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Multi-Robot Search and Rescue: A Potential Field Based Approach

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Summary. This paper describes two implementations of a potential field sharing multi-robot system which we term as pessimistic and optimistic. Unlike other multi-robot systems in which coordination is designed explicitly, it is an emergent property of our system. The robots perform no reasoning and are purely reactive in nature. We extend our previous work in simulated search and rescue where there was only one target to the search for multiple targets. As in our previous work the sharing systems with six or more robots outperformed the equivalent non-sharing system. We conclude that potential field sharing has a positive impact on robots involved in a search and rescue problem.

Keywords: potential fields, multi-robot systems, search and rescue.

2.1 Introduction

Potential fields [11] have been used in robot navigation [17] for a number of years, despite a number of well known issues [13]. An example of such a difficulty includes oscillation near obstacles and in narrow passages. Modifications to the potential field algorithm have been proposed [19] to overcome these challenges. Other approaches to potential fields include that of Reif et al. [18] in which an individual agent's motion is a result of an artificial force imposed by other agents and components of the system. Damas et al. [7] modified potential fields to enhance the relevance of obstacles in the direction of the robot's motion. Howard et al. [10] divided their potential field into two components, a field due to obstacles and a field due to other robots. Pathak et al. [17] stabilised their robot within a surrounding circular area ('bubble') using two potential field controllers. The ROBOT was centred within a bubble and then its orientation was corrected.

In our approach, a robot's motion is a result of the force imposed by obstacles. In addition, a local group of robots share information on common

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potential field regions so that a robot's motion can be a result of obstacles not perceived by the individual robot. The concept of a local group is similar to that of dynamic robot networks [5]. However, instead of broadcasting trajectories and plans of robots, in our system the potential field information is broadcast. To the best of our knowledge, no previous research using potential fields has incorporated the concept of sharing potential field information amongst robots.

Unlike perception–reasoning–execution architectures [14] the system presented in this chapter does not reason about its environment. We describe our system as a reactive system [1]. Motion is based purely on the potential field created by the sensor data in real-time. There is no concept of teamwork [6] or role selection [20] in that each robot performs actions as an individual. Robots are not aware that they are part of a collective; co-ordination becomes an emergent property of the system through the implicit sharing of potential fields by the robots.

In this chapter, we extend our previous work [2] by using a potential field based architecture to search for two targets in an unknown environment. We largely reproduce the problem description in Sect. 2 from [2] for completeness. Although this is a specific problem instance, we believe our system may be applied to many other problems such as robotic soccer [7, 12], the coverage problem [10] and robotic hunting [3].

In the rest of this chapter, Sect. 2.2 describes the potential field based implementation, Sect. 2.3 describes the experiments undertaken, Sect. 2.4 outlines the results from the experiments and, finally, Sect. 2.5 is a discussion of the results observed and possible future work.

2.2 Potential Field Implementation

Before a description of the sharing robots is given, the individual robot system will be summarised, as the sharing robots are based upon this individual robot system and they are compared against it during the experimentation described in Sect. 2.3.

The individual robot system is made up of a number of robots which attempt to solve a task individually without any communication or co-ordination with one another. The system is implemented using a model based upon Coulomb's law of electrostatic force (as described in [4]). The system is composed of positively charged particles, which are used to calculate the field by the inverse square law below (2.1):

$$F = \frac{q_1 q_2}{r^2} \tag{2.1}$$

where q_1 and q_2 represent the charges of two particles and r is the distance between them. The resultant force, F, either repels or attracts the particles to one another. Using (2.1), we calculate eight individual forces, $f1 - f8$; r is

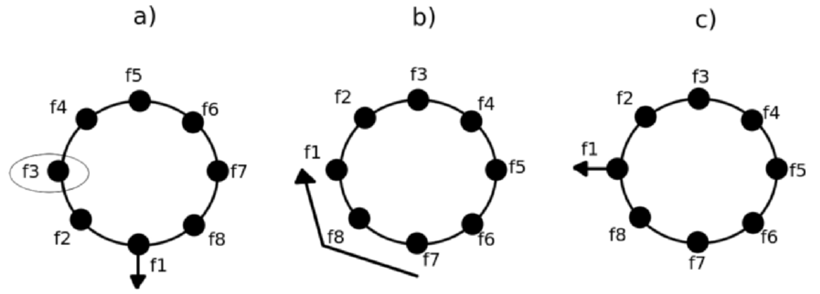

Fig. 2.1. Action selection: (**a**) the robot calculates the minimum force (f3), (**b**) the robot rotates towards the minimum force, (**c**) the robot moves forwards (towards the minimum force)

the range to an object (in metres) obtained from an ultrasonic sensor reading (see Fig. 2.1a), q_1 is the charge of the robot and q_2 is the charge of the object. For simplicity, all objects are represented by a positive unit charge.

Rather than formally resolving into a single force, the robot's motor control is a simple action selection of either *move forward* or *rotate*. When moving forward, the speed of the robot is proportional to the force acting upon it. When rotating, the angular speed is $0.5\,\mathrm{rad\,s^{-1}}$ and the forward speed is $0.025\,\mathrm{m\,s^{-1}}$. The robot calculates the minimum F (F_{min}) and rotates in the direction of F_{min}. If the direction of the robot equals the direction of F_{min} then the robot moves forwards (see Fig. 2.1).

Using this conceptually simple algorithm, the robot moves away from areas of positive charge (obstacles). As a target is indistinguishable from an obstacle to an ultrasonic sensor, a camera is used to differentiate between obstacles and targets using blob detection (targets are non-black obstacles). However, rather than giving the target a negative unit charge (-1), the task is said to be complete once the target has been found (this is a simplification due to the nature of the task described in Sect. 2.3). The orientation of the camera is fixed to the forward orientation of the robot (see Fig. 2.1a).

2.2.1 Potential Field Sharing

As noted earlier, the sharing robots are identical to the individual robots but implicitly share their potential field information with other robots within a local group. Therefore, by knowing only the relative positions (based upon odometric readings and the initial location of all robots) of other robots in the system, robots can assign themselves to a local group (the range of the local group catchment radius is set to an arbitrary value).

The world is represented as a two-dimensional plane. Simple geometric calculations (the intersection of circles and the intersection of lines and circles) are used to decide which of the ultrasonic sensors are likely (see Fig. 2.2a) to share information.

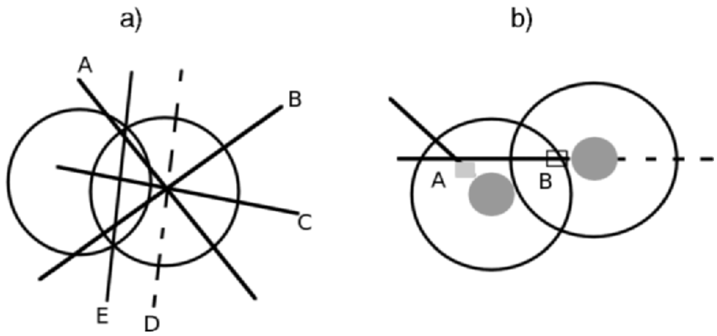

Fig. 2.2. (**a**) Likely sharing: The *circles* represent the local catchment areas of each robot. *Lines* A, B, C and D are the lines representing the ultrasonic sensors. Line E is the line intersecting the points of intersection of the two circles. (**b**) Two robots: The large circles represent the range of the robot's sensors and thus the *grey square* is an obstacle only observed by robot A. The *white square* represents what robot B would 'see' if the pessimistic system was implemented. The *dashed line* represents potential field information that is not shared

If any of these lines intersect, the line joining the points of intersection of each robot's local group catchment radius (line E in Fig. 2.2a). The intersections of lines are used to determine which lines (representing the direction of ultrasonic sensors) from any robot (within the local group radius) intersect any of the lines of another robot. Then the potential field information of the involved robot's ultrasonic sensors is shared. An example is given in Fig. 2.2b. Note that line D in Fig. 2.2a never needs to be considered, since it is parallel to line E. This process is repeated for all robots within the local catchment radius.

We describe two types of sharing systems. They are referred to as *pessimistic* and *optimistic* in the context of sensor noise. Consider, for example, the situation as in Fig. 2.2b in which robot A detects an obstacle that is not within robot B's sensor range. As they both belong to the same local group, a shared potential field is constructed. Robot A would suggest a high charge, whereas robot B would suggest a low charge. In the pessimistic system, the highest charge is selected and so an obstacle outside its own sensor range repulses robot B. In the optimistic system, the lowest charge is selected and thus the obstacle initially detected by its sensors no longer repulses robot A.

The advantage of the pessimistic system is that robots are less vulnerable to false negatives (and so avoid obstacles that they have not detected due to sensor noise), but the disadvantage is that they are more susceptible to false positives (and so avoid obstacles they do not need to). The advantage of the optimistic system is that robots are less vulnerable to false positives but are more susceptible to false negatives. Note that not all potential field information is shared amongst robots within the same local group, see Fig. 2.2b.

2.3 Experiments

As with our previous work [2], all experiments were conducted using the player/stage [8] simulator and the robots modeled in the simulator were Miabot Pros [15], with an ultrasonic range finder and avr-cam modules. The ultrasonic range finder is composed of eight ultrasonic sensors that give a 360° field of view with a range of $3\,\mathrm{cm}^{-1}\,\mathrm{m}$. The avr-cam has a field of view of 30° and can track up to eight blobs at the same time. The local group catchment radius is set to double the sonar range of 1 m. The simulated environment has approximately the same dimensions ($5 \times 3\,\mathrm{m}^2$) as our real robot arena. As an extension of our previous work [2], the simulated robots have the task of discovering two targets in an unknown environment. Once both targets are found, the task is complete. The environment consists of obstacles, robots, a deployment zone and targets. Obstacles were generated within the environment (world) randomly; the size of the obstacle, its position and its orientation all varied. The positions of the targets and the deployment zone for the robots were also generated randomly. However, these positions were fixed throughout the experiments. The only difference between each experimental run is the noise within the simulation in the form of bad data. For example, sonar passing through obstacles. The deployment zone is a position in the world that all the robots start in (evenly spaced 0.1 m from one another in concentric circles starting from this initial position, where obstacles allow).

For these experiments, three worlds were generated (see Fig. 2.3). For each world, all three of the systems (individual, pessimistic and optimistic)

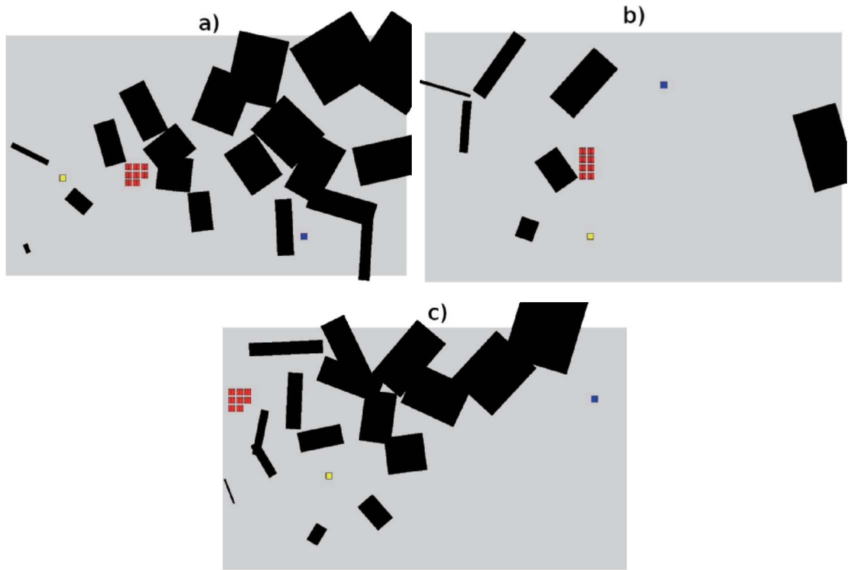

Fig. 2.3. (**a**) Simulated world 1. (**b**) Simulated world 2. (**c**) Simulated world 3. The group of eight squares are the simulated robots. The two lone squares are the targets. The *rectangles* are the obstacles

Table 2.1. Mean completion (seconds) for each system in each world for 2–8 robots, to one decimal place

	2	3	4	5	6	7	8
world 1							
ind	300.0	195.0	284.0	241.1	189.2	250.0	163.3
pes	184.5	183.5	104.8	135.1	126.3	165.0	104.0
opt	195.0	188.5	149.5	117.7	85.0	138.9	139.1
world 2							
ind	123.3	127.1	85.0	73.9	25.9	37.1	26.7
pes	70.2	48.5	53.8	62.3	37.7	28.0	25.4
opt	76.5	68.6	52.4	45.7	42.2	38.4	40.6
world 3							
ind	249.0	173.2	163.3	104.6	170.3	198.5	103.5
pes	116.2	94.5	135.7	114.5	98.8	103.6	83.3
opt	135.4	110.0	163.6	111.8	118.6	76.3	75.4

attempted 20 runs that were repeated for groups of 2–8 robots. The time recorded for both targets to be discovered was the metric recorded. Failure to complete the task within 300 s resulted in a score of 300 s. The means of the results are provided in Table 2.1.

2.4 Results

As in our previous work [2], two statistical tests were chosen to analyse the data. The Kruskal-Wallis test was chosen, as it is useful in detecting a difference in the medians of distributions. The Friedman test was chosen to detect the existence of association between characteristics of a population. Details of these tests are given in [9].

In world 1, both the pessimistic and the optimistic system perform significantly better than the individual system in all but one case (3 robots). There is no significant difference between the two sharing systems. In world 2, the pessimistic system significantly outperforms the individual system in the 2 and 3 robot cases. The optimistic system significantly outperforms the individual system in the 2, 3 and 5 robot cases. Again, there is no significant difference between the two sharing systems. In world 3, both the sharing systems significantly outperformed the individual system in the 2 and 7 robot cases and there was no significant difference between the sharing systems. The individual system performed better with 6 or more robots in worlds 1 and 2. The pessimistic system results suggest that there was no significant advantage gained by increasing the number of robots. The optimistic system performed best with 6 or more robots in worlds 1 and 2.

2.5 Discussion

The results show that the sharing systems perform significantly better than the individual system. The observation that there is no significant difference between the performance of the pessimistic and optimistic systems is also interesting as this implies that the ability to detect more obstacles has the same benefit as the ability to ignore more sonar noise. We believe that this may be due to the fact that there is a limited amount of noise within the simulation and the differences in the sharing systems' performance will be more apparent in the real world. The observation that both the individual and the optimistic system perform better with six or more robots makes sense as, in the case of the individual system, more robots in the world results in a greater area coverage. In the case of the optimistic system, as well as having the same benefits of the individual system, more robots result in more information being shared and so each robot can make better decisions. The observation that the pessimistic system did not benefit from an increased number of robots was not expected and requires further research.

A major limitation of the pessimistic and optimistic systems is their reliance upon accurate odometric readings. In the experiments carried out in this chapter, it was assumed that no errors occurred. In the real world, errors occur frequently due to wheel slippage. This will have to be accounted for in real world experiments.

Future work includes adapting the multi-robot systems to include group member recognition in order to improve robot dispersal. We also intend to investigate the effect of the local group radius (both increasing and decreasing its size). Other possible future work includes, applying this research to a very large-scale robotic system (hundreds of robots) [18] and implementing the sharing robots in other common problems such as robotic soccer [7, 12], formation control [16], the coverage problem [10] and hunting [3]. It is hoped that the work in this chapter can form a basis for future work on real robots.

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