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Multi-robot Task Allocation for Search and Rescue Missions

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Abstract. Many researchers from academia and industry are attracted to investigate how to design and develop robust versatile multi-robot systems by solving a number of challenging and complex problems such as task allocation, group formation, self-organization and much more. In this study, the problem of multi-robot task allocation (MRTA) is tackled. MRTA is the problem of optimally allocating a set of tasks to a group of robots to optimize the overall system performance while being subjected to a set of constraints. A generic market-based approach is proposed in this paper to solve this problem. The efficacy of the proposed approach is quantitatively evaluated through simulation and real experimentation using heterogeneous Khepera-III mobile robots. The results from both simulation and experimentation indicate the high performance of the proposed algorithms and their applicability in search and rescue missions.

1. Introduction

Extensive research nowadays is focusing on multi-robot systems (MRS). These systems offer many advantages as they have high potential to solve a multitude of problems such as industrial warehouses, surveillance and in search and rescue missions. MRS provide high reliability and performance of complex tasks even though they are simple in design [1]. It should also be noted that MRS possess the potential of producing poor results and/or non-deterministic performance if the design did not take into consideration the interaction and interference between the robots [2].

One of the main problems in MRS is task allocation which is the process of assigning tasks to the robots. It has to be done in order to avoid clashes between multiple robots and to increase the overall performance of the system. Therefore the allocation of the tasks to the proper robots strongly affects the performance of the system [3]. This problem is known as Multi-Robot Task Allocation (MRTA) problem.

In this paper, generic approaches are proposed to solve large-scale and heavily constrained MRTA problem. These approaches generate a solution in which the given robots are efficiently allocated to the given tasks to maximize the overall performance and minimize the total cost of the system. It takes into consideration the real world constraints of the system, the requirements of the tasks and the capabilities of

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the robots. Moreover, path-planning algorithms are implemented to enable the robots finding collision-free path from a start position to a given goal position, avoiding a collection of obstacles in any given environment.

The proposed algorithms are simulated for a search and rescue scenario with three heterogeneous Khepera-III mobile and five survivors distributed in different locations within the simulation field. The robots have different capabilities, one is equipped with a gripper, second is equipped with a camera and the third equipped with a laser range finder. The survivors have different requirements according to the needed capabilities of the robots. Thereafter, the algorithms are tested with the real Khepera-III mobile robots and experimented in an indoor arena and the survivors are represented by labeled objects. The results from both simulation and experimentation closely related which validate the performance of the proposed algorithms.

The remainder of this paper is organized as follows: Section 2 introduces the MRTA problem formulation followed by describing the proposed algorithms in section 3. Section 4 demonstrates the search and rescue scenario, simulation and real experimental work, followed by discussing the results in section 5. Finally, conclusion and future work are summarized in Section 6.

2. Multi-Robot Task Allocation Problem

MRTA problem addresses the question of assigning the task-to-robot in order to achieve the overall system goals [4][5]. The MRTA problem is a dynamic decision problem that varies in time with phenomena including environmental changes, the problem should be solved iteratively over time [6]. Thus, the problem of task allocation becomes more complex to tackle.

2.1. Formulation

Since the main objective is to solve the task allocation problem of MRS in real world applications. Therefore, through the different phases of the development of the proposed approaches, the central target was to introduce a generic approach that is capable of solving various MRTA problems of different features and challenges. This goal had to be taken into consideration during the formulation of the problem and therefore the use of the multiple traveling salesmen problem (mTSP) formulation after being extended and adapted to the MRTA problem requirements [2], see Figure 1.

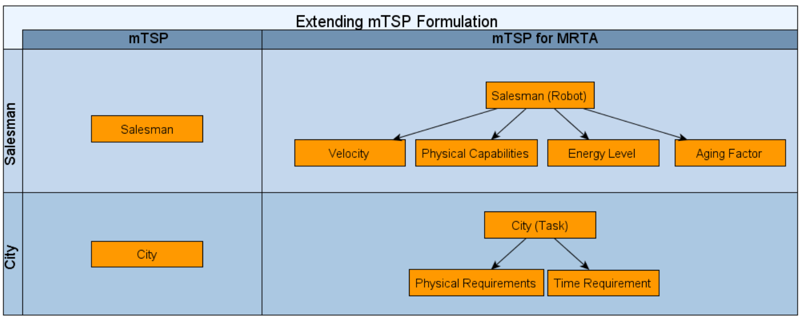


Figure 1. Extended mTSP formulation for MRTA Problem

3. Proposed Approach

MRTA approaches can be categorized as market-based approaches and optimization-based approaches. In the former, the problem is handled in the context of auctioning and in the later, the optimal is solved as an optimal assignment problem.A comparative study between these two approaches is presented in

[7]. In this paper, market-based approach is adopted due to its capability to handle complex heavily constrained MRTA problems.

3.1. Market-based approach with relinquishing and optimization

The market-based approach gained a considerable attention within the robotics research community because of several desirable features, such as the efficiency in satisfying the objective function, robustness and scalability [5]. Market-based multi-agent coordination approaches share a set of fundamentals. Auction theory provides detailed definitions for many of these fundamentals [8],[9]. The market-based approach is based on auctions, which consists of bidders and goods available for the bidding process. In the MRTA problem, the robots are considered as the bidders and the tasks are considered as the goods. The auction takes place and a centralized agent makes the final evaluation and the winner determination technique. The proposed approach is an combination of the Single-good Auctions and Contract Net Protocol (CNP) [2].

The proposed approach starts as follow:

- First step is the announcement stage, the centralized agent set a list of all the available tasks and define all their requirements in terms of skills and execution time.
- Second step is bidding stage, the robots start bidding on the available tasks taking into consideration the matching capabilities to the requirements of the tasks.
- Third step is the selection stage, the centralized agent evaluates all the bids and start the winning determination strategy.
- Fourth step is the assigning stage, the centralized agent announces the winner by assigning a robot for each task.

As described in [2], the MRTA problem is formulated as an instance of the mTSP. The the same objective function of the mTSP cannot be straightforwardly used as the objective function for the MRTA problem. Hence some variations are introduced to the objective function of the mTSP in order to be effectively used for the MRTA problem. For k sub-tours and t tasks in each sub-tour, the total traveling time is calculated as follows:

$$A = \frac{\sum_{i=1}^{t-1} \text{distance between}(\ subtour_{j_i}, subtour_{j_{i+1}}\ )}{\text{Velocity of Robot}_j}$$

$$B = \frac{\sum_{i=1}^{t} \text{task execution time}\ (\ subtour_{j_i}\ )}{\text{Aging factor of Robot}_j}$$

$$\mathrm{f}(\mathbf{x}) = \underset{j\in\{1,2,\ldots k\}}{\arg\max}\ (A+B) \tag{1}$$

It is not necessary to have a task for each robot, but it is a must to have a robot for each task. To reach near optimal solutions, relinquishing process along with simple optimization technique were implemented as enhancements to the market-based approach.

The relinquishing process is an iterative process, where at the end of each iteration, each robot waives a random task from its assigned tasks to be available again in the tasks list. This ensure some diversification in the solution, because after relinquishing a random task the robot solution (sub-tour) is changed in which in the next iteration it may give a better bidding value to a different task therefore diversification is achieved. Additionally, in the end of the algorithm, and having all robots with assigned tasks from the market-based approach, an optimization technique is applied to the sub-tour considering the robot and the tasks in the sub-tour as a single traveling salesman problem. According to previous studies in optimization techniques [10], simulated annealing is selected to be the optimization technique for the sub-tours

Algorithm 1 is the proposed algorithm used to solve the MRTA problem in this work using the market-based approach including the relinquishing process and the optimization enhancements [2].

Algorithm 1: Market-based approach with relinquishing and optimization

```
Input: Tasks list tasks, Robots list robots, Distances between tasks distances, Number of
       Iterations n
Output: Best allocation bestAlloc
Best cost bestCost
Available tasks availTasks
Bidding list biddingList
Minimum bid minBid
Current allocation curAlloc
Current cost curCost
User define percentage r_o
availTasks ← tasks
for i ← 1 to n do
    while isEmpty(availTasks) do
        biddingList ← getBids(robots, availTasks, distances)
        minBid ← getMin(biddingList)
        curAlloc ← subTour(robots, availTasks, minBid)
    end
    availTasks ← relinquish(curAlloc, availTasks) // r ← getRandomNumber(1)
    if curCost < bestCost then
        bestAlloc ← curAlloc
    else
        if r_o > r then
            bestAlloc ← curAlloc
        end
    end
end
optiAlloc ← optimize(bestAlloc) //
```

3.2. Path Planning Algorithm

The market-based approach generate the allocation of the tasks to the robots. Then for the robots to navigate from their current position to the task position, path planning algorithm is required. There are different approaches to determine the path which the mobile robots should take to navigate to the desired location given the complete map of the obstacles and the starting position. In this work, Dijkstra and A* algorithms are implemented to generate the optimal path.

3.2.1. Dijkstra Algorithm Dijkstras algorithm is a graph search algorithm that solves the single-source shortest path problem for a fully connected graph with non-negative edge path costs, producing a shortest path tree. This algorithm discretizes the terrain map to blocks, in which each block is a node. Each node has 4 edges and 4 corners. The edges and corners are used to define relations between the nodes and the cost to move form one node to the other. The cost can be represented by the function $l(x,u)$, where its costs $l(x,u)$ to move from node x by applying the action u. Thus, the summation of the edges and corner costs along the path from the initial node to the goal node results the total cost of the plan. The mathematical definition can be calculated as follows:

$$l(x,u) = \begin{cases} 0, & \text{if } x \text{ is equal to current node or there is no common edge or corner} \\ 1, & \text{if } x \text{ has a common node or edge} \\ \infty, & \text{if } x \text{ contains an obstacle} \end{cases} \tag{2}$$

3.2.2. A Algorithm* A* is a special case of best-first informed search. Its main advantage over Dijkstra algorithm is that it uses the knowledge known about the problem in form of a heuristic function to prune the search.The mathematical definition can be calculated as follows:

$$f(x) = g(x) + h(x) \tag{3}$$

$g(x)$ denotes the cost-to-go from the starting state to the successor state. On the other hand, $h(x)$ denotes the cost-to-go from this specific successor state to the goal state. The total cost $f(x)$ is computed for each successor node, and the node with the least $f(x)$ is chosen as the next successor. Thus, by choosing the most appropriate successor node, the optimal path to the goal can always be guaranteed. The costs $g(x)$ and $h(x)$ are the distances between the nodes, which can be simply determined by calculating the straight distances between the nodes.

3.2.3. Trajectory Planning After planing the path it is essential to smooth the sharp edges of the path and generate the velocity states along the path from the smoothed path as follows:

- Spline are ordinary cubic parametric polynomial functions. Since there are four unknown coefficients, four conditions must be defined in order to define the shape of the spline in order to avoid large curves which will lead to collision with obstacles. The splines used are the *Cubic Bezier Splines* [11] which have the following equation.

$$S(t) = (-P0 + 3P1 - 3P2 + P3)\tau^3 + (3P0 - 6P1 + 3P2)\tau^2 + (-3P0 + 3P1)\tau + P0 \tag{4}$$

- Velocity generation is the process of linking the trajectories created by the splines to the time parameter in order to calculate the velocities and the acceleration of the robot. A velocity limiter is defined which is based on the actual maximum value for velocity, where V_{transl} is the transnational velocity, and V_{rot} is the rotational velocity.

$$V_{max} = V_{transl} + V_{rot} \tag{5}$$

From the kinematics of the differential drive model, the transnational velocity can be calculated according to the intrinsic parameters of the robot, where L and R are the left and right wheels' velocities respectively.

$$V_{transl} = \frac{V_{max}}{1 + \frac{L}{R}} \tag{6}$$

4. Experimental Work

In order to validate the proposed algorithms, a set of MRTA problem scenarios are tested. In each scenario, the algorithm is applied and the results are reported for further evaluation through the evaluation metrics. All scenarios have three main inputs, namely, the robots, the tasks and the distance matrix representing the tasks' location. The expected output for solving the MRTA problem is the best allocation that maximizes the performance of the system. On another level, path-planning algorithms are tested to generate the near optimal path from the start to the desired goal locations, given the map with the locations of all robots and tasks.

4.1. Evaluation Scenario

Since one of the main sources of complexity of MRS applications is the size of the robot team as well as the number of tasks to be executed, it was essential to test qualitatively and quantitatively the proposed algorithms for their capability of handling complex MRTA problems. Figure 2 presents the adopted search and rescue scenario for experiments in this study.

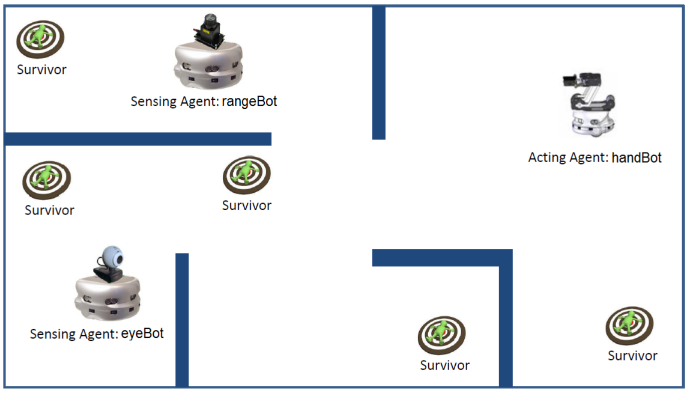


Figure 2. MRS Search and Rescue Scenario

In this proposed search and rescue scenario, five survivors (from some human-made or natural-made disaster for example) are located in the search area, these survivors have different requirements. Three robots are used in the search area to accomplish the search and rescue mission. Each robot has unique sensing and acting capabilities. In this study, the robots used are modeled by the Khepera-III mobile robots along with their peripherals. The first robot is equipped with a laser rangefinder sensor and denoted the name (rangeBot), the second robot is equipped with a gripper and denoted the name (handBot) and the third and last robot is equipped with a camera and denoted the name (eyeBot). The presented scenario is modeled in order to be able to find the best allocation of each task (survivor in this case) to the available robots. The model representation of this problem is illustrated in Figure (3).

Name	Requirements	Time Required [min]
Survivor 1	G	0.17
Survivor 2	G	0.17
Survivor 3	C	0.03
Survivor 4	LR	0.08
Survivor 5	C	0.03

Name	Skills	Velocity [m/min]	Battery Life [min]	Aging Factor
handBot	G	10.8	12	0.87
eyeBot	C	11.1	12	0.92
rangeBot	LR	8.6	12	0.81

G	Grpper
C	Camera
LR	Laser Range Finder

Figure 3. Search and Rescue Scenario Database Model

4.2. Evaluation Metrics

Evaluating the performance of mobile robots and assessing their behavior in different applications is still an open research field [12]. Although substantial progress has been made in defining the framework and standards for the evaluation process. These frameworks are usually defined according the priorities of the mission at hand. Comparisons are made between contrasting values such as: accuracy at goal versus the time taken to reach it and the length of the trajectory versus the risk of collision.

- One of the most important metrics used is the error between the reference trajectory and the actual trajectory. This shows how accurately the robots can track a given path. The trajectory is generated by the pathfinder algorithm discussed in 3.2. Instead of evaluating each state in the pose of the robot $[x, y, \theta]^T$ independently, the absolute euclidean distance defined in equation (7)was chosen as an error metric.

As a secondary part in evaluating the performance, the accuracy of the target localization process carried out by the rangeBot is considered, also the absolute Euclidean distance is used.

$$error = \sum_{i=1}^{n} \left(\sqrt{(x_{i,ref} - x_i)^2 + (y_{i,ref} - y)^2} \right) \tag{7}$$

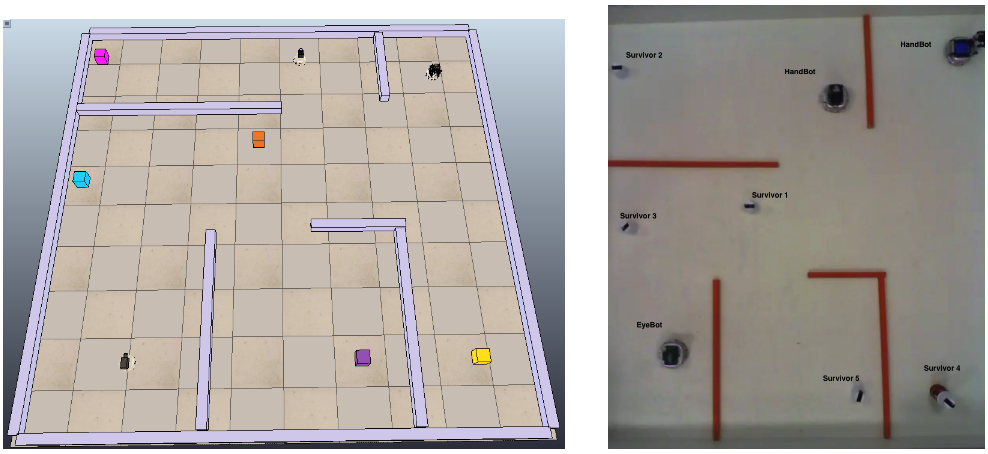
Where (n) is the total number of points generated by the pathfinder. While $(x_{i,ref}, y_{i,ref})$ are the reference x and y positions at a given sample (i), and (x_i, y_i) are the actual positions of the robot calculated through odometery.

- The final performance index used is the risk factor with respect to the obstacle. Given a function $\beta(i)$ which calculates the Euclidean distance to the nearest obstacle at sample (i). The risk factor of the complete trajectory is given by the following equation (8):

$$RiskFactor = \sum_{i=1}^{n} \frac{1}{\beta(i)} \tag{8}$$

4.3. Experimental Setup

The proposed task allocation approach is implemented using Java. Java is used in the implementation as well as in applying the algorithm over the proposed scenario and in calculating the results of the evaluation metrics. Moreover, the experiments are simulated using a free software called Virtual Robotics Experimental Platform (V-rep) [13]. This simulation environment (Figure (4-a)) includes all the modules of the Khepera-III mobile robots that are used practically to test the approach. Setting up an experiment requires understanding of both the practical and the simulation models and identifying the communication method between agents in the MRS. Three robots with different capabilities have been configured, rangeBot is a mobile robot that mimics Khepera-III mobile robot with laser-range finder module, handBot mimics a model with gripper module and eyeBot mimics a model with camera module.



(a) v-rep Simulation - Initial Positions

(b) Khepera-III Mobile Robots Initial Positions

Figure 4. Virtual and actual arena.

The real experiments are conducted in a 2x2 m^2 indoor arena. The real robots are equipped with one of the peripheral modules, namely, laser rangefinder, gripper and camera. The laser rangefinder has a scan area of 240^o with a maximum range of 4m. The sensor has an angular resolution of 0.36^o [14]. The measurements are used to determine the location of the target using *SPIKE* algorithm. The gripper can carry an object with maximum size of 50mm and maximum weight of 50gm. The camera is capable of capturing images with a resolution up to 640x480 pixels and acquisition speed up to 15 frames per second. The obstacles and survivors are placed in predefined locations similar to the simulation, as shown in Figure (4-b). The workstation used in the experiments runs a Windows operating system with a 1.7GHz processor and 6GB RAM.

5. Results and Discussion

In this study, the five survivors previously mentioned are modeled as five tasks where each task has both physical and time requirements. The robots are also modeled with their physical skills, operating velocities, their current energy level as well as their efficiency. Next step is to handover the developed problem model to the proposed algorithm to perform the required computations. The output of the algorithm is summarized in Figure (5), which represents the optimal allocation of the tasks to the robots based upon their requirements, skills as well as their initial conditions.

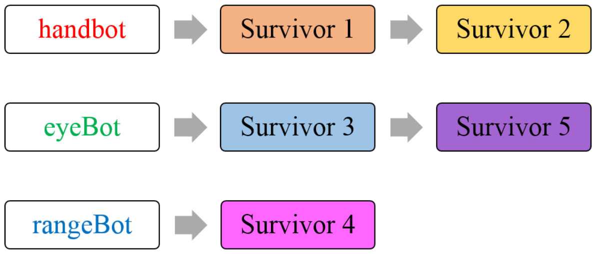


Figure 5. Search and Rescue Allocation

As can be seen in Figure (5), survivors 1 and 2 that required a gripper are assigned to the handBot robot, while survivors 3 and 5 that required a camera are assigned to the eyeBot robot, and finally survivor 4 that required a laser rangefinder is assigned to the rangeBot robot. The time chart in Figure (6) reflects the time taken by each robot for both traveling time and execution to finish its assigned tasks. Moreover, it shows the total time taken for the whole mission to be accomplished, which will be the maximum time of the three robots since the robots will be working in parallel.

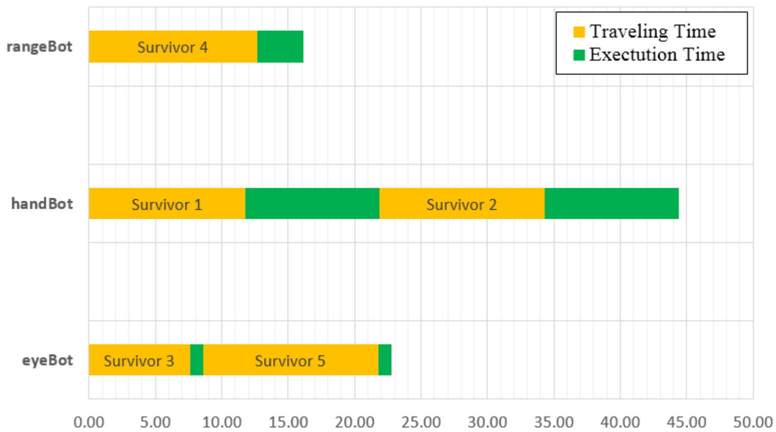


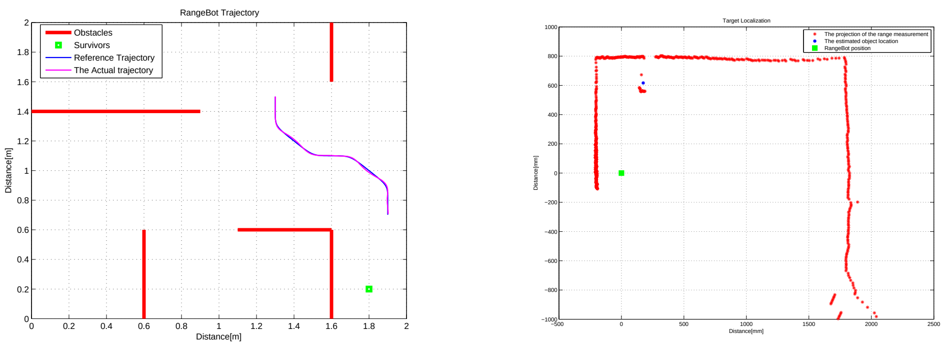
Figure 6. Search and Rescue Allocation

This scenario was implemented on the V-rep simulation software [13], as can be seen in Figure (4-a). Both market-based algorithm and path planning algorithm are implemented for each of the three robots to cooperate in solving this MRTA problem. The total simulation time was 1 minute and 23 seconds, in which the robots completed their assigned tasks to rescue their assigned survivors (represented by cube shapes in the simulation).

On another level, real life experiments are conducted using the three Khepera-III mobile robots (using the same initial conditions as the V-rep simulations), as can be seen in Figure (4-b). Robots are equipped with the designated peripheral modules; the laser rangefinder is installed on the rangeBot, camera is installed on the eyeBot and the gripper is installed on the handBot. Moreover, the survivors are modeled with white plastic cylinders with black line on top. The output from the market-based algorithm in terms of the best allocation of the tasks to the robots was integrated with the robots' code, along with the path planning algorithm. Thus, the robots can navigate through the map and locate the survivors, execute the assigned task and continue till all assigned tasks are completed.

The retrieved data from each robot after conducting the experiment include the actual trajectory evaluated from the on-board sensors using odometry, as well as the time consumed to navigate to the task location and the time consumed to finish it.

As an example for the obtained results, Figure (7) shows the rangeBot actual trajectory plotted against the reference trajectory in a two dimensional grid representing the actual map. The results of the *SPIKE* target localization algorithm showing the localized survivor.



(a) Trajectory of the rangeBot. (b) Survivor Localization using the rangeBot

Figure 7. RangeBot results

The performance of the robots is evaluated according to the metrics defined in 4.2. The first index is the error between the final position and the desired goal. In which all three robots managed to be autonomously localized within the vicinity of the desired goal with maximum absolute error of $0.0065m$. Figure 5 shows both absolute mean and maximum errors along the whole trajectory from the starting position to the goal position. The risk factor value which is the minimum absolute distance between the robot and the obstacles is reflected in Figure (5). The error bars values reflect the variances in the measured values for repeating the experiment five times.

The results prove the ability of the proposed allocation and planning algorithm in managing a set of heterogeneous mobile robots in search and rescue scenario.

6. Conclusion and Future Work

This paper presented market-based approach to solve multi-robot task allocation (MRTA) problem. The developed algorithm is responsible for optimally assign a set of mobile robot to a set of tasks. Moreover, a path-planning and landmark extraction algorithms are adopted to enable the robots to navigate through any given map and to be able to localize the target in any of the cases. A search and rescue scenario has been used to qualitatively and quantitatively evaluate the performance of the allocation algorithm and its ability to handle capabilities matching constraints in heterogeneous environments. Both simulation and

(a) Absolute error in distance between reference and actual trajectories

(b) Risk factor evaluation.

Figure 8. Evaluation metrics

experimental results reflect the efficacy of the proposed approach. Further investigation can be conducted for other aspects such as handling robot failure, alleviating communication burden, handling task-related constraints. Also, more examples can be investigated such as tight tasks that cannot be decomposed into single robot tasks or tasks with precedence constraints.

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