A Behaviour-Based Optimisation Strategy for Multi-Robot Exploration

Gu Fang
School of Engineering & Industrial Design
University of Western Sydney
NSW, Australia
g.fang@uws.edu.au

Gamini Dissanayake, & Haye Lau
ARC Centre of Excellence in Autonomous Systems (CAS)
University of Technology, Sydney
NSW, Australia
gdissa@eng.uts.edu.au
hlau@eng.uts.edu.au

***Abstract*— To efficiently explore an unknown environment with a team of robots, a coordinated strategy that maximises the exploration area is required. This is a difficult optimisation problem, as there may exist many suboptimal solutions. In order to reduce the search space to a region that is near the optimal, a behaviour-based exploration strategy is used to define the region in which an optimal solution can be found. A numerical optimisation technique is then used to find the solution in this region. In particular, the proposed strategy uses a potential-fields technique to obtain a coarse movement direction for each robot. A nonlinear optimisation method is then used to calculate the velocity and angle deviation from the coarse direction to achieve the maximum exploration for each move. Simulation results have shown that the proposed method provides an efficient exploration strategy.**

Keywords- Multi-robot, exploration, optimisation, social potential-fields

I. Introduction

A. Background

One of the fundamental challenges in mobile robotics is to explore the unknown environment efficiently and effectively. The efficiency and effectiveness of the exploration are typically measured by the map coverage, map accuracy and exploration time. In [1] an integrated exploration method is introduced to achieve the balance of speed of exploration and accuracy of the map using a single robot. To minimise the overall exploration time of robots in an unknown environment, each robot should be moving in a direction and at a speed that maximise the exploration areas. An optimisation method is usually required for calculating such directions and speeds. However, this type of optimisation problems is difficult to solve, since it has a large search space with many sub-optimal solutions.

B. Related Work

In recent years, multi-robot systems have attracted increased attention from the research community. Multi-robot systems are believed to be superior to the single robot systems in exploration due to the factors that: firstly, multiple robots can explore the environment faster than can a single robot; secondly, a multi-robot system can be made of cheaper robots due to the inherent redundant nature of the multi-robot system that has a better fault-tolerance capacity; thirdly, multiple robots provide each other with a potential localisation target.

In [2, 3] a multi-robot exploration method is introduced by using the "believe measure" to decide the target for each robot to move to in order to achieve an accurate exploration result. In [4, 5] on the other hand, a time-optimal exploration is attempted by introducing different optimal methods in selecting frontiers for each robot to go to. In [4] a market economy based optimisation method is used to select the best frontier for each robot to achieve the maximum coverage. A visibility measure is used in identifying the frontier in [5]. The visibility measure will attempt to spread the robot to explore the environment in a shortest time.

In addition to its applications in frontier-based target allocation for multi-robot exploration, time-optimal control has also been introduced to achieve other objectives for multiple robots such as in multi-robot formation [6, 7] and in multi-robot searching for a non-evading target [8].

In this paper, a method that combines the behaviour-based approach and the optimisation strategy is introduced to achieve efficient exploration with multiple robots. In particular, it uses the social potential-fields algorithm [9, 10] to obtain the coarse direction of the robot movement. Then an optimisation algorithm is applied to fine-tune the moving direction and moving speed of the robot to achieve the maximum coverage of the unknown environment.

The paper is organised in four parts. Following the introduction, section 2 describes the problem formulation and the method used to solve the optimal exploration problem. In section 3, simulation results are provided to evaluate the proposed method. Discussions are also presented in the section. Conclusions are given in section 4.

II. Behaviour-Based Optimal Exploration Method

A. Problem Description

One of the objectives of exploration is to cover an unknown environment in a minimum time. To achieve this, each robot must have a map (or a record) of the area that it has explored. In the case of multi-robot exploration, a central map (record) can be compiled using the information from individual robots. Since robots have no prior knowledge of the environment, the time-optimal exploration problem can be converted into a problem of maximising the covering rate, i.e., a robot should move to a position where it can sense the largest unknown area.

In this paper, a grid-based map is used to represent the environment. It is assumed that the robots are equipped with sensors (such as a ring of sonar sensors, or two 180 degree laser sensors mounted back to back) that have 360-degree coverage. The sensors are assumed to have a fixed finite sensing range. It is also assumed that the locations of robots are known to each other. It is assumed that the robot is controlled by a computer that accepts control commands at a fixed frequency.

The method used in the paper to achieve an optimal exploration can be separated into two parts. Firstly, a behaviour-based method is used to obtain the coarse direction of each robot's movement that will avoid obstacles and inter-robot collisions as well as will move towards the unexplored regions. Secondly, an optimisation technique is used to fine-tune the moving angle and speed of each robot, such that the coverage of the unknown environment for the movement is maximised.

In the following parts of the section, both the behaviour-based method and the optimisation strategy will be introduced.

B. Behaviour-Based Exploration

The behaviour-based method used in this paper is the "social potential fields" method introduced in [9]. This method has also been used in [10] to generate the control inputs for multi-robot exploration. In using the potential-fields method for multi-robot exploration, three forces are considered for each robot. One is the repulsive force introduced by obstacles that are near the robot. Another repulsive force is introduced by nearby robot(s). The other force is the attractive force created by the unexplored areas. In particular the robots are attracted to the "frontiers", i.e., the unknown areas that are immediately adjacent to explored empty areas [11]. The equation of the combined force $\vec{F}_{total}$ generated using the potential-fields can be expressed as:

$$\vec{F}_{total} = \sum_{i=1}^{n} \vec{F}_{obstacle,i} + \sum_{j=1}^{m} \vec{F}_{robot,j} + \sum_{k=1}^{p} \vec{F}_{frontier,k} \qquad (1)$$

where $\vec{F}_{obstacle,\ i}$, $\vec{F}_{robot,\ j}$, and $\vec{F}_{froniter,\ k}$ are the forces generated by obstacle *i*, robot *j*, and frontier *k*, respectively, to the robot, *n*, *m*, and *p* are the total number of obstacles, robots, and frontiers, respectively, in the range to be considered. The robot movement will be in the direction of $\vec{F}_{total}$.

The individual forces in (1) can be calculated using the potential-fields method and their magnitudes are assumed to be proportional to the inverse of the distances from the robot to the obstacles, frontiers and other robots. More specifically, they are calculated using the following equations:

$$\vec{F}_{obstacle,\ i} = \begin{cases} \dfrac{-G_{obstacle}\vec{d}_i}{\|d_i\|^{3/2}} & \|d_i\| \le d_{obstacle} \\ 0 & \|d_i\| > d_{obstacle} \end{cases} \qquad (2)$$

where $\vec{d}_i$ and $\|d_i\|$ are the distance vector and the Euclidean distance from the obstacle *i* to the robot, $d_{obstacle}$ is the predefined obstacle effective range within which equation (2) applies, and $G_{obstacle}$ is a predefined expulsive gain of the obstacle.

$$\vec{F}_{robot,\ j} = \begin{cases} \dfrac{-G_{robot}\vec{d}_j}{\|d_j\|^{3/2}} & \|d_j\| \le d_{robot} \\ 0 & \|d_j\| > d_{robot} \end{cases} \qquad (3)$$

where the symbols used here are similar to the ones used in (2), $\vec{d}_j$ and $\|d_j\|$ are the distance vector and the Euclidean distance from the robot *j* to the robot, d_{robot} is the predefined robot effective range within which equation (3) applies, and G_{robot} is a predefined expulsive gain of the robot.

$$\vec{F}_{froniter,\ k} = \begin{cases} \dfrac{G_{frontier}\vec{d}_k}{\|d_k\|^{3/2}} & \|d_k\| \le d_{frontier} \\ 0 & \|d_k\| > d_{frontier} \end{cases} \qquad (4)$$

The symbols used in (4) are similar to those in (2) and (3), except they represent the effects of frontiers.

By using the potential-fields based method, robots may potentially be trapped in a local minimum when the total force $\vec{F}_{total}$ generated in (1) equals zero. In this case, the behaviour-based algorithm in the paper uses a path planning method to generate a path to a reachable frontier. The path planning method used is the A* algorithm [12].

In particular, the robot will be moving towards a visible frontier in preference of a non-visible one. The non-visible frontiers are not related to the sensing range of the robot. Rather they are defined as those that are not in the line of view of the robot, i.e., there are know obstacles between the robot and the frontiers. This choice makes the robot more likely to explore the frontiers in the same segment then to explore those frontiers that are near the robot but are on the other side of a wall.

Since the potential-fields method expressed in (1) generates a moving direction for a robot based on the compromise between the attractive force of frontiers and repulsive forces of obstacles and other robots, there is no guarantee that the direction in which the robot is moving will result in a maximum exploration rate. Therefore, in this paper an optimisation method is introduced to fine tune the movement of the robot to achieve a maximum exploration.

C. Optimisation to Achieve the Maximum Exploration

The optimal exploration problem can be stated in many ways. Typical ones are area coverage, map accuracy and exploration time. In this paper, the objective of the optimisation is to explore an unknown area in a minimum time. To minimise the exploration time is equivalent to maximise the exploration area in each move.

In this paper an optimisation method is used to find the moving speeds of the robot as well as the small angle deviations from the direction of $\vec{F}_{total}$ calculated in (1) for a certain number of time steps, such that the total coverage of the unknown area in the considered time period is maximised subject to the constraints that the robot does not hit the obstacles and the robot moving speed and the angle variation are within permissible bounds.

The mathematical expression of this optimisation method for each robot can be stated as:

$$\max_{v_i, \Delta\alpha_i}\left(\sum unknown\ cells\right) \tag{5}$$

subject to:

$$v_{\min} < v_i < v_{\max} \qquad for \quad i = 1,2,...,np \tag{6}$$

$$\Delta\alpha_{\min} < \Delta\alpha_i < \Delta\alpha_{\max} \qquad for \quad i = 1,2,...,np \tag{7}$$

$$\min(d_{obstacle}) > d_{safe} \tag{8}$$

where v_i and α_i are the optimisation variables representing moving speeds and angle variations from the direction of $\vec{F}_{total}$ of the robot, *np* is the number of time steps used to predict the exploration coverage, v_{min}, v_{max}, $\Delta\alpha_{min}$, and $\Delta\alpha_{max}$, represents the bounds of the optimisation variables, while $d_{obstacle}$ and d_{safe} represent the distances from the obstacles to the robot and the chosen safe distance.

Many existing methods can be used to solve this optimisation problem. In this paper a nonlinear constraint optimisation routine in MATLAB Optimisation Toolbox [13] is used.

III. SIMULATION RESULTS AND DISCUSSIONS

To evaluate the proposed method, simulations are carried out using MATLAB. The environment to be explored is assumed to be a 40m x 40m area (Fig. 1) that contains wall partitions and some sparsely located furniture. A grid map is used to represent the environment with a grid cell size of 100mm x 100mm.

A. Exploration Using A Behaviour-Based Method

To examine the developed potential-fields based algorithm, a single robot and a team of three robots are used to explore the area. It is assumed that each robot has two laser sensors that can sense a 360-degree region. The detection range of the laser sensor is assumed to be 3 meters. It is also assumed that the speed of the robot is 1m/s. The control commands, i.e., the turning angle and moving speed, are assumed to be issued every 0.5 seconds.

The simulation results show that a single robot covers the entire region (1600 m^2) in 645 seconds (Fig. 2). By using three robots to perform the same task (Fig. 3), on the other hand, the coverage takes 340 seconds. As expected, it represents a considerable exploration time reduction (more than 50%).

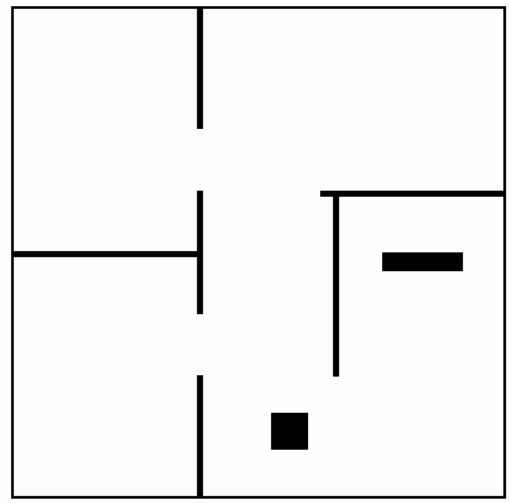
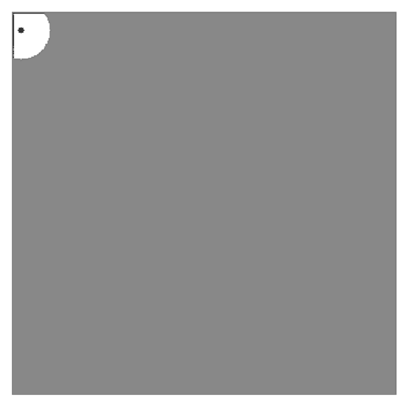
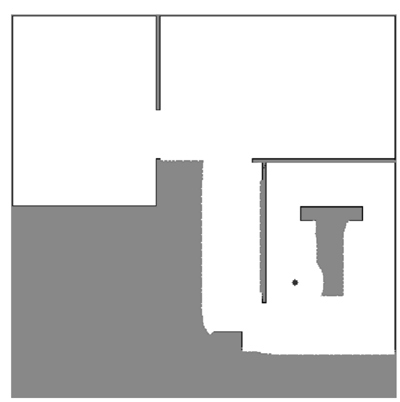


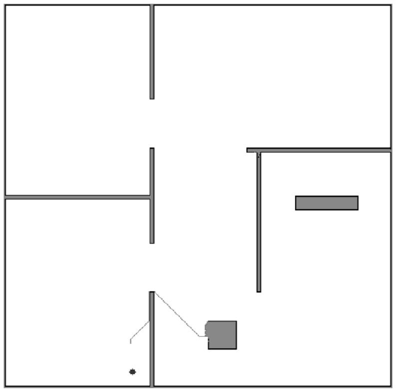
Figure 1. The environment to be explored.



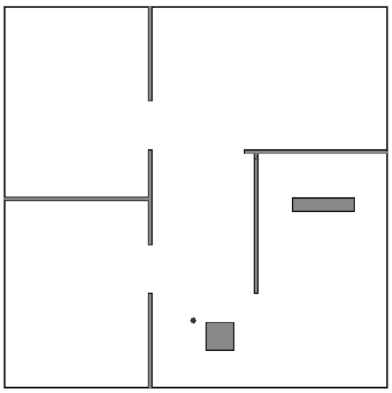
a)



b)



c)



d)

Figure 2. Single robot exploration: a). the starting configure, b), c) during the exploration, d) the final map generated.

B. Exploration Using the Behaviour-Based Optimisation Method

To examine the behaviour-based optimisation method proposed in the paper, three robots are used to explore the same environment. The coarse movement of each robot is calculated using the potential-fields method. The optimisation algorithm is then used to determine the moving speed v and the angle variation $\Delta\alpha$ to achieve the maximum exploration.

To perform the optimisation, the bounds of the variables are set to be:

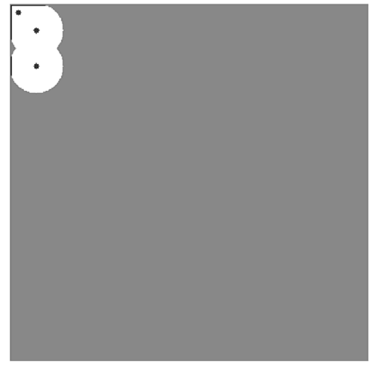
$$v_{\min} = 0.7 \quad m/s\,, \tag{9}$$

$$v_{\max} = 1.0 \quad m/s\,, \tag{10}$$

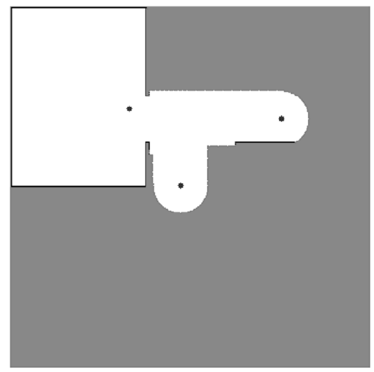
$$\Delta\alpha_{\min} = -0.2 \quad rad\,, \tag{11}$$

$$\Delta\alpha_{\max} = \ 0.2 \quad rad\,, \tag{12}$$

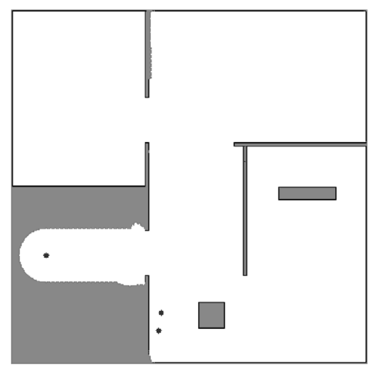
The number of time steps np in (6) and (7) is set to 3, while d_{safe} is set to 0.5 meters. The optimisation was carried out using the same initial configuration as the one presented in Fig. 3.



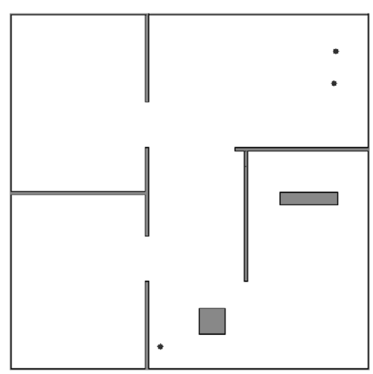
a)



b)



c)



d)

Figure 3. Multi-robot exploration: a) the initial configuration, b), c) during the exploration, d) the final map generated.

The exploration is finished in 295 seconds. This, in comparison with the result obtained using the behaviour-based method alone, represents a significant improvement in the exploration efficiency (more than 13% reduction in exploration time compared with the non-optimal multi-robot exploration). This indicates that the added optimisation method does provide a reasonable optimality into the exploration time.

C. Discussions

To further examine the optimality of the obtained results, a number of tests were carried out using the behaviour-based method with three robots. In each test, the three robots were set at a common speed between 0.7 m/s to 0.9 m/s. It was found that with the robot speed being set at 0.7 m/s and 0.9 m/s, the exploration mission could not finish due to the robot collision with the obstacles. When the speeds of robots were set at 0.8 m/s, the exploration finished in 288 seconds. This time is very close to the one that is obtained from the optimisation method. Although the true optimality of the results can never be verified, the result does show that the proposed optimisation method improves the efficiency of the potential-fields based exploration method.

IV. Conclusions

In this paper a behaviour-based optimisation method is introduced to improve the efficiency of the behaviour-based method for multi-robot exploration. In particular the social potential-fields method is used as the behavioural method to calculate the coarse direction of movement for each robot. This movement is then fine-tuned by an optimisation method. The simulation results have shown that this method does provide a way of achieving efficient exploration.

The current optimisation and simulation are done using MATLAB which is not a fast computational environment. It is envisaged that the method would be tested using the commonly used Player/Stage software and the optimisation will be performed using C++ to examine the real-time aspect of the proposed method. It is planned that this method will be tested on a team of Pioneer robots available in CAS in the next few months. In addition, with the proposed optimisation method, it is possible to include formation of the robots or the localisation using other robots into the computation to achieve a more accurate exploration result. Further work is expected to continue in these areas.

Acknowledgment

This work is partially supported by the ARC Centre of Excellence programme, funded by the Australian Research Council (ARC) and the New South Wales State Government.

References

[1] A. Makarenko, S. Williams, F. Bourgault, and H. Durrant-Whyte, “An experiment in integrated exploration,” Proceedings of the 2002 IEEE/RSJ International Conference on Intelligent Robots and Systems, Oct 2002, pp. 534 – 539.

[2] F. Kobayashi, S. Sakai, F. Kojima, “Determination of exploration target based on belief measure in multi-robot exploration.” Proceedings of 2003 IEEE International Symposium on Computational Intelligence in Robotics and Automation, July 2003 Kobe Japan, pp. 1545 – 1550

[3] F. Kobayashi, S. Sakai, F. Kojima, “Sharing of exploring information using belief measure for multi-robot exploration.” Proceedings of the 2002 IEEE International Conference on Fuzzy Systems, May 2002, pp. 1544 - 1549

[4] R. Zlot, A. Stentz, M.B. Dias, S. Thayer, “Multi-robot exploration controlled by a market economy,” Proceedings of 2002 IEEE International Conference on Robotics and Automation, May 2002, Washington DC USA, pp. 3016 – 3023.

[5] W. Burgard, M. Moors, D. Fox, R. Simmons, and S. Thrun, “Collaborative multi-robot exploration,” Proceedings on 2000 IEEE International Conference on Robotics and Automation, April 2000, CA USA, pp. 476 – 481.

[6] T. Furukawa, H. Durrant-Whyte, F. Bourgault, and G. Dissanayake, “Time-optimal coordinated control of the relative formation of multiple vehicles,” Proceedings of 2003 IEEE International Symposium on Computational Intelligence in Robotics and Automation, July 2003 Kobe Japan, pp. 259 – 264.

[7] T. Furukawa, H. Durrant-Whyte, and G. Dissanayake, “Time-optimal cooprative control of multiple robot vehicles,” Proceedings of 2003 IEEE International Conference on Robotics and Automation, Sept 2003, pp. 944 – 950.

[8] F. Bourgault, T. Furukawa, and H. Durrant-Whyte, “Coordinated decentralized search for a lost target in a Bayesian world,” Proceedings of the 2003 IEEE/RSJ International Conference on Intelligent Robots and Systems, Oct 2003, pp. 48 – 53.

[9] J. Reif and H. Wang, “Social potential fields: A distributed behavioral control for autonomous robots,” Robotics and Autonomous Systems, 27, 1999, pp171 – 194.

[10] H. Lau, “Behavioural approach for multi-robot exploration,” Proceedings of. 2003 Australasian Conference on Robotics and Automation, Brisbane, Australia, Dec 2003.

[11] B. Yamauchi, “Frontier-based exploration using multiple robots,” Proceedings of the Second International Conference on Autonomous Agents, 1998 MN USA, pp.47-53.

[12] J. Latombe, Robot Motion Planning, Kluwer Academic Publishers. 1991.

[13] The Mathworks, Optimisation Toolbox – User’s Manual,” 2003.