The Effect of Potential Field Sharing in Multi-Agent Systems

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Abstract

This paper describes two implementations of a ‘potential field sharing’ multi-agent system which we term as ‘pessimistic’ and ‘optimistic’. Unlike other multi-agent systems in which coordination is designed explicitly, it is an emergent property of our system. The agents perform no reasoning and are purely reactive in nature. The motivation behind this work is to develop a conceptually simple system that can be used in a number of applications. Experiments were conducted in the simulated search and rescue problem, although it is believed that the system is applicable to other common problems such as formation control, coverage and hunting. Statistical analysis showed that systems of six to eight agents that shared potential fields outperformed the equivalent non-sharing system. We conclude that potential field sharing has a positive impact on agents involved in a search and rescue problem.

Keywords: potential fields, multi-robot systems, multi-agent collaboration systems, autonomous systems, search and rescue

1 Introduction

Potential fields [1] have been used in robot navigation [2] for a number of years, despite a number of well-known problems [3]. Examples of problems include oscillation near obstacles and in narrow passages. Modifications to the potential field algorithm have been proposed [4] to overcome these problems. Other approaches to potential fields include that of Reif et al. [5] in which an individual agent’s motion is a result of an artificial force imposed by other agents and components of the system, and that of Damas et al. [6] in which the potential fields are modified to enhance the relevance of obstacles in the direction of the agent’s motion. Howard et al. [7] divide their potential field into two components, a field due to obstacles and a field due to other agents. Pathak et al. [2] stabilize their agent within a surrounding circular area (‘bubble’) using two potential field controllers, the agent is centred within a bubble and then its orientation is corrected.

In our approach, an agent’s motion is a result of the force imposed by obstacles. In addition, a ‘local group’ of agents share information on common potential field regions so that an agent’s motion can be a result of obstacles not perceived by the individual agent. The concept of a local group is similar to that of dynamic robot networks [8]. However, instead of broadcasting trajectories and plans of agents, 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 agents.

Unlike perception-reasoning-execution architectures [9] the system presented in this paper does not reason about its environment. We describe our system as a reactive system [10]. Motion is based purely on the potential field created by the sensor data in real-time. There is no concept of teamwork [11] or role selection [12] in that each agent performs actions as an individual. Agents are not aware that they are part of a collective; coordination becomes an emergent property of the system through the implicit sharing of potential fields by the agents.

In this paper, we use potential fields in the search and rescue problem. However, we believe our system may be applied to many other problems such as robotic soccer [6] [13], the coverage problem [7] and hunting [14].

2 Potential Field Implementation

Before a description of the ‘sharing’ agents is given, the ‘individual’ agent system will be summarised, as the sharing agents are based upon this individual agent system and they are compared against it during the experimentation in section 3.

The individual agent system, as the name suggests, is made up of a number of agents who attempt to solve a task individually without any communication or coordination with one another. The system is implemented using potential fields modelled on simple electromagnetic theory (as described in [15]).

The system is composed of positively charged particles, which are used to calculate the field by the inverse square law (Coulomb's Law) below (1):

$$F = \frac{q_1 q_2}{r^2} \tag{1}$$

where q_1 and q_2 are 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 (1), we calculate eight individual forces F_1-F_8; r is the range to an object (in metres) obtained from an ultra-sonic sensor reading, q_1 is the charge of the agent 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 agent's motor control is a simple action selection of either move forward or rotate. When moving forward the speed of the agent is relative to the force acting upon it (2), when rotating the angular speed is 0.5 r/s and the forward speed is 0.025 m/s. The agent calculates the minimum F (F_{min}) and rotates in the direction of F_{min}. If the direction of the agent matches the direction of F_{min} then the agent moves forwards.

$$S = 1 - \frac{F}{10} \tag{2}$$

Using this conceptually simple algorithm the agent moves away from areas of positive charge (obstacles). As a target is indistinguishable to an ultra-sonic sensor a camera is used to distinguish between obstacles and targets using blob detection (the camera tracks for the colour blue, the target). 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 section 3). The orientation of the camera is fixed to the forward orientation of the agent.

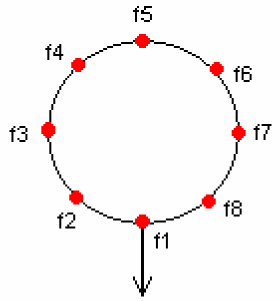

Figure 1: (Model of agent): Dots represent position of ultra-sonic sensor. The straight-line arrow indicates the forward orientation/motion of the agent.

2.1 Potential Field Sharing

As noted above the sharing agents are based upon the individual agent system. In fact, they are identical apart from the implicit sharing of potential field information. Agents share their potential field information with other agents within a local group. Therefore, by knowing only the relative positions (based upon odometric readings and the initial location of all agents) of other agents in the system, agents can assign themselves to a local group. Simple geometrical calculations (the intersection of lines/circles), are used to see which agents (if any) are in the local group. The world is represented as a two dimensional plane. If any of the lines (representing the direction of ultra-sonic sensors) from any agent intersects a circle (representing the local radius) of another agent then the potential field information of the involved agents are shared. An example is given below in figure 2.

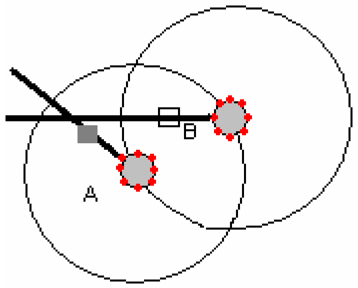

Figure 2: (Two agents): The large circles represent the range of the agent's sensors and thus the grey square is an obstacle only observed by agent A. The white square represents what agent B would "see" if the pessimistic system was implemented.

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 figure 2 in which Agent A detects an obstacle that is not within Agent B's sensor range. As they both belong to the same local group (within 2m of each other), a shared potential field is constructed. Agent A would suggest a high charge, whereas Agent B would suggest a low charge. In the pessimistic system, the highest charge is selected and so Agent B is repulsed by an obstacle outside its own sensor range. In the optimistic system, the lowest charge is selected and thus Agent A is no longer repulsed by the obstacle initially detected by its sensors. The advantage of the pessimistic system is that agents 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 agents are less vulnerable to false positives but are more susceptible to false negatives.

3 Experiments

All experiments were conducted using the player/stage [16] simulator. Real world experimentation is one of our key objectives, and as such, the robots modelled in the simulator are those that we intend to use in experiments in the future. The robots simulated for the experiments were Miabot

Table 1: Mean completion time (seconds) for each multi-agent system in each world, for two to eight agents (to 1d.p.).

	Number of Agents						
	2	3	4	5	6	7	8
Individual							
world 1	300.0	250.7	255.9	225.1	205.2	273.0	288.2
world 2	153.8	129.6	70.1	31.7	32.4	33.2	29.9
world 3	52.2	91.2	69.6	73.6	62.7	112.7	134.4
Pessimistic							
world 1	203.4	211.1	172.6	133.9	121.6	124.3	120.6
world 2	77.2	57.9	43.2	49.9	8.0	4.3	11.9
world 3	115.5	141.8	67.9	78.8	64.7	133.5	95.9
Optimistic							
world 1	262.5	198.8	150.2	109.4	98.0	110.2	116.0
world 2	132.1	42.6	31.7	26.3	11.4	4.3	9.5
world 3	115.5	128.5	70.5	105.7	66.7	106.6	110.0

Pro's [17], with an ultra-sonic range finder and avr-cam modules. The ultra-sonic range finder is composed of eight ultra-sonic sensors that give a 360° field of view with a range of 3cm – 1m. The avr-cam has a field of view of 30° and can track up to eight blobs at the same time. The environment simulated has approximately the same dimensions (5m x 3m) as our real robot arena. As an initial test-bed, the problem of search and rescue was chosen. It is defined as follows; Agents have the task of navigating an unknown environment in order to find a target (once the target is found it is presumed rescued).

The environment consists of obstacles, agents, a deployment zone and a target. Obstacles were generated within the environment (world) randomly; the size of the obstacle, its position and its orientation all varied. The positions of the target and the deployment zone for the agents 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 e.g. sonar passing through obstacles. The deployment zone is a position in the world that all the agents start in (evenly spaced 0.1m from one another in concentric circles starting from this initial position).

For these experiments, three worlds were generated. For each world, all three of the systems (individual, pessimistic and optimistic) attempted twenty runs that were repeated for groups of two to eight agents. The time recorded for the first agent to find the target was the metric recorded. Failure to complete the task within three hundred seconds resulted in a score of three hundred seconds. The means of the results are provided in table 1. 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.

3.1 Kruskal-Wallis Rank Sum Test

To investigate quantitively which system performs better we used the Kruskal-Wallis rank sum test. This involves ranking all of the times provided from each system; the mean of the sum of ranks for each (see table 2) was taken and the significant differences noted. This was repeated for all three worlds and all seven sizes of groups. The null hypothesis (h_0) and alternative hypothesis (h_1) were as follows:

h_0: The medians of the k populations do not differ.
h_1: At least two of the medians differ.

As detailed in [18], the Kruskal-Wallis H test statistic was produced whilst correcting for ranking ties. If the corrected H value was greater than the selected P-value (0.1), h_0 could be rejected in favour of our h_1. If the differences between the means of ranks (table 4) did not satisfy (3) (where $k = 3$, $N = 60$ and $z = 2.1$ (to 1 d.p.)) and was negative this meant that the first group had a significantly smaller completion time than the second group. However, if it was positive, it can be concluded that the second group had a significantly smaller completion time. This is because a larger mean difference relates to a longer completion time.

$$\left|\bar{R}_i - \bar{R}_j\right| \le z\sqrt{\frac{k(N+1)}{6}} \qquad (3)$$

3.2 Friedman Rank Sum Test

To investigate what effect the number of agents had on performance, the Friedman rank sum test was conducted. This involves ranking all of the times provided from each system from all group sizes. The sum of ranks for each (see table 3) was taken and the

Table 2: Mean rank sum for each multi-agent system in each world, for two to eight agents (to 1 d.p.).

	Number of Agents						
	2	3	4	5	6	7	8
Individual							
world 1	38.0	35.6	41.0	38.8	41.1	44.8	46.3
world 2	22.5	42.1	35.2	32.2	45.7	50.5	47.0
world 3	12.0	19.5	27.3	23.1	27.0	28.5	32.2
Pessimistic							
world 1	22.5	29.2	27.8	27.0	26.9	24.4	24.1
world 2	39.1	26.5	29.2	32.5	22.1	20.0	24.3
world 3	39.9	37.9	30.1	32.1	32.1	30.5	27.9
Optimistic							
world 1	31.0	26.8	22.7	25.7	23.5	22.3	21.1
world 2	29.9	22.9	27.1	26.8	23.7	21.0	20.3
world 3	39.6	34.1	34.1	36.4	32.5	32.5	31.5

Table 3: Column sum of ranks for each multi-agent system in each world, for two to eight agent (to 1 d.p.).

	Number of Agents						
	2	3	4	5	6	7	8
Individual							
world 1	97.5	81.0	77.0	68.5	64.5	82.0	89.5
world 2	121.0	118.0	79.0	62.5	53.0	59.5	67.0
world 3	46.5	66.0	92.5	81.0	79.0	101.5	93.5
Pessimistic							
world 1	101.5	100.0	89.5	75.5	60.0	68.0	65.5
world 2	109.0	117.0	102.5	93.5	57.0	26.0	55.0
world 3	91.5	110.0	74.0	74.0	64.5	81.5	64.5
Optimistic							
world 1	120.0	101.0	81.5	72.5	58.5	64.0	62.5
world 2	120.0	114.5	102.0	85.5	59.0	31.0	48.0
world 3	85.5	89.5	76.5	82.5	65.0	82.5	78.5

significant differences noted. This was repeated for all three worlds. The null hypothesis (h_0) and alternative hypothesis (h_1) were set as follows:

h_0: The number of agents of the k populations has no effect.

h_1: The number of agents has an effect.

As detailed in [18], the Friedman Q test statistic was calculated. If the Q value was greater than the selected P-value (0.1) the h_0 could be rejected in favour of our h_1. If the difference between column sums (tables 5-7) did not satisfy (4) (where k = 20, n = 7 and z = 2.8 (to 1 d.p.)) and was negative this meant that the first group had a significantly larger completion time than the second group. If positive, it can be concluded that the first group had a significantly smaller completion time.

$$\left|R_i - R_j\right| \leq z\sqrt{\frac{kn(n+1)}{6}} \qquad (4)$$

4 Results

Table 4 shows the significant differences between the means of ranks for the, individual system (R1), pessimistic system (R2) and the optimistic system (R3). Rows with no significant differences have been omitted for brevity. As only values above, 11.8 (to 1 d.p.) are significant it can be seen that both the pessimistic and optimistic systems perform better than the individual system, in groups of six or more in worlds one and two. For groups of less than six the results are mixed. The individual system performs significantly better in world 3 for group sizes of up to five beyond that the differences become insignificant. It can also be observed that there was no significant difference between the pessimistic and optimistic systems. Table 5 shows significant differences between the pairs of column sums for the individual system. As only values above 38.6 (to 1 d.p.) are significant, it can be seen that in world 2 the individual system performs better with four or more agents. However, for world 3 the individual system performs better with two agents only. It can also be observed that there is no significant impact of group size in world 1. Table 6 shows the same data for the pessimistic system. It appears to perform better with six or more agents in all three worlds (which is in line with the results from table 4). Table 7 again shows the same data for the optimistic system, which performs better in worlds 1 and 2 with four or more agents. There were no significant differences in world 3.

Table 4: Significant differences between the individual (R1), pessimistic (R2) and optimistic (R3) systems (to 1 d.p.)

	Differences	
Two Agents	$\bar{R}_1 - \bar{R}_2$	$\bar{R}_1 - \bar{R}_3$
world 1	15.5	7.0
world 2	-16.6	-7.4
world 3	-27.9	-27.7
Three Agents		
world 2	15.7	19.2
world 3	-18.4	-14.7
Four Agents		
world 1	13.2	18.3
Five Agents		
world 1	11.7	13.1
world 3	-9.0	-13.3
Six Agents		
world 1	14.3	17.6
world 2	23.6	22.0
Seven Agents		
world 1	20.4	22.6
world 2	30.4	29.5
Eight Agents		
world 1	22.2	25.2
world 2	22.6	26.7

5 Discussion

From the results in the previous section, it can be observed that both the pessimistic and optimistic systems perform better than the individual system (when in groups of 6 or more). It can also be observed that both the pessimistic and optimistic systems perform better in larger group sizes (6 or more and 4 or more respectively). These results make sense as the presence of more agents implies a higher probability that the agents can take advantage of potential field sharing, instead of reverting to the individual behaviour. The second observation is interesting as it shows that a system less inclined to avoid obstacles performs better with a smaller group size than a system that is inclined to avoid obstacles. This also makes sense as the smaller the group size, the less likely it is that more (previously unseen) obstacles will be discovered. 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. This finding was unexpected and requires further investigation.

Table 5: Significant differences between the numbers of agents, for the individual system. (to 1 d.p.)

	Number of Agents				
	4	5	6	7	8
world 2					
2 agents	42.0	58.5	68.0	61.5	54.0
3 agents	39.0	55.5	65.0	58.5	51.0
world 3					
2 agents	-46.0	-34.5	-32.5	-55.0	-47.0

Table 6: Significant differences between the numbers of agents, for the pessimistic system. (to 1 d.p)

	Number of Agents		
	6	7	8
world 1			
2 agents	41.5	33.5	36.0
3 agents	40.0	32.0	34.5
world 2			
2 agents	52.0	83.0	54.0
3 agents	60.0	91.0	62.0
4 agents	45.5	76.5	47.5
5 agents	36.5	67.5	38.5
world 3			
3 agents	45.5	28.5	45.5

Table 7: Significant differences between the numbers of agents, for the optimistic system. (to 1 d.p.)

	Number of Agents				
	4	5	6	7	8
world 1					
2 agents	38.5	47.5	61.5	56.0	57.5
3 agents	19.5	28.5	42.5	37.0	38.5
world 2					
2 agents	18.0	34.5	61.0	89.0	72.0
3 agents	12.5	29.0	55.5	83.5	66.5
4 agents	N/A	16.5	43.0	71.0	54.0

A major limitation of the pessimistic and optimistic systems is their reliance upon accurate odometric readings. In the experiments carried out in this paper 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-agent systems to include group member recognition in order to improve agent 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 work to a very large-scale robotic system (hundreds of robots) [5] and implementing the sharing agents in other common problems such as robotic soccer [6] [13], formation control [19], the coverage problem [7] and hunting [14]. It is hoped the work in this paper can form a basis for future work in the real world.

6 References

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