Integrating Humans with Multi-Robot Exploration

Abstract—Robots can work collaboratively to increase the efficiency of exploration tasks. In search or rescue scenarios, the participation of humans can provide intelligence and knowledge to accomplish tasks. Little work has been done to integrate humans into multi-robot systems. We aimed to integrate a human agent with a multi-robot system for exploration in this paper. The multi-robot system was built using market-based approach and behaviors of a human agent was simulated by the individual mobility model, which includes two features of human mobility (i.e. exploration and preferential return). We further developed a function to allow robots to obtain the current location of human and predict upcoming human pathways. Our main goal was to investigate the efficiency of exploration time in six different levels of information sharing scenarios between a human agent and a multi-robot system to complete an office exploration task. Results showed that sharing human agents current location and the map with the multi-robot system using our predicted function can achieve the similar efficiency compared to sharing the map and destinations. It is hard for a human to share future destination to the multi-robot system in reality. Therefore, it is relatively easy for a human agent to share the current position with the multi-robot system, for example, by carrying a GPS. Future work can obtain practical data of human exploration to tune the parameters of this human-integrated multi-robot system. Different exploration environments besides an office can further be simulated to replicate if our findings are robust.

Index Terms—Multi-Robot Exploration; Human-Robot Integration

I. INTRODUCTION

Robots can be used to explore unknown or partially unknown environments, such as planetary exploration and search. Robots can work collaboratively to increase the efficiency of achieving goals. In some scenarios, humans participate in search or rescue to provide intelligence and knowledge to accomplish tasks.

Algorithms for multi-robot systems exploration have been developed since the 1990s. Little work has been done to integrate humans into multi-robot systems. Currently, research work focused more on human-robot interfaces and humans often play supervised roles, not team partners. Therefore, we aim to develop a model to simulate human behaviors and integrate the human agent with the multi-robot system for exploration.

The market-based approach was used as the main base algorithm for this research because it is one of the most common algorithms for multi-robot systems [1]. By implementing the market-based exploration algorithm, robots can communicate with each other with price information and are allowed to exchange goals with each other. Hence, no more than two robots will move toward the same goal. This overcomes the disadvantage of the frontier-based approach. Furthermore, the market-based approach is decentralized and it also allows new robots to enter or leave the system. This feature can enhance the stability of multi-robot systems for exploration and it also allows us to add a human agent into multi-robot systems.

We simulated human mobility based on individual mobility model instead of continuous time random walk model. Individual mobility model is more realistic than continuous time random walk model because humans have intelligence and do not walk randomly and the individual mobility model considers two main features of human mobility: exploration and preferential return [2]. Since we want to maximize the human intelligence, robots should have the ability to collaborate with the human agents decision and maintain the efficiency of exploration at the same time. We further develop a function to allow robots to obtain the current location of human and predict upcoming human pathways [3].

We investigated experiments in different simulated scenarios. The human-robot system was simulated with and without the human prediction algorithm and different levels of information sharing. Our findings can help understand what levels of information sharing enhance the exploration efficiency in a human-integrated multi-robot system.

This paper is presented as follows. Section 2 investigates previous work in the area of multi-robot exploration and human modeling. Section 3 introduces our approaches to integrate a human agent with a multi-robot system for exploration. Section 4 presents the simulation results of six levels of information sharing scenarios. In section 5, we summarized the conclusions, limitations, and discussed future work.

II. RELATED WORK

Yamauchi proposed a frontier-based approach for mobile robot exploration [4], and applied the frontier-based approach to multi-robot exploration [5]. Frontiers are defined as the boundary between open space and unexplored space and used to guild exploration. Robots constantly move toward new frontier that gains most information of grid until there is no unexplored space. The shortcoming of this approach is a large amount of information must be shared between robots, and it is possible that robots would move toward the same frontier as a target.

In order to avoid robots moving toward the same target, Burgard et al. introduced a utility-based approach [6]. The task assignment is decided by the best trade-off between the utility and costs of unexplored locations. The utility is defined as when reaching a target position, the size of the unexplored space within the coverage of a robot’s sensors, and the cost is defined as the optimal path from the current position to the target location. When a target location is assigned to a robot, the approach reduces the utility of other visible
and unexplored space from this location for other robots. However, this approach results in increased computational load. Simmons et al. also proposed a simple bidding protocol to keep robots away from each other [7]. A central agent receives bids and assigns tasks to maximize overall utility while minimizing the coverage overlapping among robots. This approach relies on communication with a central agent heavily. Once the central agent is unable to reach, the system would fail.

Reducing the dependence on perfect communication, Zlot et al. proposed a market-based approach to decentralize the multi-robot system [1]. Robots allow to bid on targets and negotiate their assignments with each other. Every robot in the multi-robot system can start an auction starting price as the profit, the utility minus cost, it made from this goal, and other robots can offer their bidding price. If the highest bidding price is higher than original profit, the auctioneer robot will give the goal assignment to the winner. Because of the decentralized scheme, this approach can adapt dynamic introduction/loss of team members and the interruptions or failures of communication.

Based on the frontier concept, Bautin et al. proposed the MinPos algorithm for multi-robot exploration [8]. Each robot evaluates its relatively close rank towards each frontier. Then, assigning the frontier to the robot with the lowest rank. Recently, Benkrid et al. presented a distributed approach which considers robots’ energy consumption [9]. This approach reduces the total exploration time comparing to frontier-based and utility-based approaches.

In many scientific fields, economics, computer science, physics, epidemiology, etc., in order to observe behaviors of simulated processes, the behaviors modeling was applied. Random walk model was first introduced by Karl Pearson [10]. The process is stochastic, and the path consisted of a series of random steps based on mathematical space. Later, Montroll et al. proposed the idea of continuous time random walk model [11]. This model integrated a random waiting time between walks. In the process, the walk lengths and waiting times are stochastic. This model is still based on random-ism, and cannot capture human mobility features. Song et al. proposed the individual mobility model [2], which can mimic humans’ two mobility behavioral features: exploration and preferential return. The distribution of predicted results from their model matched the empirical data collected from cell-phone GPS. Hence, in this paper, we adapted this individual mobility model to simulate our human behavior model.

Our main goal was to investigate the efficiency of exploration time in six different levels of information sharing scenarios between a human agent and a multi-robot system to complete an exploration of an office. And, we based on simulation results to find the most suitable collaboration approach for a human-integrated multi-robot system for exploration.

III. APPROACH

A. Market-based exploration

For our multi-robot system, we used the market-based exploration algorithm. In this system, every robot is using price information to communicate with each other and they are allowed to exchange goals, to-be explored locations, with each other. The communication data amount is comparatively small because robots only exchange the price information for bidding. The profit is calculated by the revenue (R) minus the cost (C), and every robot would attempt to maximize their own profit. The revenue is paid by an operator executive to the individual robot for the gained information they provided. The cost is calculated by the estimated distance to the goal.

Steps for each robot: (1) Generate goals based on goal selection strategy. (2) Check with the operator executive to make sure goals are new. If the goal is not new, eliminating non-new goals. (3) Rank goals greedily based on expected profit. (4) Auction off goals to each reachable robot. If a bid from other robot is higher than its self-profit, the robot sells the goal to the highest bidder. (5) When all auctions are closed, the robot explores highest-profit goal. (6) If the goal is reached, the robot generates new goal points. The pseudo-code of the market-based exploration algorithm is shown in Algorithm 1, and the flowchart is shown in Figure 1. The pseudo-code of the auction mechanism is shown in Algorithm 2, and the flowchart is shown in Figure 2.

Algorithm 1 Market-based exploration

1: while map is not complete do
2: for each robot do
3: Generate goals based on goal selection strategy
4: if goals are new then
5: Store new goals
6: else
7: Delete non-new goals
8: end if
9: Rank goals base on expected profit
10: Auction off goals to other reachable robots
11: Move toward the highest-profit goal
12: end for
13: end while

To illustrate an auction scenario for two robots, we used a grid map to represent the world as shown in Figure 3. Grey squares represent unknown space, black squares represent occupied space, and white squares represent open space. The goals are represented by yellow squares in the grid for robots to explore. For every goal in the grid, the cost (C) is the distance to reach a goal. The revenue (R) is the number of unknown cells around the goal, including the goal. The profit is the revenue minus the cost. For robot 1 (R1) in Figure 3, the cost is 7 and the revenue is 9. The profit for R1 is $9 - 7 = 2$. For robot 2 (R2), as shown in Figure 4, the cost is 4 and the revenue is 9. The profit of the same goal for R2 is $9 - 4 = 5$. 

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Algorithm 2 Auction off a goal

1: Compute the revenue = # of unknown cells near goal
2: Compute the cost = distance for auctioneer to reach goal
3: Compute the profit = revenue - cost
4: Set profit$_{max}$ = profit
5: Set winner = auctioneer
6: for every other robot, do
7: Compute the cost$_i$ = distance for robot$_i$ to reach goal
8: Compute the bidding$_i$ = revenue - cost$_i$
9: if bidding$_i$ > profit$_{max}$ then
10: Set profit$_{max}$ = bidding$_i$
11: Set winner = robot$_i$
12: end if
13: end for
14: Assign the goal to winner

R2 has a higher profit than R1 so this goal will be assigned to R2.

Since the communication among robots is not synchronous, robots must be able to process a message at any time. In an auction, every robot can only offer one bidding. However, it is possible that one robot participates more than one auction. Hence, a robot might be the winner of multiple auctions at the same time. We set a maximum goal number of the goal list for each robot to avoid the unbalanced task assignment.

B. Individual mobility model

In order to run simulations of human-integrated multi-robot exploration, we need to build a human mobility model to simulate humans behavior. Here, we used the individual mobility model to simulate the human agent exploration behaviors. The individual mobility model was proposed by Song et al. [2]. Unlike random walking, this model accounts for two main features of human mobility: exploration and...
preferential return. (1) Exploration: Based on research data, when a person already visited lots of places, the tendency to explore additional new places will decrease. 

\[ P_{\text{new}} = \rho S^{-\gamma} \]

where \( S \) is the number of distinct locations, and \( \rho \) and \( \gamma \) are parameters for probabilities. The initial \( S = 1 \), the range of \( \rho \) is \((0, 1]\) and \( \gamma \geq 1 \). Parameters \( \rho \) and \( \gamma \) control user’s tendency whether to explore a new location. (2) Preferential return: the research data also show that people have the propensity to return to the locations they have visited frequently before, e.g. home, workplace. 

\[ P_{\text{return}} = 1 - \rho S^{-\gamma} \]

Our human exploration algorithm includes following steps: (1) A human agent uses the greedy exploration algorithm to generate a goal. (2) Compute \( P_{\text{new}} = \rho S^{-\gamma} \). (3) Generate a random number \( x \in [0, 1] \). (4) If \( x \leq P_{\text{new}} \), the human agent moves toward the goal. Otherwise, the human agent goes back to original start location and reset \( S = 1 \). (5) If a goal is reached, the \( S \) increases by 1, and the mechanism will also start to generate a new goal. Repeat these steps until the map is completed. The pseudo-code is shown in Algorithm 3, and the flowchart is shown in Figure 5.

### Algorithm 3 Human mobility model

1: while map is not complete do
2:   for each human do
3:     Generate goal based on greedy exploration algorithm
4:     Compute exploration probability, \( P_{\text{new}} = \rho S^{-\gamma} \)
5:     Generate a random number, \( x \in [0, 1] \)
6:     if \( x \leq P_{\text{new}} \) then
7:       Move to the goal
8:       Increment goalCount, \( S = S + 1 \)
9:     else
10:       Move back to original start location
11:       Set goalCount to one, \( S = 1 \)
12:   end if
13: end for
14: end while

C. Predicted function

The purpose of a predicted function is to increase the efficiency of exploration and avoid human to share its destination. The steps are as follows: (1) Robots have goal lists based on the market-based algorithm. (2) Human shares current position to robots when human arrives the destination. (3) Robots predict human’s next destination. (4) Robots remove the closest goal from their goal lists based on the prediction. The pseudo-code is shown in Algorithm 4, and the flowchart is shown in Figure 6.

### Algorithm 4 Predicted function

1: for each robot do
2:   Get the goal list based on the market-based algorithm
3:   Get human current location
4:   Set distance\(_{\text{min}}\) = infinity
5:   Set goal\(_{\text{eliminate}}\) = null
6:   for goal\(_i\) in the goal list do
7:     Compute distant(goal\(_i\), human current location)
8:     if distant\(_i\) < distance\(_{\text{min}}\) then
9:       Set distance\(_{\text{min}}\) = distant\(_i\)
10:      Set goal\(_{\text{eliminate}}\) = goal\(_i\)
11:   end if
12: end for
13: Remove goal\(_{\text{eliminate}}\) from the goal list
14: end for

For example, in Figure 7, there is a robot (R) and a human (H). The robot has four goals in its goal list \{G1, G2, G3, G4\}. Since the current location of the human agent is closed to G1, the robot will remove G1 from its goal list and assume the human agent will take care of G1. The robot will explore \{G2, G3, G4\} first.
D. Simulation settings

The program was written in Java, and the simulation was conducted on a 2.7 GHz Intel Core i5 processor with 8GB RAM. In this paper, we simulated six different communication levels (Table I) between one human agent and two robots in a multi-robot system using market-based exploration algorithm. The task was to explore an office map as shown in Figure 8.

The first scenario is the baseline. The human shares no information with the multi-robot system. In the second scenario, the human agent shares a current position with the multi-robot system. The third scenario, the human shares a map with the multi-robot system. Fourth scenario, the human shares map and current position. Fifth scenario, the human shares map and destination. Sixth scenario, the human shares map, current location and destination with the multi-robot system. We used total exploration time in seconds to compare the efficiency. For parameters of the individual mobility model, we used $\rho = 1$ and $\gamma = 0.05$ to increase the exploration probability compared to original parameter since our exploration area was smaller [2].

### TABLE I

SIMULATED COMMUNICATION LEVELS BETWEEN HUMAN AND ROBOTS

<table>
<thead>
<tr>
<th>Scenario</th>
<th>Human agent shared information</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>None</td>
</tr>
<tr>
<td>2</td>
<td>Current location</td>
</tr>
<tr>
<td>3</td>
<td>Map</td>
</tr>
<tr>
<td>4</td>
<td>Map, current location</td>
</tr>
<tr>
<td>5</td>
<td>Map, destination</td>
</tr>
<tr>
<td>6</td>
<td>Map, current location, destination</td>
</tr>
</tbody>
</table>

IV. RESULTS AND DISCUSSION

For each scenario, we run the simulations for ten times and calculated the mean values of exploration time. The simulation results are shown in Table II and Figure 9.

### TABLE II

SIMULATED RESULTS

<table>
<thead>
<tr>
<th>Scenario</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
</tr>
</thead>
<tbody>
<tr>
<td>mean time (n=10)</td>
<td>1132</td>
<td>1207</td>
<td>1004</td>
<td>963</td>
<td>975</td>
<td>920</td>
</tr>
</tbody>
</table>

In the first scenario (baseline), the average exploration time was around 1,100 seconds. In the second scenario, where the human shared the current location, the average exploration time (1,206 seconds) was worse than the baseline. The multi-robot system would adjust their optimal exploration path based on human current position. However, the human agent did not share the map so the robots were not able to know if the human already explored the area. This decreased the efficiency of the collaboration. The third scenario, where the human agent shared the map with robots, improved the collaboration efficiency slightly and the mean exploration time was around 1,000 seconds. The collaboration efficiency in the fourth and fifth scenarios, where a human shared the map with current location or shared the map with destination, both improved around 15% and 14% compared to the baseline scenario. The sixth scenario, where the human shared the map, current location, and destination with robots, can achieve the best collaboration efficiency. The mean exploration time was around 920 seconds.

Base on the simulation results, we found that the col-
laboration efficiency improved significantly when the human shared the map with the multi-robot system. In addition to sharing the map, sharing current location and/or destination can also improve the collaboration efficiency. There was no significant difference between the fourth and fifth scenario based on simulated results. This is a meaningful and helpful result because it is hard for a human to share future destination to the multi-robot system in reality. On the other hand, it is relatively easy for a human agent to share the current position with the multi-robot system, for example, by carrying a GPS. The result shows that by sharing the current location with a map, the multi-robot system can use predicted function to reach the same level of efficiency as sharing the map with destinations.

V. SUMMARY AND CONCLUSION

In this project, we investigated different scenarios of information sharing between a human agent and the multi-robot system for exploration. We built an individual mobility model to simulate human behaviors. The mobility model includes two features of human mobility: exploration and return behaviors. The probability of human to explore new location decreases when the number of visited places increases. Human also tends to return a preferential location visited frequently before. We also added a predictive function into a multi-robot algorithm to increase the efficiency of human-robot collaboration. Our simulation setting includes one human agent and two robots using the market-based exploration algorithm. The simulation results showed that sharing the map and human current location to a multi-robot system can achieve the similar efficiency of sharing the map with destinations.

In conclusion, the simplest way that humans can help the robotic exploration process is through sharing current location with a map. For the future work, the number of simulations can be increased to see the distribution of execution time. The human mobility model was based on virtual parameter settings. If we can obtain practical data of human exploration, we can tune the parameters to match the reality. Different exploration environments besides an office can be simulated to see if our findings are robust.

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REFERENCES