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Leveraging area bounds information for autonomous decentralized multi-robot exploration

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**Abstract**

This paper proposes a simple and uniform, decentralized approach to the problem of dispersing a team of robots to explore an area quickly. The Decentralized Space-Based Potential Field (D-SBPF) algorithm is a potential field approach that leverages knowledge of the overall bounds of the area to be explored. It includes a monotonic coverage factor in the potential field to avoid minima, realistic sensor bounds, and a distributed map exchange protocol.

The D-SBPF approach yields a simple potential field control strategy for all robots but nonetheless has good dispersion and overlap performance in exploring areas with convex geometry while avoiding potential minima. Both simulation and robot experimental results are included as evidence, and performance, speedup and efficiency metrics for each are presented.

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1. Introduction

This paper addresses the problem of developing an effective control strategy when multiple robots are deployed to an unknown environment to explore and collect information about the environment. Practical examples of such missions include search and rescue, location of explosive devices, and internal reconnaissance of a structure. In a counter weapons of mass destruction (C-WMD) mission, the robot mission designer may know there is a bomb in the building. In this case, the critical point of the mission is to search as much of the area within the building as possible in the shortest time to locate the WMD so that it can be assessed. In a search and rescue scenario, where there may be injured victims in the building, the critical point of the mission is also to search, in this case to locate victims and assess their condition so as to quickly address their needs. Such missions are time-critical and detailed environment information is not needed, rather a fast, effective scan with the on-board sensors is much more crucial for the mission. It is reasonable to propose that deploying multiple robots will allow the building to be searched more quickly [1]. If multiple robots are being used to increase exploration efficiency, and all areas of the building are considered equally important, then prioritizing dispersion and reducing overlap in scanning are potential strategies to improve performance. However, if members of the team disperse within the building, then it is likely that the communications to a centralized, remote server will be intermittent. In the case of a decentralized approach, it is likely that the team members will lose and regain contact with each other from time to time as they explore. For simplicity and efficiency, it is preferred to have the robots depend and communicate with each other as little as possible, and for the control strategy of the robots to be as uniform as possible.

In prior work [2], we proposed the following as reasonable and useful assumptions to make about the mission: (1) the robot mission designer knows something about the environment, but not ev-
erything. (E.g., the rough dimension of the building to be searched is known but not the indoor floor map details); and (2) some interrobot communication is possible, but only a minimum amount of data transfer is preferred. That work did not address the decentralized communication between members of the robot team. In this paper, a decentralized system architecture and map update algorithm is proposed and evaluated using a simple and uniform potential field dispersion and navigation mechanism based on that in [2].

In the next section relevant prior literature is reviewed. Section 3 presents the proposed decentralized map update and navigation control algorithm. It begins with a review of the potential field mechanism proposed and evaluated in [2] as well as the modifications added for the decentralized implementation evaluated in this paper. Section 4 reports a series of evaluation results, where the algorithm is evaluated in simulation using a number of metrics and compared to existing work, as well as the results of implementation on a pair of Pioneer 3-AT robots. Section 5 concludes by summarizing the results and discussing future challenges.

2. Prior work

Burgard et al. [1] introduced a centralized approach to multirobot exploration that assigns target location goals to team members by locating a robot and frontier point (a point on the boundary of explored and unexplored space) that balances exploration utility and travel cost. Rogers et al. [3] develop a centralized scheme to coordinate frontier-based exploration by large robot teams and investigate which robot coordinate strategies are effective. Decentralized schemes have been introduced by Visser & de Hoog [4] and Chand & Carnegie [5] for heterogeneous teams by assigning different roles to team members.

Potential field methods have been leveraged for robot navigation (e.g., [6–8]) because they offer intuitive and efficient implementations. While primarily used to describe single robot motion (e.g., Arkin [6]), the potential field approach was also used to specify manipulator configurations (e.g., robot manipulators, Khatib [7]; dexterous hands, Lyons [8]). Multirobot exploration offers challenges beyond single robot exploration [1]. More recently potential field approaches have been extended to handle multiple robot exploration (e.g., Arkin and Diaz [9], Lau [10]), formation (e.g., Schneider [11]) and map improvement (e.g., Julia et al. [12]). Our motivation in pursuing a potential field approach is its potential for an intuitive and efficient solution.

Our focus in this paper is addressing the multirobot exploration problem by leveraging a distributed potential-field method. Similar approaches include that of Lau [10], Julia et al. [12], Renzaglia [13], Baxter [14], Cepeda [15] and Popa [16]. Baxter [14] presents a potential field approach in which the field is shared among robots. Cepeda [15] proposed a behavior based approach for multi-robot exploration, but such an approach has difficulty in robot exploration status synchronization. Popa [16] uses potential fields for dispersion of sensor networks, but does not discuss exploration or path-planning. Batalin [17] presents an approach with good dispersion results but which is not as strong on path-planning and searching. Min [18], Mi [19] and Schwager et al. [20] all provided novel topological approaches for dispersion and coverage of multi-robot exploration, and Jensen [21] proposed using wireless signals for the same purpose; however the detailed path-finding strategy is not part of the solutions.

One of the key issues that any potential field method must address is how local minima in the field are handled [22]. These are undesirable locations at which the field sums to zero, resulting in robots being stuck or stalled, delaying or halting exploration. Arkin [6] uses random noise, to eject robots from minima, and spin fields, to move robots along the surface of obstacles, to address minima issues. Julia et al. [12] and Renzaglia [13] use the potential field method for decentralized robot control, and a frontier-based approach for breaking out of potential field minima. Julia et al. [12] represent the space to be explored using an occupancy grid map enhanced so that each cell also represents the degree of exploration of that area. Each cell generates an attractive force on each robot inversely proportional to the amount of exploration of the cell. Furthermore, landmark locations for landmarks not yet precisely enough known generate attractive force. Whenever a local minimum is detected, the robot plans a path to the nearest frontier cell. Renzaglia [13] has two classes of robot: one (follower) which is potential-field driven, and one (leader) which is always planning the path to the frontier. The follower robots are influenced by the explored area and the position of the other robots, whereas the leader robots are uninfluenced by the other robots (and hence local minima). In both schemes, communication and calculation of information shared between the robots, as well as the transition between roles of leader and follower (Renzaglia) or detection of minima (Julia et al.), become crucial and risk failure if any link in this cooperation fails.

The approach proposed in this paper is similar to that of Julia et al. in maintaining an extended occupancy grid with cumulative sensor coverage information per cell, and to Renzaglia’s potential field for dispersing follower robots. However, no frontier is maintained, and only one class of robot exists: a substantial simplification. Potential minima will be handled by adding a monotonic coverage factor to the potential field equations of Renzaglia, and by the noise and vortex methodology of Arkin. Furthermore, the exchange of information between robots will be explicitly formalized here in terms of transfer of extended occupancy grids.

In [23] Ozisik et al. described an occupancy-grid based SLAM method, however it was not optimized for multiple robot efficiency. In [24] Birks shows how to merge occupancy grid maps from multiple robots, as does Herath [25]. However they focus on feature-recognition and merging data from multiple robots. Lyons et al. [26] discuss grid-based methods to combine maps so as to avoid transitory readings from other robots. In this paper, the occupancy grid contains information about obstacles sensed and information about exploration coverage. However, no SLAM module will be included; this simplification is made to focus on the coverage, rather than the mapping, issues of the problem.

3. Decentralized navigation

The proposed approach is presented in two components. The first is the decentralized navigation algorithm—which is based on our prior work [2]. The second component is the decentralized communication and map update.

3.1. The space-based potential field approach

The potential field approach [6] has been used previously for directing robot motion toward a goal while avoiding obstacles. A key aspect of the approach, as introduced in our prior work [2], is that the unexplored area needs to act as an attractive goal for robots. The unexplored area is not modeled as a frontier as in [13,12] but rather the unexplored area itself exerts an attractive force on all robots. Because we assume we know the overall boundaries of the area, we know the maximum area to be explored and can calculate the attractive field. All robots are drawn to the unexplored areas of the map.

The proposed approach represents space by a map divided into multiple grids/cells, where each cell has a potential level representing the level of exploration or scanning by each robot’s sensors. Initially the potential level for each cell is zero. The effect of a zero potential is to generate an attractive force on all robots. As robot sensors cover an area of the building once or more, the
of the exploration, the robot will be driven away from previously explored areas as well as the other robots. As coverage increases, the repulsion from walls and other robots decreases, allowing the robot to explore more closely into corners and niches as well as closer to other robots. Furthermore, if any robots are stalled in minima, a narrow corridor for example, then as coverage increases the situations giving rise to the minima are also changed.

If the robot is at a location \( q \), then it incurs a repulsive force from each other cell in the map \( q_i \), due to this potential function, \( F_{\text{rep}} (q) = -\nabla U_{\text{rep}} (q) \) as follows:

\[
F_{\text{rep}} (q, q_i) = \begin{cases} 
\frac{1}{\rho_{\text{rep}} (c)} (1 - \delta(q_i)) \left( \frac{1}{\rho(q, q_i)} - \frac{1}{\rho_0} \right) q - q_i, & \rho(q, q_i) \leq \rho_0 \\
0, & \rho(q, q_i) > \rho_0 \end{cases}
\]  

(3)

The summation of the repulsive force from each other cell with a potential level produces on the robot at location \( q \) a repulsive force \( F_{\text{rep}} (q) \) that drives it away from obstacles, other robots and previous visited areas.

\[
F_{\text{rep}} (q) = \sum_{i=1}^{n} F_{\text{rep}} (q, q_i).
\]  

(4)

### 3.3. Attraction to unexplored areas

When a cell in the occupancy map has zero potential level, then this area has not been scanned or visited by any robots. Such a cell contributes an attractive potential to the field for each robot. The proposed approach differs from an approach that models an unexplored frontier, since it treats every unexplored cell as an attractive potential goal. Because an unexplored frontier perimeter does not need to be maintained or calculated, this approach is less demanding computationally. Of course, being area based, it can have larger memory requirements since the entire map, though empty, is present in memory from the start. Note, however, that variable resolution occupancy grids methods such as quad trees or binary space partitioning trees could be used to address this [27].

The attractive potential field, modified from [13], is

\[
U_{\text{att}} (q, q_i) = \frac{1}{4} h_{\text{att}} (c) \delta(q_i) \rho_{\text{goal}}^4(q_i)
\]  

(5)

\( \delta(q_i) \) ensures that only zero potential cells contribute to the field. The function, \( h_{\text{att}} (c) \) gives an attractive scaling factor for coverage, \( c \). In this paper, we gain select a simple linear function for this:

\[
h_{\text{att}} (c) = k_{\text{att}} / c.
\]  

(6)

The principal addition to the field used in [13] is the coverage factor \( h_{\text{att}} (c) \delta (q_i) \). The use of the coverage factor in the equation make the attractive force get larger with smaller coverage and smaller as coverage grows. This complements the reduction in repulsion as coverage increases, pulling the robot to explore corners and niches toward the end of the mission. Furthermore, it also acts to dislodge robots from minima by varying the field conditions as coverage changes.

The attractive force is given by

\[
F_{\text{att}} (q, q_i) = h_{\text{att}} (c) \delta(q_i) (q_i - q) \rho_{\text{goal}}^2.
\]  

(7)

And summing up all the attractive cells (cells with a potential level of zero) we can get the sum attractive force applied to a robot at map location \( q \).

\[
F_{\text{att}} (q) = \sum_{i=1}^{n} F_{\text{att}} (q, q_i).
\]  

(8)
3.4. Sum of forces

This summation of force will attempt to drive the robot away from the other robots, obstacles and previously visited areas, toward unexplored areas.

\[ F_{\text{total}} = F_{\text{rep, explored area}} + F_{\text{rep, other robots}} + F_{\text{rep, obstacles}} + F_{\text{rep, unexplored area}} = m\ddot{\mathbf{v}} - \mathbf{v} \cdot \mathbf{q} \]  

where \( m \) is the mass of the simulated robot and \( \mathbf{v} \) a viscous damping factor. These are used as in [13] to generate smooth trajectories.

Due to the coverage factor in the repulsion and attraction force, in the beginning of an exploration mission where the map coverage is small, the robot will tend to focus on spreading out or moving away from the explored area while at a later stage of the mission, the coverage control factor will focus on drawing the robots to unexplored areas, and fill up the empty sections on the map.

Any map that contains a completely enclosed space (i.e., the space internal to a column, elevator shaft, etc.) would form a permanent attractive zone. Since line of sight prevents any robot from scanning such an area, the potential level of grid cells representing the area will remain at zero. This attractive zone will distract robots from dispersing through the building. The approach to this problem laid out in [2] will be followed here also: Any area internal to a closed obstacle boundary (as determined by the state of the map) is also considered as an obstacle rather than an attractive region.

3.5. Decentralized control

A major innovation of the decentralized Space-Based Potential Field (D-SBPF) approaches is that it incorporates the knowledge of map exploration into the map and takes that information into consideration while calculating desired motions. Since the potential level of each cell can only increase after sensing (i.e., become more repulsive), the history of the exploration and sensing for each robot is integrated into the map and is easily transferred and compared to the map from a different robot. If the potential level of the same cell from two different robot maps are compared, then assuming a static map, the one with the higher potential level represents a later (and more up to date) value. Also, the approach allows easy communication between members of the robot team. It is expected that as the robot team moves through the building, robots will lose contact with each other from time to time and subsequently regain contact. When a robot recovers contact with another robot, they exchange copies of their maps. They each update their maps to the latest values from this exchange, and hence each acquire knowledge of the exploration history.

Before addressing map update, the implementation of the wireless ad-hoc network component of the algorithm is discussed. Since each member of the robot team can handle the path-planning locally with its own sensors and potential field map, they only need to share location information to avoid collisions, and share the change in potential levels of each cell to indicate the level of exploration. This is implemented using an ad-hoc wireless network for robot communication between team members.

In many traditional robot control schemas, each robot serves as a sensor terminal, taking commands from the central server (see Fig. 1(a)), and sending back robot sensor readings as well as other information collected back to the central server. However, in an ad-hoc network scheme, as shown in Fig. 1(b), each robot is both an individual terminal as well as a server. The robots do their own obstacle avoidance and path-planning, calculate the potential field map, then share the map with the other robots in the network. This allows stand-alone exploration for each robot in the team, even when the network connectivity is limited. While connected, robots can share information and work collaboratively, and can easily handle the loss and restart of the connection to other robots.

Putting aside for a moment the mechanisms of setting up the ad-hoc network, it is important to consider which network protocol is most useful for this problem. Using the TCP protocol, the sender of a message requires a confirmation from the receiver, or it will continue sending the message; this is the way TCP ensures secure package delivery. In the cases that the connection is not stable, if for example the other robot travels out of wireless signal range, the sender robot will be stuck in the transmission state until the connection is regained. However, the UDP protocol requires no confirmation upon receiving the message, therefore the sender can move on to next state of map exploration as soon as the packet is sent out. For this reason, the UDP protocol is used in the D-SBPF algorithm.

3.6. Packet transfer and map update

Let \( T \) be the set of robots in the team. Let \( Map_i, i \in T \) be the potential level map for robot \( i \) in the team. \( Map(x, y) \) refers to the map cell with coordinates \( x \) and \( y \). All robots in the team know the spatial extent of the map, which we simplify here to a rectangle \( (SX, SY) \), and the map resolution \( (rx, ry) \). Each robot map therefore has the following number of cells:

\[ (x_{max}, y_{max}) = \left( \left[ \frac{SX}{rx} \right], \left[ \frac{SY}{ry} \right] \right). \]  

Each robot maintains localization information \( (ox_i, oy_i, \theta_i) \). In this way, each robot can translate its location \( (x_i, y_i) \) to common map coordinates \( (x, y) \) using

\[ \begin{bmatrix} x \\ y \end{bmatrix} = \begin{bmatrix} \frac{1}{rx} & 0 \\ 0 & \frac{1}{ry} \end{bmatrix} \begin{bmatrix} \theta_i & 1 \\ 1 & \theta_i \end{bmatrix} \begin{bmatrix} x_i \\ y_i + \frac{ox_i}{oy_i} \end{bmatrix}. \]  

All robots are initialized with an unexplored map, that is with \( Map(x, y) = 0 \) for all cells. As each robot explores, it updates its own map to reflect its sensor coverage as described in prior sections. Periodically robots exchange information with each other by sending their current location, so that they can treat each other as repulsive potential sources. Periodically they also send out their current map \( Map \) and listen for maps from other robots, \( Map \) for
some \( j \neq i \). When robot \( i \) gets a new map from robot \( j \), it compares its old map to the received map, and updates to a new map as follows:

\[
\text{Map}_{i, \text{new}}(x, y) = \text{MAX} \{\text{Map}_{i, \text{old}}(x, y), \text{Map}_j(x, y)\}
\]

\( x \in 0 \ldots X_{\text{max}} - 1, y \in 0 \ldots Y_{\text{max}} - 1. \)  
(12)

Since MAX is a binary associative operator, it does not matter in what order the robots exchange maps, the result from one full set of exchanges will always be unique. Notice that this map rule is a conservative estimate of the exploration level for each map cell. If both robots have scanned the same cell, then a more accurate estimate of the coverage might be the sum of the two levels. However, without tagging the cell with the ID of the robot or robots that generated the coverage level, there is no way to determine if the coverage estimates are independent and hence can be added. It also assumes a static environment. That latter assumption could be relaxed by associating timestamps with each cell, and by updating based on which map cell had the latest timestamp.

Consider a robot team exploration mission consisting of three robots: if robot #3 moves too far away from robot #1 and loses direct communication, it is still able to update its own potential field map, as well as getting the map update packet from robot #2 which contains the most recent area exploration data from both robot #1 and #2. Even if any of the robots moves out of wireless communication range, it is still able to perform standalone exploration and attempt to update and synchronize its potential field map with the other members. Once communication resumes, the robot can compare the highest potential level for each cell in the maps it receives, integrating the most recent level of exploration and obstacle information.

There is an additional important advantage of this approach: assuming one robot moves out of the wireless communication signal range of some robots in the team, it can still communicate as long as there is an intermediate robot. The intermediate robot operates effectively as a forwarding node, a relay robot, sending information to the rest of the team. In a centralized server control scenario, once the robot moves out of wireless signal range of its sensor, it will not be able to communicate with the other members of the team. In short, the ad-hoc network significantly increases the robustness of the wireless communication infrastructure of the team.

3.7. System architecture

The decentralized Space-Based Potential Field algorithm is explained in Fig. 2.

The algorithm is split into two main stages: the initialization stage, and the explore stage. When each robot starts, it enters its initialization stage. At the initialization stage, the robot broadcasts a request-for-joining message to all the other robots containing its own IP address and robot information, including position and heading. The robot then waits for the reply to the request message from other robots. When it receives a reply message which contains another robot’s information, it adds the other robot to its local contact list. Initialization ends when the robot has not received a reply for some threshold time.

After the initialization has finished, the robot then starts the exploration stage. It uses its sensors to gather environment information and constructs its local potential field map. Periodically, the robot communicates with the other robots in its local contact list, sending its map and collecting their maps. Upon receiving the potential field maps from the other robots, the robot updates its map using the map update rule (9).

Using the updated map, the robot calculates the potential field force that will drive the robot to explore. It checks the map for overall map coverage. If the map coverage goal has not been met yet, the robot will then go back to the first step of the exploration stage, proceed and repeat until the map has been fully explored.

4. Simulation results

In this section, simulation results for the D-SBPF algorithm are presented that demonstrate its effective use of multiple robots, deployment locations and times (when available) as well as its effective dispersion of the robot team to search a building quickly. The algorithm is tested on a set of three maps, similar to those used by Renzaglia [13], which offer challenges to potential-field based approaches. However, unlike Renzaglia, we will assume that the robots are equipped with laser sensors that have a field of view constraint of angle \( \alpha \leq \pi \). The section begins by introducing the three maps that will be explored. It then presents a series of metrics that will be used to measure performance on each of the maps, and then presents the results for each.

4.1. Maps and metrics

The algorithm’s performance will be evaluated on three examples of building maps (Fig. 3(a)–(c) respectively). All of the maps are 10 \( \times \) 10 m\(^2\) and are represented on a 30 \( \times \) 30 grid. The first example uses a map of an empty building. The purpose of this example is to show how the algorithm directs the robot team to spread out and head toward unexplored areas in an open area. While missions may occasionally need to be carried out in such examples (e.g., an empty warehouse), the main purpose is demonstrate nominal behavior for the algorithm for homogeneous teams of 1–3 robots, as well as with temporal and spatial starting delays (leveraging the capability of the decentralized algorithm to handle the loss and regaining of contact with team members).

In the second example map, two rooms with open doors are added to the empty space of the first example. The robots need to go in and out of two rooms in order to explore the building fully. This example is one that can give rise to potential field minima between the two rooms. Also, because each room is surrounded by the walls, the net repulsion from the walls outside of the room will form a force preventing a robot from entering the room. In addition, once the robot is inside the room, the net repulsion from the surrounding easily trap a robot inside.

The final map adds several enclosed obstacles strewn across the empty space of the first map. The robots will attempt to reach
the other side of a building to complete the search despite several internal obstacles. The effect of the enclosed space inside obstacles needs to be discounted or it will attract, and distract, the team from finishing the search.

The percentage of coverage, that is the area of the room that has been searched, will be used as the principal metric of performance. If \( c(t) = \alpha \) is the coverage at time \( t \), then we define the performance to reach that percentage of coverage as \( P_\alpha = 1/t \). This has the conventional effect of defining faster coverage as larger (and hence better) performance. In the case where more than one robot is being used, then the speedup associated with using two robots is defined for coverage \( c(t) = \alpha \), by analogy with parallel computing, as the performance of the \( n \) robot case \( P_{n,\alpha} \) divided by that of the one robot case \( P_{1,\alpha} \) for the same coverage:

\[
S_{n,\alpha} = \frac{P_{n,\alpha}}{P_{1,\alpha}}.
\]  

(13)

We will typically adopt a coverage of \( \alpha = 95\% \) as our ‘mission succeeded’ coverage threshold. This is an arbitrary threshold chosen to allow timely generation and comparisons of multiple runs. Speedup is a measure of how much more quickly a multirobot team operates than a single robot. A linear speedup, i.e., \( S_{n,\alpha} = P_{1,\alpha}/n \), is the desirable case where using \( n \) robots is \( n \) times as quick as using a single robot.

Another useful metric that will be calculated is efficiency, the benefit of each additional robot that is added, or how effectively on average each additional robot contributes to the mission.

\[
E_{n,\infty} = \frac{S_{n,\infty}}{n} = \frac{P_{n,\infty}}{nP_{1,\infty}} = \frac{T_{1,\infty}}{nT_{n,\infty}}
\]  

(14)

where \( n \) is the number of robots, \( T_{1,\infty} \) is the time required to finish the exploration using one robot, and \( T_{n,\infty} \) is the time required to finish the exploration using \( n \) robots. An efficiency of 1.0 means that on average each robot contributes fully and equally to the mission performance. An efficiency less than 1.0 means that on average each robot is not as efficiently used as in the one robot case, while an efficiency greater than 1.0 means that on average each robot is more efficiently used than in the one robot case. This latter can be due to the team leveraging a characteristic of the problem: For example, two people folding a sheet can typically do the job in less than half the time of one because of the nature of the task.

The next sections present the simulation and physical robot results. The D-SBPF algorithm is programmed using C++ under Linux. The MobileSim software from Adept MobileRobots is used to simulate the performance of the Pioneer 3-AT equipped with SICK laser. The D-SBPF program sends motion commands to, and receives sensory data from MobileSim as it would to and from
one or more physical Pioneer 3-AT robots. The same D-SBPF implementation is used in the physical robot experiment at the end of this section, with the physical robots substituted for MobileSim. A graphing utility called GNUPlot is used to visualize and output the potential field map as well as the information for the robots.

4.2. Open space example

The first example is an empty map with no obstacles. This example shows how the D-SBPF algorithm directs the robot team to spread out and head toward unexplored areas. The algorithm is carried out with different numbers of robots from 1 to 3. Fig. 4 shows three snapshots from the execution of the D-SBPF exploration of this map with one (top), two (middle) and three (bottom) robots. The left column of Fig. 4 is the initial situation, with all robots starting in the upper left. The center column shows a time intermediate to full coverage, and the right column shows the final situation, where 95% coverage is the mission conclusion threshold. The time to achieve this coverage varies in each case, of course, and the time (in seconds) at which image in Fig. 4 is take appears in the title for that image. In Fig. 4 the arrows indicate the direction of the potential field at each point in space (i.e., at that cell in the occupancy grid), and the thick black lines show the regions that the robot sees as obstacles or walls. Each robot is indicated by gray dot, the shaded cone-shapes indicate the sensor-sensing region for each robot, and the darkness of the shade of each cell represents the value of the potential level for that cell, where a darker cell means higher potential level values. If the map is mostly covered then most cells will have been heavily shaded.

In Fig. 4(e), (h), we can see that the robots have successfully spread out at the early stage of exploration. In Fig. 4(f), (i) we see the robots successfully spread out at the final stage of exploration. In addition to the robots dispersion in location, the robots also have different headings and have minimally-overlapping sensing areas. Overlaying the coverage versus time graphs for the 1, 2 and 3 robot cases, as shown in Fig. 5, where each graph is the average of 10 simulation runs, we can see that the 3-robot-team is able to reach 95% coverage at 17 s, the two-robot-team at 46 s while the 1-robot-team requires 82 s to reach the same level of coverage. The overall exploration performance $P_{95}$ for single-robot team is 0.012, for two-robot team is 0.022 and for three-robot team is 0.058. Table 1 shows the performance, speedup and efficiency metrics for this example.

In the two robot case, the improvement in performance is almost doubled. We observe some strong synergy when multiple robots are working as a team in a map as open as this, as evidenced by the speedup and impressive efficiency for the three robot case. By the end of the single robot case (Fig. 4(c)), the robot has circled the center and made forays to each corner. However, in the multiple robot case (Fig. 4(f), (i)), when one robot finishes exploring the diagonal, it does not need to move to the other sides of the room: instead the second or third robot has already taken care of that due to the empty nature of the room.

Observing the final phase of exploration shown in Fig. 5, we can see very little difference from the result shown in [2], the centralized control version of SBPF algorithm. The decentralized version simply moves the calculation of the potential function to the robots from the controlling server, and implements the communication functionality and map update. However, it is now possible to dynamically change the size of the robot team, and hence determine the effect of this on the coverage performance compared to the coverage of a fixed-size robot team.

Fig. 6 shows the coverage graph for 1, 2 and 3 robots for the empty room map. However, now each robot starts 10 s later than the previous one. This allows preceding robots to explore the map some amount before later robots start. All robots start in the same upper left area on the map as in Fig. 4. Table 2 shows the metrics.

The delayed start strategy with 2 robots reached 95% coverage at 73 s, and has an overall exploration performance $P_{95}$ of 0.014, the exploration performance is better than using a single-robot team ($P_{95} = 0.012$), but still not as good as using 2 robots from the beginning with $P_{95} = 0.022$. The performance when using delayed additional robots is still higher than using a single robot.

<table>
<thead>
<tr>
<th>Num. robots</th>
<th>Start</th>
<th>Performance</th>
<th>Speedup</th>
<th>Efficiency</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>–</td>
<td>$P_1 = 0.012$</td>
<td>$S_1 = 1.0$</td>
<td>$E_1 = 1.000$</td>
</tr>
<tr>
<td>2</td>
<td>–</td>
<td>$P_2 = 0.022$</td>
<td>$S_2 = 1.80$</td>
<td>$E_2 = 0.916$</td>
</tr>
<tr>
<td>3</td>
<td>Delay</td>
<td>$P_3 = 0.014$</td>
<td>$S_3 = 1.16$</td>
<td>$E_3 = 0.561$</td>
</tr>
<tr>
<td></td>
<td>Delay</td>
<td>$P_3 = 0.019$</td>
<td>$S_3 = 1.58$</td>
<td>$E_3 = 0.536$</td>
</tr>
</tbody>
</table>

Table 2 Exploration performance for empty room map with delayed starts. (Coverage = 95%; omitted from subscripts for clarity.)
Fig. 8. Decentralized-SBPF map coverage examples, two room map.

<table>
<thead>
<tr>
<th>Num. robots</th>
<th>Start</th>
<th>Performance</th>
<th>Speedup</th>
<th>Efficiency</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>–</td>
<td>$P_1 = 0.012$</td>
<td>$S_1 = 1.00$</td>
<td>$E_1 = 1.00$</td>
</tr>
<tr>
<td>2</td>
<td>–</td>
<td>$P_2 = 0.022$</td>
<td>$S_2 = 1.80$</td>
<td>$E_2 = 0.916$</td>
</tr>
<tr>
<td>2</td>
<td>Delay</td>
<td>$P_{2d} = 0.014$</td>
<td>$S_{2d} = 1.16$</td>
<td>$E_{2d} = 0.56$</td>
</tr>
<tr>
<td>2</td>
<td>Delay, different location</td>
<td>$P_{2ds} = 0.037$</td>
<td>$S_{2ds} = 3.08$</td>
<td>$E_{2ds} = 1.01$</td>
</tr>
</tbody>
</table>

although the rate of increase of coverage over time is not as high as when all start at the beginning of experiment. Note that at the early stage of the exploration, since the robots start from the same starting point they inevitably have to move through some previously-explored area, so the improvement in exploration performance is not significant. Using one additional, delayed robot raises the exploration performance $P_{d,95}$ from 0.012 to 0.014, and using two additional, delayed robots allows the team to complete the exploration in 51 s, and further raised the overall exploration performance $P_{3d,95}$ to 0.019. However, in each case, it is clear from the efficiency metrics (Table 1) that the additional deployed robot is always less efficient than in the simultaneous start case (0.56 < 0.91, and 0.53 < 1.6) (see Table 2).

Let us now consider the case where that the robots that join the exploration later start from a different location (Table 3). The additional, delayed robots join the exploration team from the lower left corner of the map, while the initial robots start the mission from the upper left corner of the map. In this scenario the robot team is able to reach 80% coverage in 19 s, and finish the exploration at 27 s. The overall exploration performance $P_{3d,95}$ is 0.037, higher than the cases using two robots or one additional delayed robot. The additional delayed robots do not re-cover any previously explored area, and therefore there is an improvement in coverage efficiency above that of separately starting robots in the same starting region (Fig. 7).

4.3. Two room example

In the next example map, the two room map, the robots need to go in and out of each of the rooms to explore the building fully. Recall that this is a map that can give rise to potential field minima and possibly trap a robot that uses a potential field method for path-planning.

Fig. 8 shows examples of the D-SBPF algorithm results for the one, two and three robot cases for the two room map. It is organized similar to Fig. 4. The simulation correctly captures the line-of-sight constraint for the laser sensors, i.e., robots are unable to acquire information through walls. (This is visible in the shading of the grid cells; but the sensor cone is always drawn with the same shape.)

Fig. 9 shows the coverage graph for this example for one to three robots on a team. As before, the graph and metrics in Table 4 are averaged from 10 runs of the algorithm in each case. The graph shows in every case the robot team can achieve its objective. A noteworthy improvement in performance is seen when using two robots compared to just using one robot. The repulsion from one robot is able to push the other robot to unexplored areas faster. Using two robots, the coverage reaches 80% in 80 s and the exploration finishes at 169 s; less time than required when using a single robot. That case took 152 s to reach 80% coverage and finishes the exploration at 193 s. The single-robot team has an overall exploration performance $P_{1,95} = 0.0052$, and the two-robot team has $P_{2,95} = 0.006$; a speedup of 1.14, much less impressive than the empty room example of course.

In this map the doorway prevents two or more robots from moving forward to unexplored areas while maintaining dispersion at the same time. Using three robots allows the team to reach 80% coverage at 43 s, but later the rate of growth decreases dramatically and does not finish exploration until 134 s, resulting in an overall
Table 4
Exploration performance for the two room map.

<table>
<thead>
<tr>
<th>Num. robots</th>
<th>Performance</th>
<th>Speedup</th>
<th>Efficiency</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>( P_1 = 0.0052 )</td>
<td>( S_1 = 1.00 )</td>
<td>( E_1 = 1.00 )</td>
</tr>
<tr>
<td>2</td>
<td>( P_2 = 0.0060 )</td>
<td>( S_2 = 1.15 )</td>
<td>( E_2 = 0.57 )</td>
</tr>
<tr>
<td>3</td>
<td>( P_3 = 0.0074 )</td>
<td>( S_3 = 1.42 )</td>
<td>( E_3 = 0.47 )</td>
</tr>
</tbody>
</table>

Table 5
Exploration performance for the two room map with delayed start.

<table>
<thead>
<tr>
<th>Num. robots</th>
<th>Start</th>
<th>Performance</th>
<th>Speedup</th>
<th>Efficiency</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>–</td>
<td>( P_1 = 0.0052 )</td>
<td>( S_1 = 1.00 )</td>
<td>( E_1 = 1.000 )</td>
</tr>
<tr>
<td>2</td>
<td>Delay</td>
<td>( P_{d1} = 0.0054 )</td>
<td>( S_{d1} = 1.03 )</td>
<td>( E_{d1} = 0.518 )</td>
</tr>
<tr>
<td>3</td>
<td>Delay</td>
<td>( P_{d2} = 0.0067 )</td>
<td>( S_{d2} = 1.29 )</td>
<td>( E_{d2} = 0.428 )</td>
</tr>
</tbody>
</table>

Fig. 9. Graph of coverage versus time for the two-room scenario.

Fig. 10. Graph of coverage versus time for the two-room map with delayed start.

Table 6
Exploration performance for two room map with delayed start and different start locations.

<table>
<thead>
<tr>
<th>Num. robots</th>
<th>Start</th>
<th>Performance</th>
<th>Speedup</th>
<th>Efficiency</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>–</td>
<td>( P_1 = 0.00520 )</td>
<td>( S_1 = 1.00 )</td>
<td>( E_1 = 1.000 )</td>
</tr>
<tr>
<td>2</td>
<td>Delay</td>
<td>( P_{d1} = 0.0054 )</td>
<td>( S_{d1} = 1.03 )</td>
<td>( E_{d1} = 0.518 )</td>
</tr>
<tr>
<td>2</td>
<td>Delay, different location</td>
<td>( P_{d2} = 0.0071 )</td>
<td>( S_{d2} = 1.37 )</td>
<td>( E_{d2} = 0.689 )</td>
</tr>
</tbody>
</table>

already explored by previous robots. Thus, they cannot make contributions to map coverage until they have moved to unexplored areas. This effect is even more serious for the third robot. Since the previous two robots (that started twenty and ten seconds earlier) have moved and covered any undiscovered region ahead, the robot that joins the team later cannot reach an undiscovered region quickly and is not able to provide any extra coverage capability until later in the exploration mission. Thus, we propose that having a second (or third) robot start from a different place will have a bigger impact on performance; even better perhaps than using two robots that start at the same time.

Consider the scenario where a second delayed robot joins the exploration team from the lower left corner of the map, while the initial robots starts the mission from the upper left corner of the map. This robot team that reaches the threshold coverage earlier than the other robot teams (Fig. 11), and finishes the exploration at 140 s. This is earlier than the 169 s obtained when using two robots from the beginning and the 186 s obtained with one additional, delayed robot with same starting position. This team achieved an overall exploration performance of \( P_{3d, 95} = 0.0071 \), a speed of 1.37 compared to 1.03 for just a delayed start, and comparable with the exploration performance of using three robots, \( P_{3, 95} = 0.0074 \) (Table 6).

4.4. Internal obstacle example

In the third example map, as shown in Fig. 12, the robot team must explore to reach the other side of a building that has several internal obstacles and walls including a permanently enclosed area.
Comparing the intermediate phase and final phase of Fig. 12 with 1, 2 and 3 robots, it can be seen that the robots move toward different sub-regions based on the number of the robots. In Fig. 12(b), the robot moved to the lower half of the map, the largest unexplored sub-region, and finished the exploration after making a circle. On the other hand, the robots separate as shown in Fig. 12(e) and (h), heading toward the upper half and lower half respectively (two robot team), and upper half, middle half and lower half (three robot team). They later complete coverage of the map after the robot that traveled to the lower half makes a circle and returns.

As reported in Fig. 13, coverage shows an almost linear increase rate at the early stage of the mission, as the robots are driven to the larger blank areas. The rate then decreases slightly, moving to 95% coverage as the robots are drawn toward, and see behind, the obstacles. Since the robot sensors are line-of-sight sensors, the map coverage will increase by a greater amount when the robot goes around an occlusion and is able to see behind it.

From the results shown in Fig. 13 and in Table 7, we can see that the two-robot team reaches 95% map coverage at 155 s with an overall exploration performance $P_{2,95} = 0.0065$. With a speedup of 1.8, this is close to half the time required when using one robot (287 s and exploration performance $P_{1,95} = 0.0035$). Due to the crowdedness of the map, the performance of the third robot in this case is even more constrained. Using three robots has only a slight improvement in performance over using two robots, compared to the improvement from one robot to two robots. The team of three robots finished the exploration and reached 95% map coverage at 125 s and the exploration performance $P_{3,95} = 0.008$. With a speedup of 2.29, the time saved and improvement of exploration performance from upgrading a two-robot team to three-robot team is smaller than the case of switching from a one-robot team to two-robot team with each robot being use with 0.76 efficiency as opposed to 0.92.

Fig. 14 reports on the results of using team members that are delayed, and delayed with different start locations. Since this map geometry is divided into smaller regions by the obstacles, the first robot will not quickly achieve high coverage of the entire region, due to the occlusions blocking the line of sight of the sensors. The robot has to choose one portion (which has higher attractive potential) for exploration. When the second robot joins the exploration, it is able to cover the other portion of the unexplored map and thus able to increase the map coverage soon.

The robot team using one additional, delayed robot finished the exploration at the 186 s. This team increased the overall exploration performance of the single-robot team from $P_{1,95} = 0.0035$ to $P_{2,95} = 0.0053$. Furthermore, if the additional, delayed robot joins the exploration from a different starting position, the robot team is able to finish the exploration at 141 s. This has an overall exploration performance $P_{2,95} = 0.007$, higher than two-robot team’s exploration performance, $P_{2,95} = 0.0065$. Again we can see that if the robots start from different locations in the map, the exploration performance is much better than the case where two

**Fig. 12.** Decentralized-SBPF map coverage examples, internal obstacle map.

**Fig. 13.** Graph of coverage versus time for the internal obstacle map.

**Table 7.** Exploration performance for the internal obstacle map.

<table>
<thead>
<tr>
<th>Num. robots</th>
<th>Performance</th>
<th>Speedup</th>
<th>Efficiency</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>$p_1 = 0.0035$</td>
<td>$S_1 = 1.00$</td>
<td>$E_1 = 1.00$</td>
</tr>
<tr>
<td>2</td>
<td>$p_2 = 0.00650$</td>
<td>$S_2 = 1.80$</td>
<td>$E_2 = 0.92$</td>
</tr>
<tr>
<td>3</td>
<td>$p_3 = 0.0080$</td>
<td>$S_3 = 2.29$</td>
<td>$E_3 = 0.76$</td>
</tr>
</tbody>
</table>
robots start from the same starting point. The improvement in exploration performance is superior to the case of using one robot and two robots that start from the same place, finishing the exploration earlier than the other cases (see Table 8).

4.5. Robot implementation

To demonstrate that the D-SBPF method transfers from simulation to real implementation, results are presented from carrying out this algorithm with a team of one and two Pioneer 3-AT robots. The room to be explored is $5 \times 5 \text{ m}^2$, arranged as shown in Fig. 15. The central partition is placed to block the robot’s line of sight; complete coverage cannot be attained unless the robots move into out of the enclosed area. Each robot is equipped with the pre-installed ARIA library control and a SICK LMS-200 laser sensor with $180^\circ$ sensing field of view and 10 m sensing range. Because MobileSim was used for the simulation experiments reported previously, the same implementation of the D-SBPF algorithm can be used with the physical robots.

However the Pioneer 3-AT implementation differs from the simulation in one important aspect: The robot takes its motion direction from the potential field, and the magnitude depends on both the potential force magnitude and direction. But, when the direction points directly behind the robot, then the robot will reverse and back off in addition to turning away. Furthermore, the robots are allowed to move at 1 m/s maximum velocity, and will slow down or stop if another object is in the path of movement. The program terminates normally if the map is 95% explored, and terminates in failure if any robot stays in the same position for more than 10 s due to collision with robots or obstacles.

In the two experiment, the robots will start asymmetrically. Robot #1, as shown on the right of Fig. 15(b), will start first. Ten seconds after robot #1 starts, robot #2, as shown on the left of Fig. 15(b), will join the exploration. The experiment was carried out 5 times and map coverage percentage was recorded. Fig. 17 shows the graph of coverage over time for the average of the 5 runs for both one and two robot teams. The averaged performance shows 95% coverage in 145 s for the one robot team and 125 s for the two robot team, for $P_{1.95} = 0.0068$, and $P_{2.95} = 0.008$ and $S_{2d} = 1.16$.

The potential field map (e.g., Fig. 16) showed some differences with the actual map geometry, for example the section between the sub-regions is distorted while it should remain a straight line. The error is caused by bad localization: No separate mapping and localization module was run as part of the algorithm; not a problem for the simulation, but an issue for the real robots. Although the error makes the potential field map inaccurate compared to the actual map, the map is still sufficient for indoor exploration missions and allows the robot to reach the threshold map coverage without collisions.

Comparing the result shown in Fig. 17 with the centralized SBPF method reported in [2]: first we can see both algorithms finish the exploration in a similar amount of time. The two robot case results in one robot exploring part of the map while the robot that starts later can just head toward the unexplored region. However, the speedup is very impressive in this case given the small space explored and the issues with localization.

5. Conclusion and future work

The principal contribution of this paper is a novel approach to motion planning for multi-robot search problems, the decentralized Space-Based Potential Field (D-SBPF) method. The method assumes that the overall size of the area to be searched is known and information is used to develop a simple, uniform potential field framework. The method uses an extended occupancy grid to represent the space, where each cell can be attractive (if undiscovered) or repulsive (if discovered). A non-monotonic fieldscale factor proportional to coverage is also used to improve searching of corners and niches and to assist in moving robots out of potential minima. A second contribution of the paper is a fast, decentralized map exchange and update method. An advantage of this approach is that robots can leave/join/rejoin the team at any stage, as might be expected as robots traverse a building and lose mutual connectivity.

Several simulation results were presented to show the performance of the approach. The non-monotonic field approach introduced here can be compared successfully with other potential field approaches in terms of the effect of potential minima. Despite the opportunity in maps two and three for many field minima as discovered by Renzaglia [13], our one, two and three robot teams were able to navigate the maps without stalling or needing a role-based approach to pull robots from minima.

Metrics of performance, speedup and efficiency, based on similar parallel computation metrics, were introduced and calculated for all these examples. These metrics tease out the benefits of team size, allowing robots to start at different times, and selecting differing starting locations made possible by the decentralized algorithm. The results can be summarized as follows:
The D-SBPF uses a simple max operator to map coverage information. However, this is conservative and may ignore contributions to coverage. This causes a shelf in the coverage graphs for maps two and three. An improvement is to further extend the occupancy grid so that not only is cell coverage stored, but also a tag which indicates which robot made the coverage. The additional tag allows a less conservative update rule to be evaluated. The method introduced is limited to static maps, but an extension to dynamic maps was briefly mentioned.

No SLAM module was included in the system architecture used to evaluate D-SBPF so as to focus attention on just the coverage problem. However, a crucial step in conducting more physical robot evaluations is to add a SLAM implementation. Julia et al. [12] for example integrate their extended occupancy map approach with FastSLAM. Future work will include the additional of SLAM and the evaluation of less conservative map update rules.

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References

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