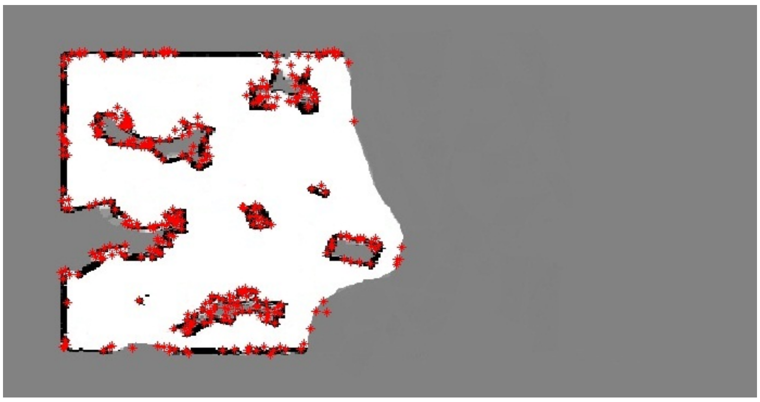


Figure 4.15: Eliminated key-points of occupancy grid environment map.

Next step is to make a detailed fit to the nearby data for location and scale, using the intensity change between key-point and the neighboring pixels of each key-point. Properties of each key-point are computed relative to the key-point orientation, so this provides rotation invariance property. Orientation and magnitude assignments are done for each key-point and its neighbors using the following pixel differences shown in Equation 4.16 to Equation 4.19.

$$M(x,y) = \sqrt{m_x(x,y)^2 + m_y(x,y)^2} \tag{4.16}$$

$$\Theta = tan^{-1}(\frac{m_x(x,y)}{m_y(x,y)}) \tag{4.17}$$

$$m_x(x,y) = L(x+1,y) - L(x-1,y) \tag{4.18}$$

$$m_y(x,y) = L(x,y+1) - L(x,y-1) \tag{4.19}$$

In the Equations given above, Gaussian smoothed image is denoted as $L(x,y)$ and the pixel gradient magnitude and orientation is represented by $m(x,y)$ and $\Theta(x,y)$, respectively. After the calculation of gradient orientation and magnitude for each key-point and its neighboring pixels (for one case in Figure 4.16), orientation of the key-point is selected in the direction of dominant orientation in the neighboring pixels of key-point. The previous stages have assigned orientation for each interest point location in robot maps $M(x,y)$. The next step is the computation of the key-point descriptor which is used for matching key-points between robots' environment maps. Then, similar regions between maps are labeled using these corresponding points. It is calculated by the gradient magnitude and orientation of neighboring pixel intensity change gradient vector in a local region around the interest point. 128 element key point descriptor is used based on the surrounding gradients of key-point.

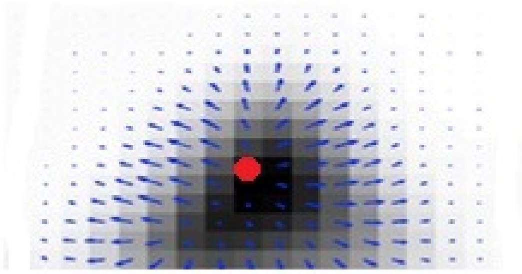


Figure 4.16: Gradient values in neighborhood pixels of key-point.

4.2.1.3 Key Point Matching

After the calculation of invariant feature descriptor vector for each key-point in the environment map of each robot, they are stored into a database in order to be matched with occupancy grid environment map of another robot. Nearest neighbor correspondence points is obtained as the key-point with minimum Hausdorff distance which measures how far the neighbor pixel intensity variation of two key-points are from each other. this yields most discriminative corresponding key-point pairs.

Figure 4.18 shows some matched key-points between the maps of robots presented individually in Figure 4.17 after implementation of the above procedure. Correct key-point matches are represented by blue colored lines and wrong ones are represented by red lines. When the number of wrong matching increases due to sensor failure or noise bound, map merging cannot be done. Hence, to increase the performance of the map merging task, area based key-point selection and matching methodology is presented in the following subsections. Also wrong key-point matching elimination and transformation estimation between robots' maps are introduced in the following part of the thesis.

4.2.2 Area Based Feature Extraction

The performance of intensity based key-point localization and matching method described above is sufficient when the number of key-points is enough for merging

Figure 4.17: Partial Environment occupancy grid map of robots.

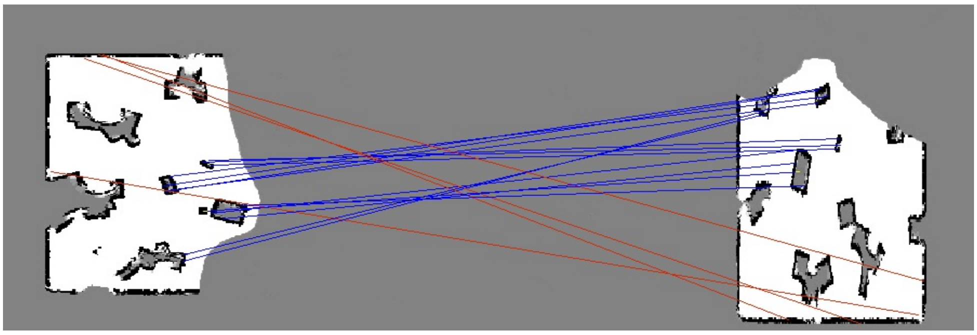


Figure 4.18: Key points matching between robot maps.

occupancy grid map of robots with almost same measurement capability. However, some sensors can crush or noise rate of sensors can vary during the task execution, so some parts of maps obtained by one robot can be different from another one such as in Figure 4.19.a,b. There are some intensity differences between the maps of the same obstacle, as seen in the difference map of Figure 4.19.c. Intensity based methodology cannot localize sufficient correct and stable key-point because of different sensing ranges and error bounds. Hence, more feature points are necessary to compensate for errors in intensity based key-point localization method. Obstacle related areas are used to extract extra interest points using binary image version of generated occupancy grid maps. Hence, a hybrid key-point extraction methodology is presented in this part, namely area and intensity based.

The details of area based key-point extraction and matching strategy are described below. Our work environment is unstructured and so there are lots of obstacles (con-

(a) (b) (c)

Figure 4.19: Obstacle map, extracted by different sensing capable robots: a) first robot, b) second robot, c) difference.

nected components) which can give extra information about the translational and rotational differences between robot maps. Connected component analysis is used to extract the orientation and location of the obstacles which are then used as extra features, using the following procedure;

1. Occupancy grid environment map is thresholded to yield a binary version of itself which is a simplified version of occupancy grid maps. Then, connected components (obstacles) can be found more precisely than the original ones such as in Figure 4.20. In the original occupancy grid map, many cell values vary between zero and 1. Hence, this property make obstacle localization very complex. So, to overcome this limitation, original occupancy grid maps are converted into binary using intensity spectrum thresholding method.

(a) (b)

Figure 4.20: Occupancy grid environment map and its binary version, respectively.

2. Two Pass algorithm [66] is used to detect closed boundary regions which are about obstacle related area in the occupancy grid maps. First pass of the al-

gorithm finds equivalences and assigns temporary labels to each pixel and the second pass is required for finding remaining equivalences and conduct final labeling. Figure 4.21 shows the location of connected component by multiplication sign for the environment map presented in Figure 4.20.

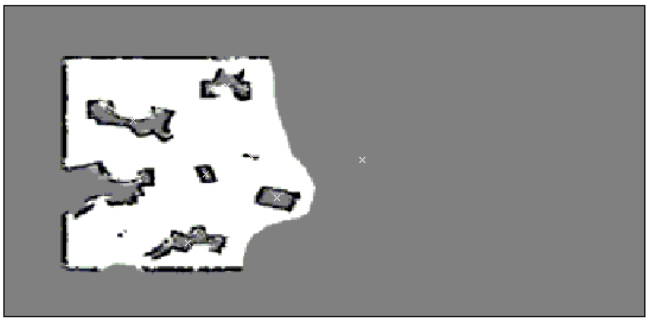


Figure 4.21: Connected component determination and labeling.

3. After the detection of connected components which are related with obstacles, some important features are extracted such as; center of mass, area and orientation of each connected component in the map. These features are very important for the proposed intensity and area key-point based map merging methodology, since, similar region or similar obstacles between robot maps can be extracted using area based features.

$$\overline{x} = \frac{\int xb(x,y)dxdy}{b(x,y)dxdy} \tag{4.20}$$

$$\overline{y} = \frac{\int yb(x,y)dxdy}{b(x,y)dxdy} \tag{4.21}$$

Where $b(x,y) = 0$ for background and $b(x,y) = 1$ for connected component related area. The area and orientation of each connected component is calculated using Equation 4.22 and Equation 4.23, respectively.

$$A = \iint b(x,y)dxdy \tag{4.22}$$

$$tan(2\Theta) = \frac{b}{a - c} \tag{4.23}$$

Where,

$$a = \iint (x')^2 b(x', y') dx' dy' \tag{4.24}$$

$$b = 2 \iint (x'y') b(x', y') dx' dy' \tag{4.25}$$

$$c = \iint (y')^2 b(x', y') dx' dy' \tag{4.26}$$

Where x' and y' are about obstacles center of mass in the x and y direction respectively. The derivation of orientation calculation of any connected component is given below.

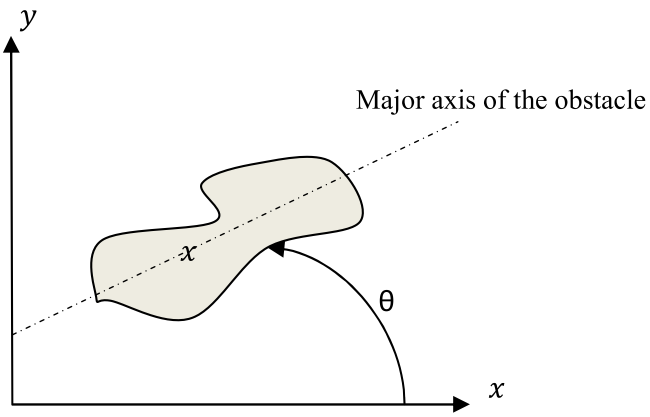


Figure 4.22: Orientation of an obstacle.

Orientation calculation of an obstacle is found using the following derivations: find a major axis which passes throughout the center of mass such as in Figure 4.22 for which the integral of the square of the distance to the obstacle points is a minimum. Minimize $E = \iint r^2 b(x, y) dxdy$ with respect to a line where r is the perpendicular distance from the point (x, y) to the orientation line. The equation of a line shown in Figure 4.23 can be written as in Equation 4.27 using Figure 4.23.

$$xSin(\Theta) - yCos(\Theta) + \rho = 0 \tag{4.27}$$

Write the parametric equations of the line as:

$$x_0 = -\rho Sin(\Theta) + sCos(\Theta) \tag{4.28}$$

$$y_0 = +\rho Cos(\Theta) + sSin(\Theta) \tag{4.29}$$

Where s is the distance along the line from the point (x_0, y_0) closest to the origin. Given obstacle point $(\tilde{x}, \tilde{y})$, find the closest point (x_0, y_0) on the line whose minimum distance is given by $r^2 = (\tilde{x} - x_0)^2 + (\tilde{y} - y_0)^2$

$$r^2 = (\tilde{x}^2 + \tilde{y}^2) + \rho^2 + 2\rho(\tilde{x}Sin(\Theta) - \tilde{y}Cos(\Theta)) - 2s(\tilde{x}Cos(\Theta) + \tilde{y}Sin(\Theta)) + s^2 \tag{4.30}$$

In order to make the distance minimum, differentiate r^2 wrt. s and equate to zero.

$$\frac{dr^2}{ds} = -2(\tilde{x}Cos(\Theta) + \tilde{y}Sin(\Theta)) + 2s = 0 \tag{4.31}$$

$$\Longrightarrow s = \tilde{x}Cos(\Theta) + \tilde{y}Sin(\Theta) \tag{4.32}$$

Insert s into the related equations:

$$\tilde{x} - x_0 = +Sin(\Theta)(\tilde{x}Sin(\Theta) - \tilde{y}Cos(\Theta) + \rho) \tag{4.33}$$

$$\tilde{y} - y_0 = -Cos(\Theta)(\tilde{x}Sin(\Theta) - \tilde{y}Cos(\Theta) + \rho) \tag{4.34}$$

$$\Longrightarrow r^2 = (\tilde{x}Sin(\Theta) - \tilde{y}Cos(\Theta) + \rho)^2 \tag{4.35}$$

Minimization equation can be written as in Equation 4.36.

$$E = \iint (xSin(\Theta) - yCos(\Theta) + \rho)^2 b(x,y)dxdy \tag{4.36}$$

$$\frac{dE}{d\rho} = 2\rho \underbrace{(\iint b(x,y)dxdy)}_{\text{Area}} + 2Sin(\Theta) \underbrace{(\iint xb(x,y)dxdy)}_{\overline{x}\text{A}} - 2Cos(\Theta) \underbrace{(\iint yb(x,y)dxdy)}_{\overline{y}\text{A}} \tag{4.37}$$

$$\Longrightarrow \overline{x}Sin(\Theta) - \overline{y}Cos(\Theta) + \rho = 0 \tag{4.38}$$

$(\overline{x}, \overline{y})$: center of the obstacle related area. Axis of the second moment passes throughout the center of area. Define new coordinates: $x' = x - \overline{x}$, $y' = y - \overline{y}$

$$E = \iint [(x' + \overline{x})Sin(\Theta) - (y' + \overline{y})Cos(\Theta) + \rho^2] b(x' + \overline{x}, y' + \overline{y})dx'dy' \tag{4.39}$$

$$E = aSin^2(\Theta) - bSin(\Theta)Cos(\Theta) + cCos^2(\Theta) \tag{4.40}$$

Where a, b, c values are given as in Equation 4.23.

$$E = \frac{1}{2}(a + c) - \frac{1}{2}(a - c)Cos(2\Theta) - \frac{1}{2}bSin(2\Theta) \tag{4.41}$$

$$\frac{dE}{d\Theta} = (a - c)Sin(\Theta) - bCos(2\Theta) = 0 \tag{4.42}$$

$$\frac{Sin(2\Theta)}{Cos(2\Theta)} = \frac{b}{a - c} = tan(2\Theta) \tag{4.43}$$

After the calculation of all features described above about connected component of each occupancy grid map robots, similar regions between map can be matched as follows. Center of mass of each connected component are used as a key-point location. Since area of the connected component is rotation and transitional invariant,

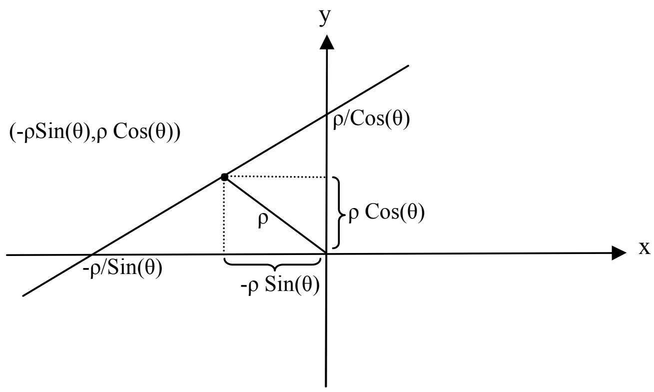


Figure 4.23: Paremetric representation of a line.

same connected components are obtained using nearest neighbor of area of connected components based on Euclidean distance. Orientation of them are used into following section.

Now, each robot has intensity and area based key-points together with their correspondences in the other occupancy grid maps. Translational and rotational difference, transformation, between robot maps are estimated using the procedure described in the coming section.

4.2.3 Transformation Computation

Transformation between robot maps in order to align them can be estimated precisely when all correspondence points are correct. However, there exist some wrong matched key-points between occupancy grid maps such as the correspondences are shown by red colored lines in Figure 4.18. Correct matches are called as inlier and wrong ones as outliers. Hence, to combine partial robot maps, we have to eliminate outliers from all correspondence point space. RANdom Sample Consensus (RANSAC) [67] algorithm which is a probabilistic parameter estimation method is used to discard wrong matches. In this methodology, two correspondence pairs $[x_1, y_1]$,$[x'_1, y'_1]$ and $[x_2, y_2]$,$[x'_2, y'_2]$ are selected randomly from correspondence point space, if these points are obtained by using intensity based key-point localization algorithm described in the above sections, transformation parameters are calculated using Equation 4.44 for orientation and Equations 4.45, 4.46 for translation estimation.

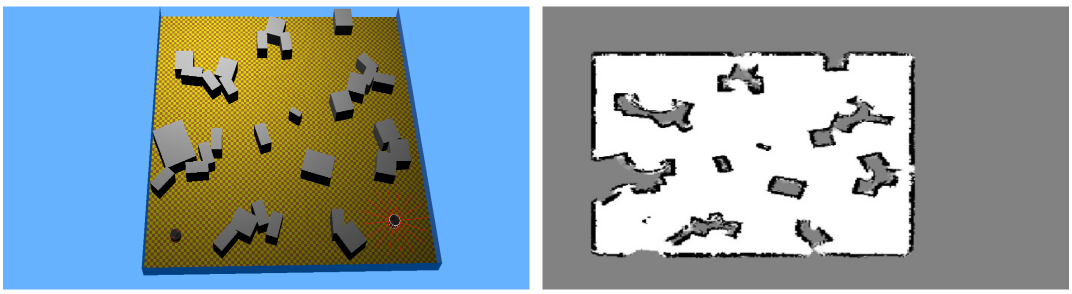
$$\Theta = atan(\frac{\beta\gamma - \alpha\sigma}{\alpha\beta + \sigma\gamma}) \tag{4.44}$$

$$t_x = x'_1 - cos(\Theta)x_1 + sin(\Theta)y_1 \tag{4.45}$$

$$t_y = y'_1 - sin(\Theta)x_1 - cos(\Theta)y_1 \tag{4.46}$$

Where $\alpha = x'_1 - x'_2$, $\beta = (x_1 - x_2)$, $\gamma = y'_1 - y'_2$ and $\sigma = (y_1 - y_2)$.

If randomly selected correspondence points are obtained by using area based key-point localization method, orientation is obtained by taking the difference of matched connected components' orientations, and translation is estimated by subtracting their center of mass in the x and y axes. Then, all key-points in the second map are transformed into the first map by using calculated transformation. Error in the sense of Euclidean distance is calculated using the distance between key-points of the first map and transformed second map key-points. The above procedure continues until the number of predetermined iterations is terminated and transformation parameters are selected with minimum error at the end of the iteration procedure.



(a) (b)

Figure 4.24: Disaster area (a) and occupancy grid map of it (b), obtained by our proposed map merging methodology.

4.2.4 Map Merging

Once the transformation matrix T as in Equation 4.47 between reference frames of robots is calculated, second robot's environment map is transformed using Equation 4.48 such that it aligned with the first robot's map. Then transformed occupancy grid map of second robot M_2' can easily be fused with first robot's map using Equation 4.49; if any pixel (x, y) is not located in the overlapped area, its intensity value remains same, otherwise, weighted sum of pixel intensities are used to obtain overlapped area.

$$T = \begin{bmatrix} cos(\Theta) & -sin(\Theta) & \Delta x \\ sin(\Theta) & cos(\Theta) & \Delta y \\ 0 & 0 & 1 \end{bmatrix} \tag{4.47}$$

$$M_2' = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \end{bmatrix} .T(\Delta x, \Delta y, \Theta).M_2 \tag{4.48}$$

$$M(x,y) = \begin{cases} M_1(x,y) & \text{for} \quad (x,y) \in M_1 \\ \alpha M_1(x,y) + \beta M_2'(x,y) & \text{for} \quad (x,y) \in M_1 \cap M_2' \\ M_2'(x,y) & \text{for} \quad (x,y) \in M_2' \end{cases} \tag{4.49}$$

Here $0<\alpha$, $\beta<1$ and $\alpha + \beta = 1$ are called measure of reliability and their values are given to the system by the user according to the noise margin of the related robot's distance measurements.

After the above procedure, robot maps shown with Figure 4.17 are merged using our proposed method and the resultant global map of real work environment given in Figure 4.24a is obtained as in Figure 4.24b. The map merging performance results are discussed in detail in the upcoming Simulation Results section.

CHAPTER 5

SIMULATION RESULTS

To evaluate the proposed percolator inspired multi-robot coordination control algorithm for victim search operations in disaster environments, various survivor search scenarios are performed with different number of robots.

Firstly, the performance of the particle filter (PF) based simultaneous localization and occupancy grid environment mapping algorithm, described in the Mathematical Background chapter of this dissertation, is presented using a sample disaster area simulation experiment. Then, secondly, our proposed novel goal oriented multi-robot exploration methodology for victim search and rescue operations is evaluated. In these experiments, it is assumed that each robot has unlimited communication range. Hence, robots can exchange all sensor measurements with other robots. Work environments complexity is increased step by step. The comparisons between our exploration methodology and the existing strategies in the literature have been done. In these simulation experiments, each robot tries to grow their environment map to obtain information about structural characteristics of the work space.

Thirdly, occupancy grid map fusion simulation results are given using two partial map of robot and the performance of the proposed map merging algorithm is evaluated according to the obstacle density of the work space using different disaster areas. Then,the performance of the overall goal oriented multi-robot victim search operation is evaluated and analyzed through some simulation results. Map merging module is added prioritized multi-robot coordination control strategy. Hence, unlimited communication range assumption is relaxed using map merging ability to make search and rescue system more applicable to real world applications.

Finally, sensitivity analysis on overlapped area, noise bound difference between robot sensing ability and environment complexity have been done to evaluate in which of these cases, our presented method works more efficiently.

5.1 Simultaneous Localization and Mapping

Figure 5.1 is generated to model a complex and unstructured disaster environment for multi-robot victim search and rescue operations. There are a lot of obstacles with different shape, size and orientation. Two robots equipped with simultaneous localization and mapping algorithm is deployed to extract internal structure of the work space to localize buried victim efficiently. Each robot starts exploration operation from their own starting position as seen in Figure 5.1.

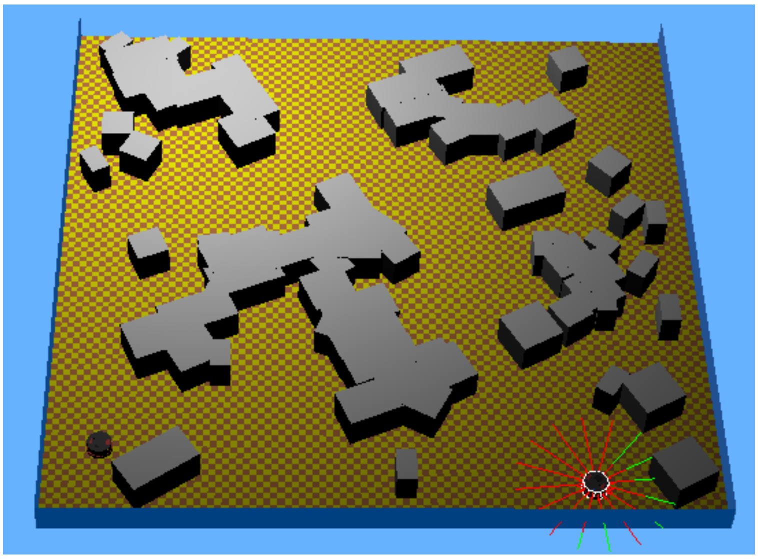


Figure 5.1: Example simulation environment and two robots are deployed for search and rescue operation.

Particle Filter based simultaneous localization and mapping algorithm described in mathematical background part the of thesis is used to obtain the occupancy grid map of work space. Figure 5.2 shows the resultant environment map after robots cover entire catastrophe area. Since, robots have noise in distance sensor measurements, generated environment map is not exactly same with as in Figure 5.1. This SLAM ability is used throughout this dissertation frequently.

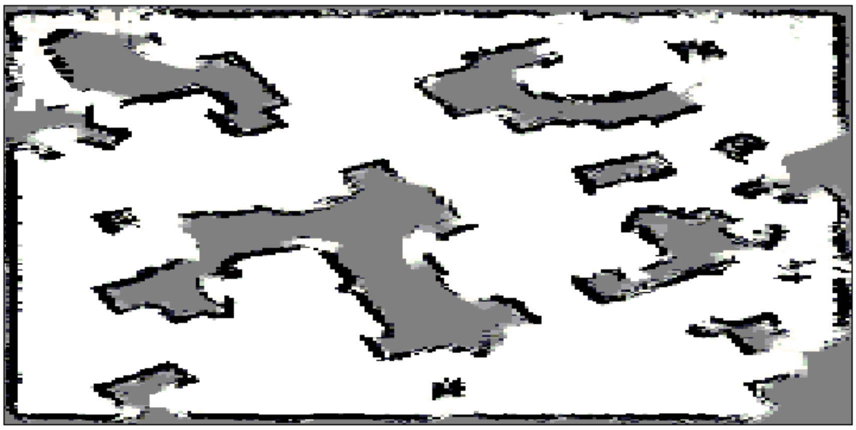


Figure 5.2: Resultant occupancy grid map of disaster environment.

5.2 Goal Oriented Multi-robot Exploration for Victim Search and Rescue Operations, with Unlimited Communication Range.

Previous simulation experiment is performed to evaluate the performance of the simultaneous localization and mapping algorithm. These Particle Filter based SLAM solutions are used in the following sections to generate the simulation results. In this subsection, experiments about goal oriented multi-robot exploration strategy in different search and rescue scenarios are done to demonstrate the efficiency of the proposed percolation theory inspired multi-robot coordination control approach. It is assumed that each robot has unlimited communication range to only focus on prioritized exploration strategy. Map growing performance of the multi-robot system is evaluated. In other parts of the simulation experiments, this assumption will be relaxed to make overall system more realistic for real world SAR applications.

Firstly, we focus on only goal oriented and percolation inspired exploration strategy within a simple environment such as in Figure 5.3 which has only a few obstacles and two robots to clearly show the performance of the percolation theory inspired multi-robot coordination control algorithm. Then, the simulation experiments are made more complex by adding more obstacles with different sizes, shapes and orientations. The size of the disaster environment will also be expanded. In this chapter of the thesis, proposed exploration strategy will be also compared with existing multi-robot environment exploration works in the literature which are summarized in literature survey part of the thesis.

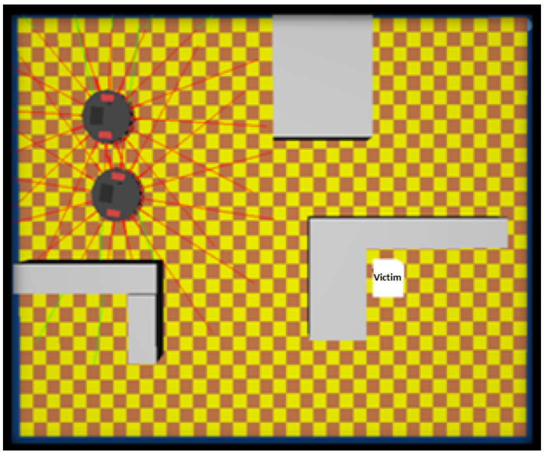


Figure 5.3: A simple search and rescue environment, two Magellan robots are deployed for localizing buried victim.

First experiment is performed by using a simple disaster environment such as in Figure 5.3. The complexity of the work space will be improved step by step in the following experiments. The simulation environment (Figure 5.3) is constructed by using Webots commercial mobile robot software developed by Cyberbotics Ltd.. Two Magellan robots, represented by brown circles, equipped with 16 infra red (IR) distance sensor with unlimited sensing range, aredeployed for search and rescue operation in disaster areas to localize buried victim as soon as possible. Obstacles are represented by gray color and victim position is represented as a white colored box.

We only focus here on developing time and space effective multi-robot coordination control algorithm for victim search in debris, so it is assumed that there is no error in the motion measurements. However, sensor measurements are noisy with additive noise in order to represent measurement errors in real world applications. It is also assumed that robots have unlimited communication range. Hence, they can share all distance and encoder sensor measurements with other members of the robot team. They can build a common occupancy grid environment map. There is no need for map merging task execution in this scenario.

Two autonomous robots R1 and R2 explore the environment simultaneously in a cooperative manner by using the proposed algorithm of percolator guided multi-robot exploration strategy. Resultant occupancy grid map of catastrophe work environment is generated by search robot team such as in Figure 5.4. Black cells in the map are obstacle related area, white cells are about free space where robot navigates safely and unexplored part of the work space is represented with gray cells. Colored lines show us the navigation path for each robot, red line is related with first robot and blue colored one is about the second robots path.

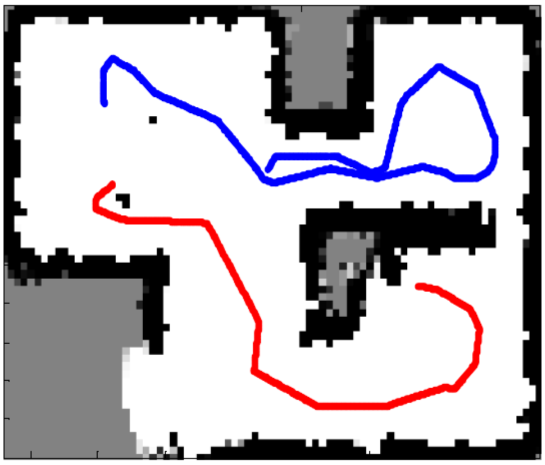


Figure 5.4: Resultant occupancy grid environment map of work space and each robot's path.

As can be seen from Figure 5.4, two autonomous robots start to explore task space cooperatively using proposed goal oriented and percolation inspired controller. They follow very separate navigation paths due to selection of next observation point from different regions related frontier cells of the unknown space. Hence there is no disaster area which is explored by more than one robot. Redundant exploration of same environment space is prevented. This ability increases the efficiency of the overall system in the sense of time and energy, because robots find buried victims by traversing minimum region such as in Figure 5.4. Robots are forced to unknown regions by the algorithm and they do not traverse on the same regions.

Disaster areas like semi collapsed buildings after an earthquake are not structured as in Figure 5.3. This kind of structured and small environment is tested to give the idea behind the robot motion control strategy. Hence more complex and unstructured environment is generated such as in Figure 5.5 where different size obstacles are located more randomly than in Figure 5.3. Obstacle density of some regions are increased intensionally according to other part of the work space, to test the response of robot units on these areas.

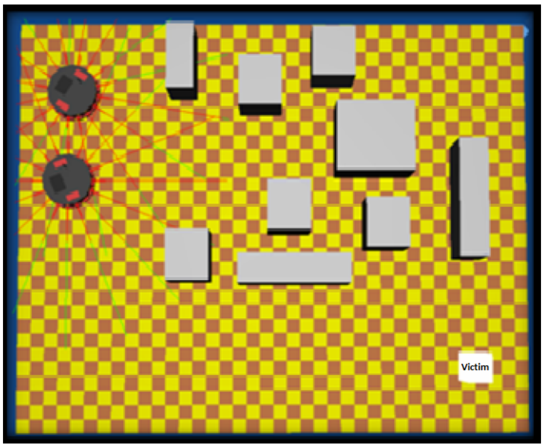


Figure 5.5: Search and rescue environment and two Magellan robots are deployed for localizing buried victim.

Figure 5.6 shows the resultant occupancy grid environment map of the work space which is generated by two search and rescue robots. Red and blue colored lines represent navigation paths of each robot. Yellow colored region indicate explored region by only first robot. In the same way green area is explored only by the second robot and the cyan-stained area is about overlapped area, meaning that this region is explored by both robots.

After a certain period of a time, it is observed that, blue colored robot enter a obstacle crowed area while searching buried victim. Then, robot unit decides that the probability of finding buried victim in that area is very small and our proposed percolation inspired control strategy forces the robot into other large and connected spaces, because, the probability of finding survivor in big connected voids is higher than small and obstacle crowded areas. And it is also observed that each robot try to separate its navigation as soon as possible from each other to prevent repeated area coverage which reduces the efficiency of the exploration operation dramatically.

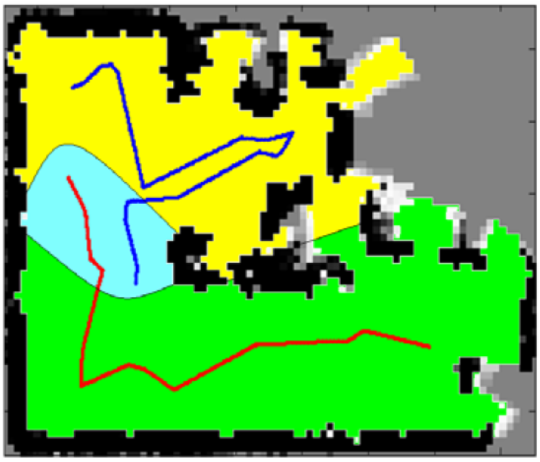


Figure 5.6: Search and rescue environment and two Magellan robot deployed for localizing buried victim.

To evaluate the performance of the proposed goal oriented prioritized multi-robot victim search operation, the size of the disaster area is increased and different shaped obstacles are inserted with varying sizes and orientations as in Figure 5.7. Two robots enter the disaster area from different parts and start exploration of the environment simultaneously.

In this part of the simulation experiments, robots generate occupancy grid map of the environment using same mapping frame to focus on only goal oriented exploration task execution. The resultant occupancy grid map of the disaster area and navigation path of each the robot is presented in Figure 5.8, after finishing the task of finding the buried victim by second robot unit. Red colored navigation path is about first robot which is deployed on the left bottom hand side of the area and the second robot path is represented blue colored line.

It is observed from Figure 5.8 that, each robot firstly tries to explore large, connected and obstacle free spaces using percolator guided navigation control strategy to localize buried victim. If the navigation path of the robot is directed into the obstacle crowded area where the possibility of finding survivor is low and robots may be trapped into small voids, the controller guides the robots towards other parts of the environment as in Figure 5.8. For example, red colored robot path initially go towards the obstacle crowded part of the work space, then it changes its navigation strategy to

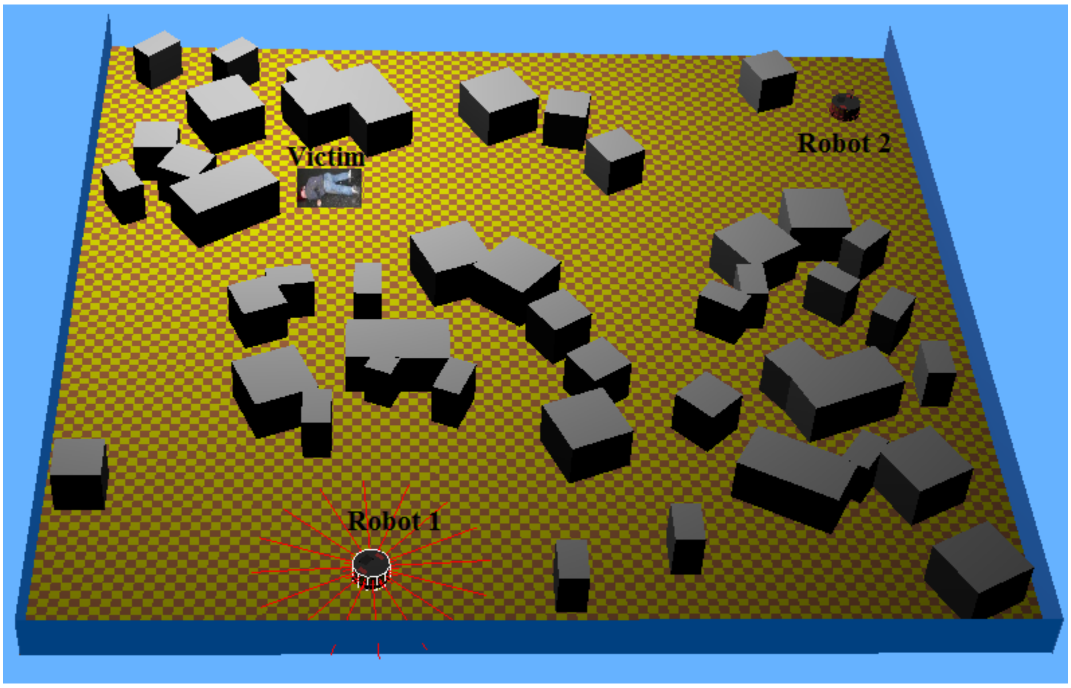


Figure 5.7: Disaster area, two robots are deployed for victim localization operation.

the left hand side of the disaster area, because, the possibility of finding buried victim in obstacle crowded area is becoming less and the controller changes the direction of the robot towards other parts of the work space. Task execution is ended after the discovery of the injured by the second robot whose navigation path is blue.

In order to make detailed analysis about performance of our proposed prioritized goal oriented multi-robot coordination control strategy for victim search and rescue operation, presented in the methodology chapter, the above victim search scenario is performed 20 times in completely unstructured environment as in Figure 5.7 using different number of robots; one, two and three. Initial position of the robots and the location of the buried victim are selected the same for each simulation run for comparative analysis. After the deployment of robots in the disaster environment, each robot starts to explore the work space using simultaneous localization, and mapping algorithm. Percolation inspired coordination control methodology conducts the decision making about navigation direction of the each robot units in the search and rescue team. Search and rescue operation is terminated after the discovery of the injured by

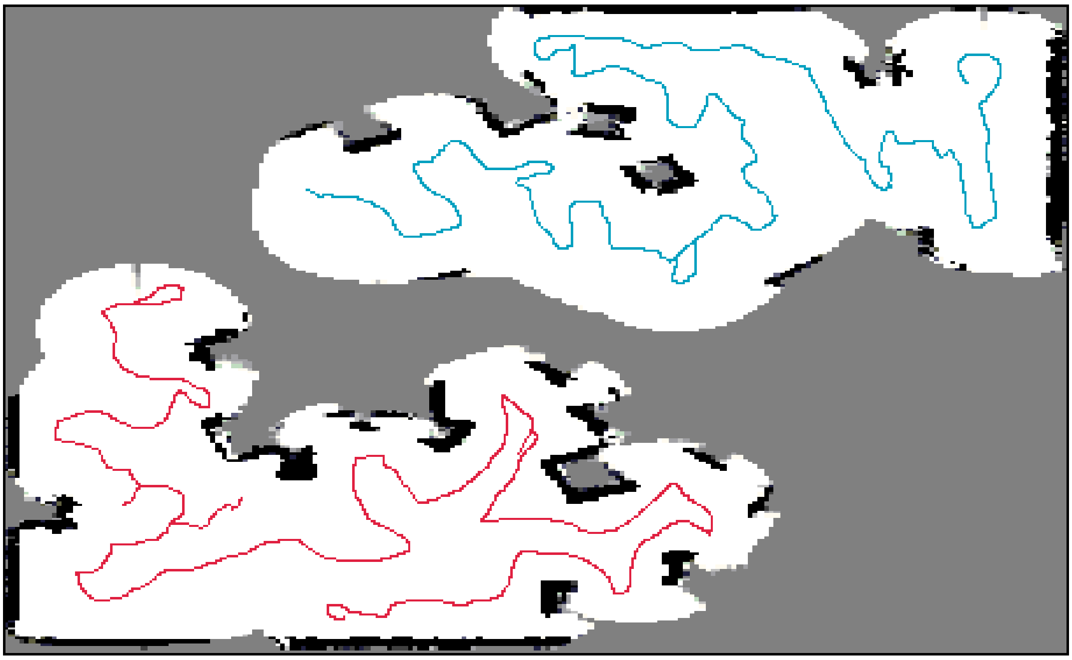


Figure 5.8: Generated environment occupancy grid map of the work space and navigation path of each robot, red colored for first robot and blue colored for other robot unit.

any one of the robot team members.

Figure 5.9 shows the average robots' path length for different number robots which use two different exploration control strategies. Blue colored bar is about average path length after the execution of victim search scenario twenty times using nearest frontier cell based exploration methodology. Standard deviation of path length is given on top of the each bar with a blue line. In this approach, each robot selects its next observation point towards the nearest frontier cell which are about boundary related region between free space and unexplored part of the mission area to obtain much more information about localization of the survivor. This algorithm is very popular in the multi-robot space exploration literature. Proposed percolation inspired and goal oriented multi-robot search and rescue approach performance is presented with red colored bar. Standard deviation of total traversed distance for victim localization for each methodology is represented with blue lines on the top of each bar.

First of all, it is observed from Figure 5.9 that, multi-robot systems, for each control

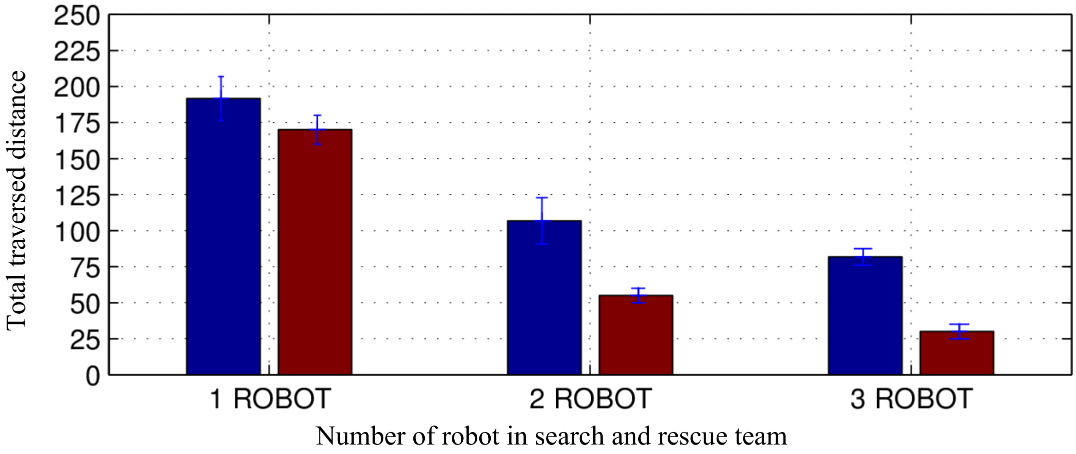


Figure 5.9: Average exploration distances with different number of robots and different control strategies.

strategy, are more efficient than single robot systems in the sense of total path length and inherently due to coordination and cooperation between robot units. Average distance difference between victim localization task executions is very small for both single robot systems which are controlled by proposed methodology and closest frontiers strategy which is mostly used in the literature. It can be concluded that search and rescue systems should consist of more than one robot units.

When the number of robot is increased, the average path length of robots decreases. However, computational burden increases dramatically with the number of robots and so robot number has to be kept within feasible range according to the size of the disaster area. It is observed that, prioritized percolation inspired multi-robot exploration strategy is seen to increase the task accomplishment performance because of the nonexistence of multiple area coverage, comparing with the other methodology. Percolator module also prevents robot units from trapped position into obstacle crowded area and dead ends by estimating the possibility of finding buried victim into following motion direction. It is observed from Figure 5.9 that, the traversed average distance differences between two multi-robot coordination control methodology is increasing with the number of robot units. For example, although there is twice traveled distance difference occurring between two algorithms using robot teams which consist of two robot, our proposed methodology accomplish task twice as much faster than the other exploration strategy using three robot coordinated team.

In the following subsection of the thesis, simulation experiments are performed to evaluate the performance of the proposed novel occupancy grid environment map merging strategy.

5.3 Map Merging

For efficient multi-robot coordination control methodology for victim search and rescue in wide disaster environments, each robot has to exchange their generated partial occupancy grid maps which are extracted from different parts of the work area and fuse them to obtain a global and joint occupancy grid map of the disaster area. This ability is very important to increase the efficiency of the decentralized exploration task in the sense of time and energy. A victim search scenario as seen in Figure 5.10 is performed to evaluate the occupancy grid map merging ability of the proposed approach. Consider a victim search and rescue scenario in a complex, unstructured and initially unknown disaster environment like semi-collapsed wide building occurred after an earthquake. The simulation environment is constructed with square disaster area (250x250 grid cell) by using Webots [68] commercial mobile robot software developed by Cyberbotics. There are a lot of obstacles, represented with gray color, scattered into environment randomly. Their sizes, orientations and positions are completely different and independent from each others due to model catastrophe area as soon as possible.

Two Magellan robots equipped with sixteen IR distance sensor with limited sensing range deployed for the survivor search and rescue operation. They have autonomous navigation and Simultaneous Localization and Mapping abilities with different sensor noise bounds.

The main goal of each robot is to generate internal structure of the work space and localize buried victim by using simultaneous localization and mapping algorithm. And generated occupancy grid map of each robots are merged when each robot notice other one using their communication ability. Each robot starts to explore the environment starting from different initial positions as seen from Figure 5.10 to explore mission space and localize any survivor quickly; fist robot is on the lower left hand

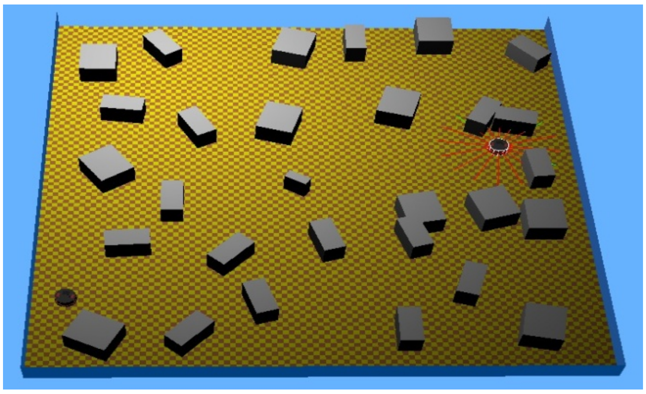


Figure 5.10: Complex and unstructured disaster are and two Magellan robots are deployed for victim search and rescue operation.

side and the other one is located on top and right hand side of the environment to be explored.

Robots simultaneously navigate through the obstacles and construct the map of the surroundings with respect to their own mapping reference frames which are different for each robot unit, because initial position and orientation of each robot are totally different and they are not known from other robot units. Hence, rotational and translational differences occur between the occupancy grid maps of robot team members such as in Figure 5.11 for the first robot and Figure 5.12 for the other robot unit. Rotational and translational differences between generated occupancy grid maps are observed by considering the overlapped area between robot unit maps. It can be observed that, to obtain a consistent global environment map representation, the second robot map has to be rotated 90 degrees in the clockwise direction and translated with a proper values in x any y directions. After these rotation and translation operations, same traversed regions of each robot coincide with eachother and so occupancy grid map of two robots can be merged easily by an addition operation.

During the search and rescue operation, each robot extracts occupancy grid map of its traversed region to localize buried victim efficiently. At a specific time, robots can enter the other robot's communication range and so they notice each other via communication ability. Then, they exchange their generated local map of their own traversed region to obtain the global and consistent environment map. This map fusion ability

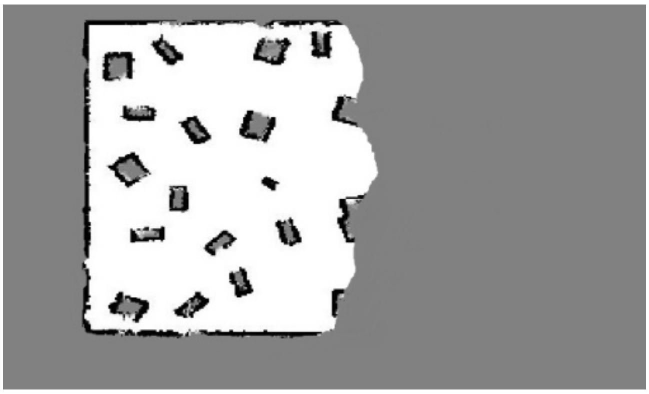


Figure 5.11: Partial occupancy grid environment map of first robot after search and rescue operation.

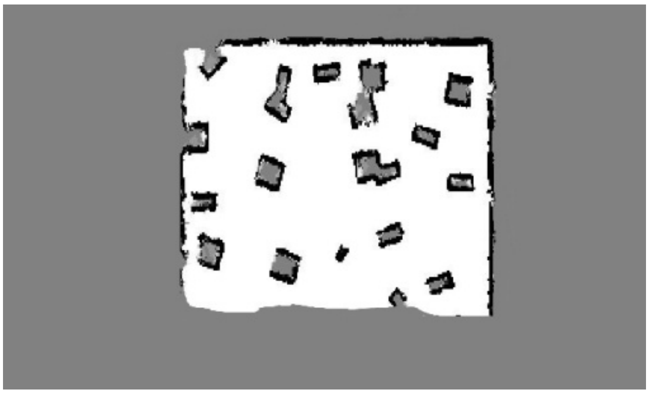


Figure 5.12: Partial occupancy grid environment map of first robot after search and rescue operation.

provides map information to each robot about other part of the environment where are not explored by other robot units. Hence, efficiency of the overall system is improved in the sense of time and energy.

Since feature based (door, wall, corridor, corners) methodologies cannot work efficiently in disaster environments, occupancy grid based mapping strategy is developed in this thesis, because feature extraction such as corner, wall, or intelligent landmarks are not easy in complex and initially unknown work spaces. And also noise in the distance sensor measurements cause wrong feature detections. Hence, we have based our map merging methodology into intensity changes of cell, namely, occupancy grid mapping.

In order to merge the occupancy grid map of each robot as in Figure 5.11 (first robot) and Figure 5.12 (second robot), rigid transformation between mapping frames of robots has to be calculated. To calculate rigid transformation between robot mapping frames, correspondence points between each robot partial maps are calculated by using proposed intensity and area based key-point extraction methodology. Intensity based key-point localization is performed as given in the methodology chapter of the thesis.

After the localization of intensity based key-points, area based key-points are located using connected component analysis of each occupancy grid robot map which is also described in Chapter 3. Occupancy grid maps of each robot map has been converted to binary map to label connected components (obstacles) and to extract features of them as in Figure 5.13 for first robot and Figure 5.14 for other robot. There are two grid cell intensity value, *White* (free space) or *Black* (obstacle related area).

Figure 5.13: Occupancy grid map of first robot and binary representation of it, respectively.

Then, connected components (obstacles) are labeled as in Figure 5.15 and 5.16 for each occupancy grid map. Extra map features such as; orientation, center of mass and size of them are extracted to obtain more information about similar regions between environment map of robot units. These extra features are used to localize key-points for each map.

After the localization of stable key-points, they are matched as seen in Figure 5.17 to calculate transformation between them. Cyan colored correspondence points are

Figure 5.14: Occupancy grid map of second robot and binary representation of it, respectively.

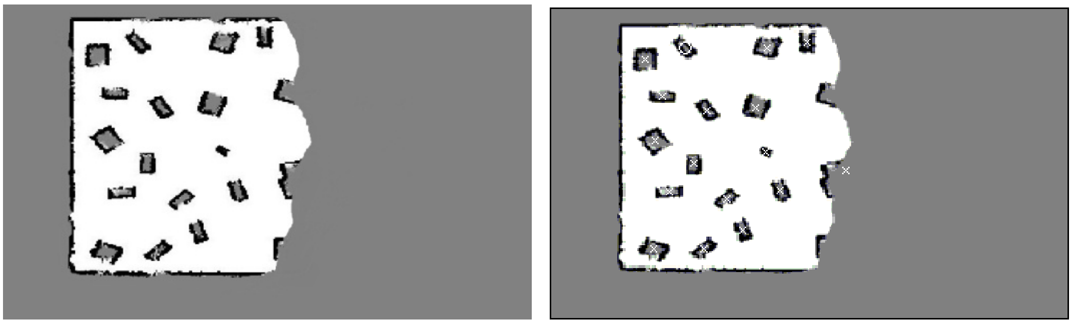


Figure 5.15: Connected component (obstacle) labeling for first robot map, using binary map.

about correct matched key-points and red ones are related with wrong pairs. Wrong correspondence points are eliminated using proposed RANSAC based key-point elimination procedure. In this example, the number of wrong matching points is a tolerable number, for a successful map merging operation, the percentage of wrong key-points cannot be greater than 15.

Detailed sensitivity analysis have been done in the Section 5.5 of this thesis. After the matching correspondence key-points between partial robot maps, occupancy grid maps of robots are merged using our proposed map merging methodology described in previous chapters using correct correspondence points.

Finally, fused occupancy grid map of the disater environment is obtained as in Figure 5.18.

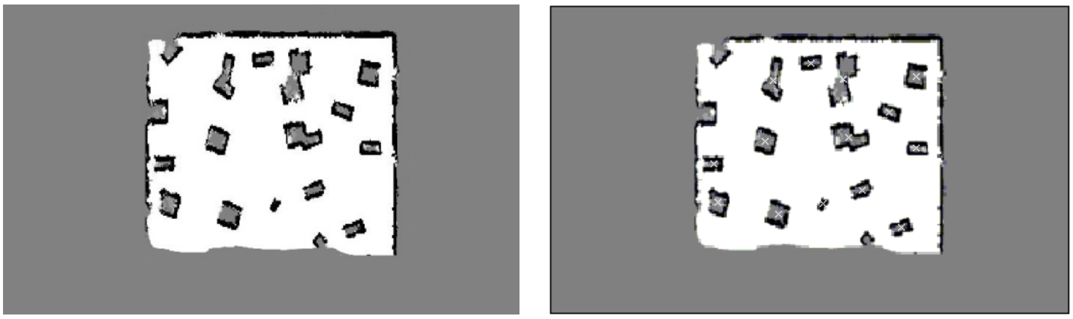


Figure 5.16: Connected component (obstacle) labeling for second robot map, using binary map.

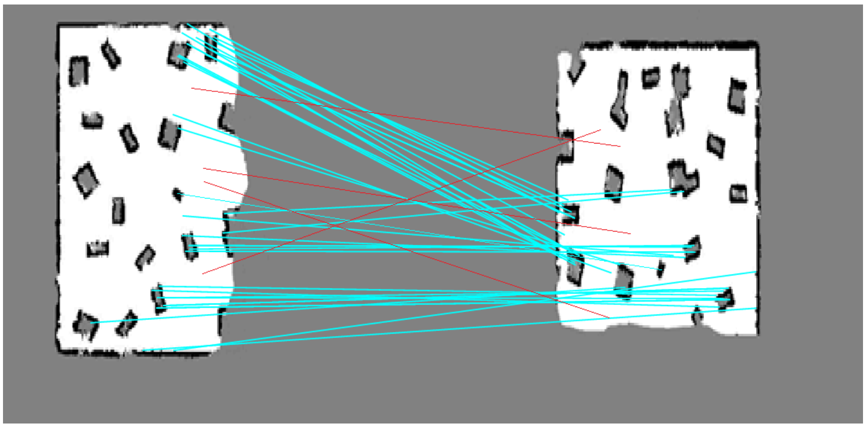


Figure 5.17: Correspondence key-points between partial environment map of search and rescue robots.

To evaluate the overall performance of the proposed occupancy grid map merging methodology according to obstacle density of the mission environment, simulation experiments are performed for different disaster environments where obstacle density is made to vary. Figure 5.19 shows map merging success of the presented algorithm according to the obstacle density. In the x axis of the Figure 5.19, zero means that there is no obstacle in the disaster area (most simple case) and one means that environment is completely occupied with obstacles. It can be observed from Figure 5.19 that, success of the proposed map fusion strategy is approximately 85 percentage for complex environments with obstacle density between 0.65 to 0.75. The performance of the map merging algorithm is low for most simple of obstacle density in the range 0 to 0.4 and most crowded areas with obstacle density is greater than 0.85, because occupancy grid map of robots do not have sufficient feature for map merging opera-

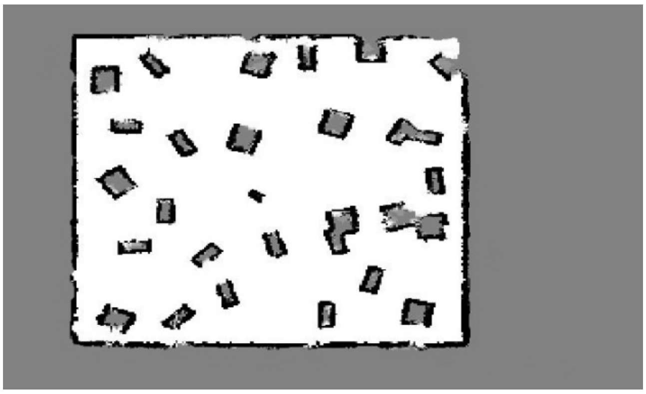


Figure 5.18: Joint and global occupancy grid map of search and rescue environment after the map merging operation.

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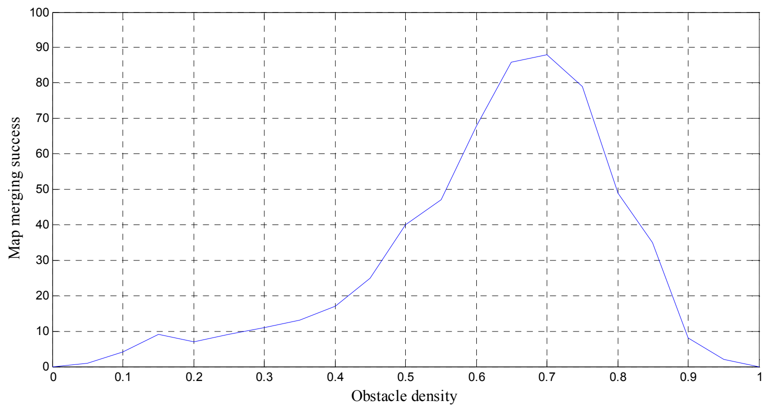

Figure 5.19: Map merging performance according to the environment complexity.

In Figure 5.20, the performance of the map merging algorithm is tested with complex environments which have same obstacle density, but consisting of different shaped and differently located obstacles. It can be observed from Figure 5.20 that, success of the proposed map fusion algorithm is approximately the same than with other mission spaces.

In the following subsection, the overall system performance of the proposed goal oriented multi-robot coordination control algorithm for victim search and rescue operations is evaluated by giving simulation results about different disaster areas. Un-

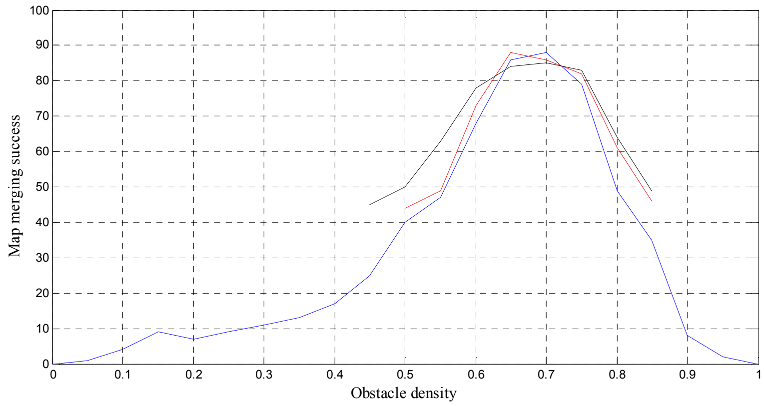

Figure 5.20: Map merging performance according to the environment complexity for different environments.

limited communication assumption is relaxed in this subsection to make victim search strategy more realistic for real world applications. Map merging methodology is integrated into our percolator inspired multi-robot coordination control mechanism.

5.4 Goal Oriented Multi-robot Exploration for Victim Search and Rescue Operations, with Limited Communication Range.

In sections 5.2 and 5.3 of the thesis, occupancy grid map merging and goal oriented multi-robot exploration simulation results are presented for several victim search and rescue operations. In this subsection, several simulation experiments are performed to evaluate the performance of the percolation inspired survivor localization algorithm which uses the map merging ability during the exploration. In these experiments, each robot has limited communication range and hence, occupancy grid mapping reference frames of each robot are completely different which makes the proposed solution more realistic for real world application. Moreover, in real application, robots enter the disaster area from different parts and start map generation task independently from each other. Communication in the disaster areas is very limited due to their structural characteristics.

During the simulation results, some assumptions about the overall multi-robot search and rescue system have been done to focus only on the effect of map merging ability on the overall performance of the proposed victim localization methodology. These assumptions can be summarized as follows:

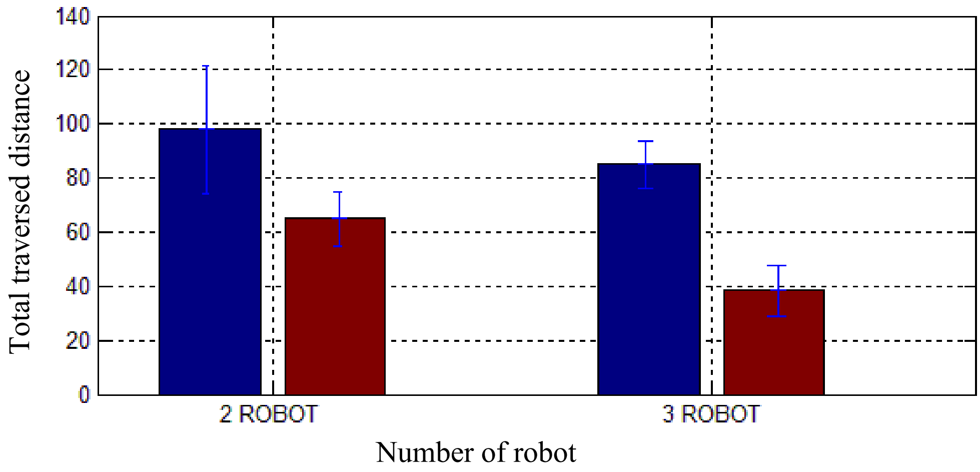

Figure 5.21: Average exploration distances with different number of robots.

- Main assumption is about communication range, each robot has limited communication range in the team and it is same for each of them. Hence robots can only share generated occupancy grid maps about traversed mission spaces, when they enter their communication range. Distance and encoder sensor readings of any robot are not given to other robots.

- During the map merging operations, it is assumed and provided that there is at least 35 percentage overlapped area between occupancy grid map of the robot units.

- Noise bound difference between robot distance measurement abilities is not greater than 40 percentage.

- Exploration operation is terminated when any one of the robot team member reaches the buried victim.

Figure 5.21 shows the performance of the proposed percolation inspired multi-robot coordination control methodology when each robot have occupancy grid map merging ability. The comparison has been done using the proposed percolation inspired victim search algorithm which has not map merging capability(blue bar) and which is equipped with the map merging ability (red bar). Same disaster environment is used as in section 5.3 with different number of robot, two and three. As it can be seen from Figure 5.21, the performance of the search and rescue team with occupancy grid map merging ability is better than other one, because, with the help of map merging, each robot unit can obtain information about structural characteristics of the other part of the work space where robot did not traverse on there. And robots navigate according to this extra information. Hence, multiple area coverage is obstructed.

When Figures 5.21 and 5.9 are compared, it can be observed that the performance of the unlimited communication related system (map growing) is a bit more successful than limited communication related one. In unlimited communication case (map growing simulation experiments), each robot share all their distance and encoder sensor measurement information at each step of the operation and so they construct a unique and global occupancy grid map. However, unlimited communication assumption makes this solution unrealistic in multi-robot search and rescue operation in hard disaster environments.

In the following Section of this dissertation, several experiments are also performed to evaluate the effectiveness of proposed partial occupancy grid environments map merging methodology by using disaster area as in Figure 5.10 in the sense of overlapped area between robot maps, noise bound differences between robot sensing abilities and obstacle density of the disaster area.

5.5 Sensitivity Analysis

In the literature, existing map merging methods claim that a huge overlapped area is necessary for accurate merging operation such as: 70 percent of the overall mission space has to be explored by same robots for a successful map fusion task execution. However, this overlapped area rate reduces the efficiency of the overall multi-robot victim search operation, because the performance of the system is dramatically increasing proportional with the decreasing overlapping area between partial map of each robots. And also, the number of wrong correspondence key-point matching increases when there exists very limited overlapped area between maps, because, similarity between occupancy grid map of robots is not sufficient.

Figure 5.22 shows us the performance of the proposed map merging methodology according to the overlapping area percentage between occupancy grid maps of robot to be merged. The sensitivity of the system according to the overlapped area between robot maps is evaluated in terms of estimated transformation error between mapping frames, i.e. map merging error versus overlapping area percentage between occupancy grid maps of robot units.

It is observed from Figure 5.22 that if robots try to merge their partial occupancy grid maps in which percentage of overlapped area between them is nearly zero, map merging error is approximately 100 percent, hence, mission fail. This case occurs when robots do not navigate into the same area, i.e., there is no overlapped area between maps. Hence, correct correspondence key-points cannot be localized between generated maps as virtual landmarks for accurate map fusion, since there is not enough similarity between robot partial maps. Hence, map merging operation is completely failed.

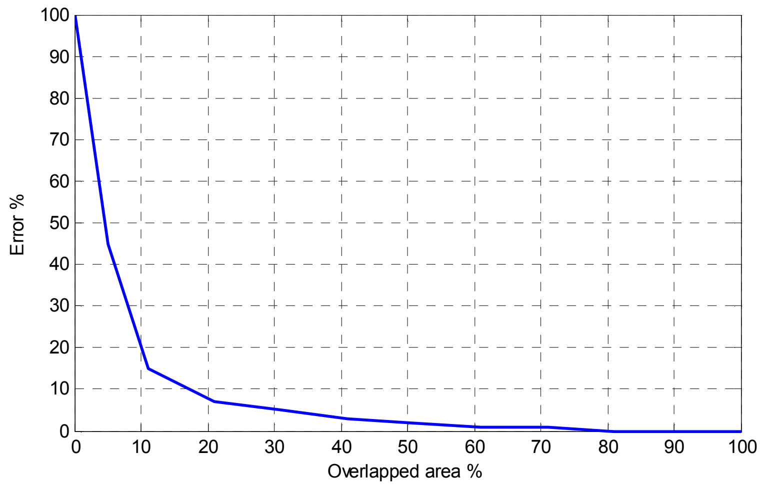

Figure 5.22: Map merging error according to the overlapped area between occupancy grid robot maps.

If the percentage of overlapped area between robot maps is increased, merging error decreases dramatically and 30 percent overlapped area can be enough for occupancy grid map merging operation in desired error range which is lower than 5 percent. This error can be tolerated by using neighbor connected components positions and localizations. Figure 5.22 also shows that, when robots navigate through same mission space and each robot nearly extract similar occupancy grid maps, overlapped area percentage between occupancy grid map of robots is approximately hundred percent and map merging error converges to approximately zero, because there are huge amount of similarities and information between generated occupancy grid environment maps is enough.

Another experiments are performed to test the performance of presented map merging method with two robots which have different noise bounds on their distance sensor measurements. Different noise bound means that each robot has different mapping ability. Hence, the sensitivity of proposed map merging methodology is evaluated according to the noise margin differences between robot distance sensor measurements.

In simulation experiments, each robot has different noise model which means that each robot can detect the distance of obstacles differently from each other. For example, if first robot has 10 percent uniform noise in its distance measurements, while the second robot noise bound is 15 percent, there occurs 5 percent noise bound difference between robot distance measurements. This noise difference causes different occupancy grid map representation around some cells.

Figure 5.23 shows the sensitivity of our proposed map merging methodology according to the noise margin differences in distance measurements of robot units. It is the plot of occupancy grid map merging error versus noise bound difference between two robot units.

All simulation experiments are implemented using environment map of robots where overlapped area between maps is constant, approximately 40 percent, because, the sensitivity of noise bound differences is determined only. This ratio is constant and it is enough for good merging performance according to the overlap area criteria, since, the effect of noise margin differences on map merging performance can tested.

It is observed from Figure 5.23 that if there is no difference between robots noise bounds which means that these two robots have exactly same mapping ability or

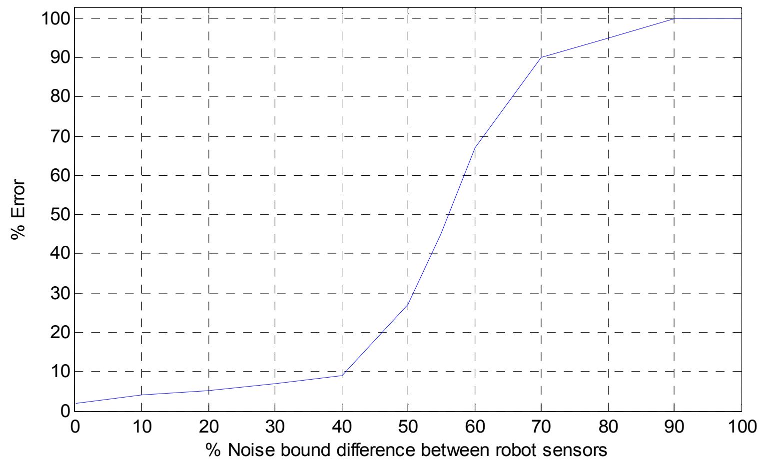

Figure 5.23: Map merging error according to the noise bound difference between robots.

these maps are generated by same robot, occupancy grid map merging error is very small. When noise bound difference between robots distance sensor measurements increases step by step, map merging error remains in tolerable limits up to 40 percent noise bound difference. This value is determined as a threshold for correct occupancy grid map fusion task execution. If we give the most extreme case such as, noise bound difference increases to one hundred percentages, map merging cannot be done correctly due to huge amount of transformation estimation error and so intolerable map merging error occurs.

According to all above sensitivity analysis experiment results about overlapped area and noise bound difference in distance measurements for complex and unstructured disaster areas, it is concluded that limited overlapped (35 percentage) area is sufficient for accurate multi-robot occupancy grid map merging task execution. And also, noise margin differences up to 40 percent can be tolerated to obtain consistent global environment map from partial environment of robots. These improvements are evaluated according to existing works in the occupancy grid map merging literature.

To evaluate the performance of proposed multi-robot victim search strategy according to the complexity of the disaster area, Figure 5.24 and Figure 5.25 are generated. These two environments represent extreme cases, most simple (there is no obstacle) and very complex one respectively. Performance of the given system is also compared

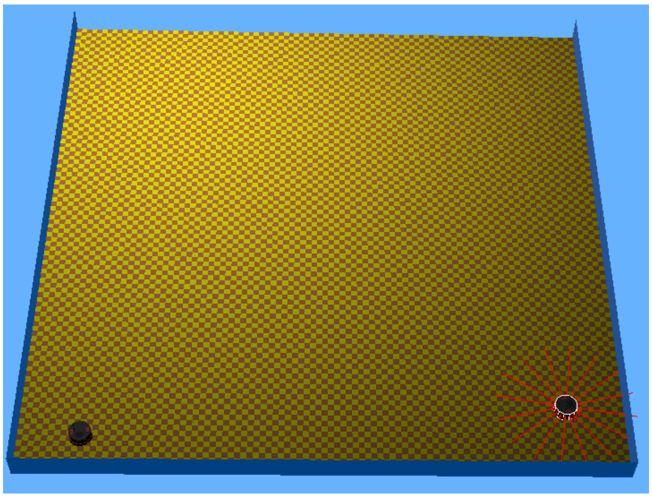

Figure 5.24: Most simple work enviroment, extreme case.

with the popular “closest frontier”based control algorithm of the literature according the number and size of the obstacles.

Figure 5.26 show the total visited distance of robot units which are controlled by two different coordination control methodology. Horizontal axis show the complexity level of the disaster environment. 0 value is about most simple disaster work space (Figure 5.24). Figure 5.25 gives the related environment of obstacle density level is 1, considered most complex case. Complexity levels are evaluated according to the obstacle area, linearly. Hence, disaster environments which have complexity level between 0 and 1 are generated. Vertical axis of the Figure 5.26 is about total visited distance until the victim localization. Two robots are used in this experiments. Blue bar represents simulation experimental results about our proposed percolation inspired victim search strategy and red colored bars are about closest frontier based multi-robot coordination control approach.

It can be observed from the figure that total visited distance in most simple case and 0.25 complexity level case are approximately similar, there is no significant difference. In 0.5 and 0.75 environment complexity levels, the performance of the proposed percolator inspired exploration strategy is very high. However, visited distance difference is decreased in most complex disaster environment experiment. The reason of that is as follows: the number of obstacles in Figure 5.25 is very high and per-

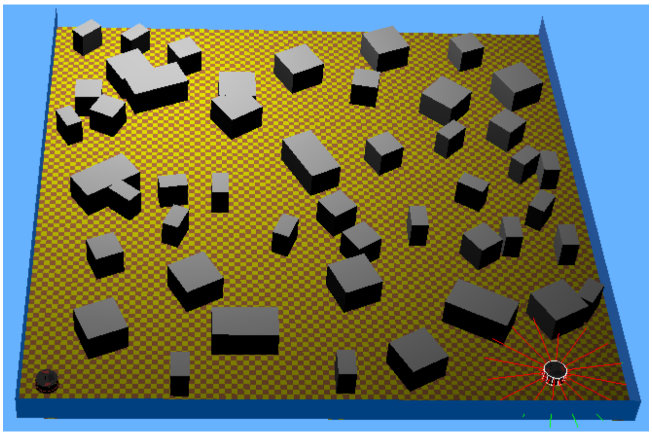

Figure 5.25: Most complex disaster enviroment.

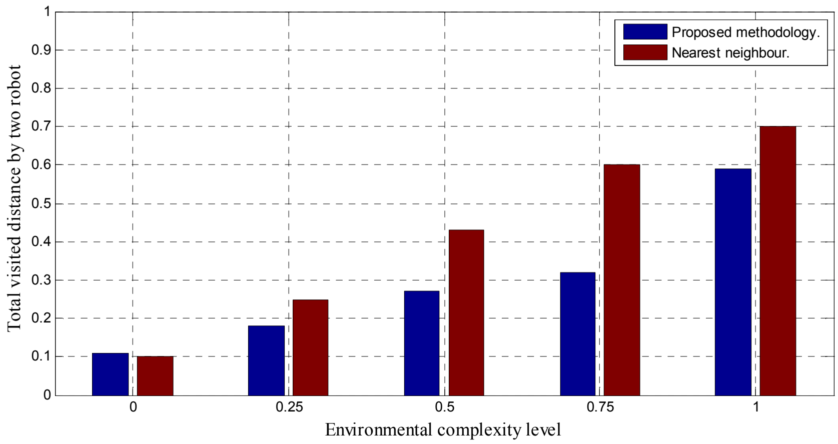

Figure 5.26: Environmental complexity versus total visited distance plot.

colator guided robots cannot easily navigate because of small connected voids. The percentage of large, connected and free space is very limited. However, percolator inspired multi-robot exploration strategy is more efficient than closest frontier based exploration methodology.

CHAPTER 6

CONCLUSION AND FUTURE WORK

In this thesis, a novel multi-robot coordination control methodology is developed for complex, unstructured and unknown disaster environments to localize buried victim in the debris efficiently. Robots can cooperatively extract the internal structure of the catastrophe area using prioritized exploration strategy and can localize buried victim without covering entire area. Four main modules, robot position estimation, environment map generation, occupancy grid map merging and intelligent coordination control of robot units, are combined for efficient victim search and rescue task execution.

Occupancy grid map merging is a challenging task especially for real time multi-robot search and rescue operations in complex disaster environments. Combining partial maps of robots into a global one allows robot team to avoid repeated exploration of some regions by different robots. In this work, a novel map merging methodology is developed for occupancy grid maps to obtain a global and consistent environment map for multi-robot exploration operations in search and rescue environments.

The proposed approach possess the following properties which are not be covered by existing works in the literature due to their limitations:

- Disaster areas such as semi collapsed building due to earthquake are completely unknown and unstructured, hence map fusion strategy is proposed for which not only for mapping in structured environments, but also used efficiently in unstructured and complex environments.
- Presented algorithm is also capable of successfully merging partial occupancy

grid map of robots which have limited degree of overlapping regions between their maps.

In this dissertation, a new prioritized decision theoretic multi-robot exploration strategy is presented for multi-robot SAR systems. Robot try to make maximum coverage of the environment following the prioritized direction of the connected voids, thus avoiding dead ends. Percolation model and entropy based switching generating a hybrid navigation controller is presented for the navigation control of each robot for search and rescue operations.

Thus, in the presented prioritized exploration strategy, coverage does not become a primary issue. There, the optimality of time and special exploration optimality is aimed using guidance through prediction of upcoming voids. Proposed method guides robots navigation toward the biggest cluster of connected voids in the disaster area using a percolation model based controller.

Existing exploration strategies try to explore the entire disaster area with a minimum amount of time to localize buried victim. If there is no information about the internal structure of the building such as locations of the living room or corridors, our percolator-based second proposed method guides the robots navigation toward the biggest cluster of connected voids in the disaster area for uninterrupted navigation. Simulations results show that our proposed approaches is more time effective as expected than unguided exploration strategies.

Main contributions of this dissertation is summarised as follows, details of which are introduced throughout the thesis.

- A novel multi-robot victim search strategy is developed for disordered disaster areas.
- A novel occupancy grid map merging algorithm is introduced for unstructured work spaces. Advantages of the proposed map merging are given below.
  - Limited overlapped area between partial maps of robots is enough for good merging performance.

  - Unstructured and complex partial occupancy grid environment maps can be merged efficiently.

- A novel percolation theory inspired prioritized environment exploration methodology is presented for multi-robot search and rescue teams.

6.1 Future Work

We have developed prioritized multi-robot coordination control strategy for victim search operations in complex and unknown disaster areas. After the localization of survivor into debris using presented methodology, there should be another multi-robot control mechanism for rescue operation. Rescue phase of the search and rescue operation needs hybrid robot team, consisting of different capabilities and coordination control algorithm to handle physical uncertainties and limitations of the disaster area.

Three dimension environment map generation and merging those maps are another challenging research topic for SAR operations in complex and unknown disaster environments. Two dimensional mapping strategies take certain slice samples from the traversed region and they are merged to obtain more information about the structural characteristic of the mission environments. 3D map representation of work area give more detailed volumetric information about the disaster area.

Mechanical development of hybrid robot teams which consist of different capable robots is another future work for search and rescue operations. For example, reconfigurable robots provides high navigation capability in complex areas by modifying their shape according to the internal structure of the environment which is extracted by mapping abilities. These robots increase the performance of the SAR operation. After the development of high capable robots, our proposed victim localization strategy can then be applied into the real world complex and initially unknown disaster environments.

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CURRICULUM VITAE

PERSONAL INFORMATION

Surname, Name	: Topal, Sebahattin
Nationality	: Turkish (TC)
Date and Place of Birth	: 25 August 1980 , Eskişehir, TURKEY
email	: stopal@metu.edu.tr, sebahattin80@yahoo.com

EDUCATION

Degree	**Institution**	**Year of Graduation**
PhD	: METU, Electrical and Electronics Engineering,	2011
BS	: Süleyman Demirel Univ., Electronics and Tel. Eng.,	2002
High School	: Prof. Dr. Orhan Oğuz Süper Lisesi, Eskişehir,	1998

WORK EXPERIENCE

Year	**Place**	**Enrollment**
2002–Present	: METU, Department of Electrical and Electronics Eng.	Research and Teaching Assistant

FOREIGN LANGUAGES

English

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