An enhanced frontier strategy with global search target-assignment approach for autonomous robotic area exploration

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Abstract
Frontier strategy is an effective robotic area exploration mechanism that exploits the boundaries information between known area and unknown area to determine the next best target location for robots to explore autonomously. A typical frontier strategy employs a greedy-based local search approach to select a target location, also known as goal-assignment task, thus may slow down the exploration process. This paper presents a modified frontier strategy with a global search target-assignment paradigm. The proposed method optimises the target-assignment task by using genetic algorithm to provide a global search mechanism by carefully examining path distances between frontiers. A set of possible routes to visit all frontiers is generated heuristically by the genetic algorithm. After several generations, the first frontier of the shortest route is chosen as the next target location. The proposed enhanced frontier strategy outperforms the canonical frontier strategy in terms of the performance of area exploration by 31% to 50%.

Keywords
Genetic algorithm, Target assignment, Frontier strategy, Robotic area exploration.

1. Introduction
The demand for autonomous robotic area exploration increases significantly as hazardous or dangerous real-world tasks such as search and rescue require safer operation procedures for human operators. With the advancement of robotic technologies, autonomous robots can be utilised to autonomously explore an unknown area, generating an environmental map of the area and accomplished desired missions. In such an autonomous robot system, the exploration mechanism is one of the main factors that determines the performance of the robot to accomplish a given mission successfully. In a multi-robot system, the exploration mechanism must be carefully designed such that no redundant exploration occurs among robots [1].

Considering the exploration mechanism for two-dimensional environmental map generation, a well-known frontier strategy [2] mechanism is widely used due to its effectiveness in guiding the robot to the boundaries of unknown areas and low computational processing required to run the algorithm. Typical frontier strategies employ a greedy-based local search approach to select the next best target location for the robot, or also known as a target-assignment task. The local search approach works by simply evaluating the path distance and effort required to reach every candidate target location, also called frontier point. A frontier with the minimum path distance and effort from the robot position is selected as the next target. Consequently, the greedy approach may degrade the exploration performance such as exploration completion time or total travelled path.

In this work, the development of a modified frontier strategy with a global search approach target-assignment is investigated. In contrast to the local search approach, the proposed global search approach examines in depth the relationship of the path distance and effort not only between the robot and each frontier but also from a frontier to another. By
having such depth analysis, the target-assignment module can choose the next global optimum target location that gives the shortest hypothetical path distance and effort to visit all available frontiers. By using such an approach every time the target-assignment module is being called, exploration performance can be improved significantly.

This paper presents an enhanced frontier strategy with the global search target-assignment using the genetic algorithm (GA) technique. GA adopts the natural evolution concept that iteratively refines populations of potential solutions by providing a guided directed search process to converge into the optimal solution systematically. The objectives of this paper are:

1) To design a framework for a global search target-assignment of frontier strategy based on the GA technique.
2) To investigate the effectiveness of the proposed GA-based global search task-assignment in improving robotic exploration performance.

The following section presents the literature review of the related past works. Section 3 describe in details the proposed framework of the GA-based global search target-assignment approach. In section 4, the results of the simulated experiment are discussed. Finally, section 5 concludes the overall findings of the work.

2. Literature review

Urban search and rescue [3], surveillance [4], subterranean [5], and underwater [6] exploration missions are just a few examples that can benefit from the technology of autonomous mobile robots. From the past research works, the frontier exploration strategy was widely implemented in autonomous robots that are capable to perform area exploration ranging from aerial, ground or underwater environments. The canonical frontier strategy developed in [2] originally implements a local search target-assignment paradigm. The local search approach uses a utility-cost function to rank detected frontiers and choose the frontier with the highest function value as the next target. The local search approach has been evolved over time to meet various purposes of robotic exploration.

Most of the past work focuses on optimising the evaluation function to rank frontiers. For example, work by [7] proposes a random frontier points optimization (RFPO) algorithm. The algorithm considers three variables: information gain, navigation cost and the precision of the localization in the function. The reported results only show an average improvement of robot travelled distance around 17% among various local search target-assignments.

Local search approaches can also be optimized by performing the segmentation of detected frontiers. As reported in [8], an additional pre-processing procedure is added to semantically classified a frontier as either a free area or a transit area based on the geometric map information. The algorithm considers a transit area, an edge point between two semantically different area, as having a higher priority to be chosen compared to common free areas. Similarly, work by [9] presents a Frontier-graph structure to segment frontiers. Breadth-first search (BFS) algorithm is used to select the next best target by combining the grid map and frontier-graph to a single grid map update problem. The idea of using hybrid maps in evaluating frontiers is extended in [10]. The work integrates a hybrid map consisting of a generalized Voronoi diagram (GVD) and a grid-based metric map. By using the hybrid map, the target-assignment will prefer the next target location that is near to “stem” or the main road generated by the GVD in the metric map. However, the generation of a dual map approach increases the required computational processing power.

In contrast, there are also works that consider reducing the complexity of the evaluation function that ranks frontiers. This is the case in a low computational power system such as unmanned aerial vehicles (UAV) that commonly have a light-weight low power onboard computer. Work by [11] develops an autonomous inspection of infrastructure system with UAV. The work applies a greedy local search frontier strategy based on information gain to find the next best target for the UAV. Another reason of using the simple function is to consider the generation of a 3D environmental map involving different altitude. Another work by [12] proposes a clustered frontier exploration for UAV. The approach optimizes its target-assignment by clustering the detected frontiers but uses only the information gain variable to select the next target.

On another hand, the frontier strategy can also be implemented in multi-robot systems. The work by [13] compares various multi-robot frontier strategy approaches. The multi-robot systems are categorized into a centralized system and a decentralized system. A sub-optimal search target-assignment approach is
utilized in most centralized systems by considering every robot location relative to the detected frontiers to avoid redundancy in target selection. Meanwhile, the decentralized systems mostly deploy a local search target-assignment approach due to loose collaboration among robots in making decisions.

3. Methods
This section is divided into two sections. The first section describes the system configuration of the proposed framework in terms of software, robot and simulator configurations. The later section presents the proposed GA-based global search target-assignment of the enhanced frontier strategy in detail.

3.1 System configuration
This work focuses on the autonomous robotic exploration for a ground mobile robot. To perform exploration, a differential drive robot is utilised. This work uses a simulated robot based on an open platform mobile robot called Turtlebot 3 Waffle as the robot model. The robot moves via two servo-motor wheels that can be controlled independently. The robot is also equipped with a light detection and ranging (LiDAR) sensor that can measure distances to surrounding objects and acts as the main input to build an environmental map. On the software part, the overall system configuration is developed using an open-source Robot Operating System (ROS) platform. In addition, an open-source Gazebo simulator is also adopted and integrated with ROS to simulate the exploration environment and the robot model. Figure 1 shows the Gazebo simulator interface with simulated Turtlebot 3 Waffle. A complete robotic exploration program requires several ROS packages to be integrated together for the robot to have autonomous exploration capability. Important ROS packages required are move_base navigation, gmapping simultaneous localisation and mapping (SLAM) and frontier_exploration strategy. Note that, the frontier_exploration package was modified to implement the proposed global search target-assignment framework by integrating it with an open-source GA library called GAlib. Figure 2 shows the dataflow between packages and the robot.

Figure 1 Gazebo simulator interface with simulated Turtlebot 3 waffle

Figure 2 Overall dataflow on the autonomous robotic exploration system
The dataflow starts from the robot’s LiDAR sensor. The LiDAR data are periodically passed to the gmapping SLAM so that an occupancy grid map of the environment can be updated accordingly. Then, the built grid map as well as the current robot position are published to frontier_exploration for the robot to execute the selection of the next best target location task. A sub-module ‘Frontier detector’ generates a set of frontiers as the candidate target locations and passes the frontiers information to the proposed global search goal-assignment sub-module. In this stage, GA is activated to find the best next target location based on the algorithm that will be explained in section 3.2. Once the target is selected, the target information is relayed to move_base navigation to calculate the trajectory of the robot to reach the target. move_base navigation periodically sends the desired velocity to the robot’s low-level controller to control the wheels accordingly. The processes are repeated until all areas are explored.

3.2 The proposed GA-based global search target-assignment

In this work, the model of the travelling salesman problem (TSP) is adopted to develop the proposed target-assignment. According to the TSP model, the proposed solution should be able to find a solution to the following statement: “Given a set of candidate target locations (frontiers) and path distance between each pair of frontiers, find the shortest total path distance to visit all frontiers exactly once”. Note that all frontiers have no restriction to be accessed from another frontier.

By implementing a global search perspective, target-assignment is modelled as an undirected weighted graph. The graph has frontiers as the vertices and all paths that connect between two frontiers as the edges. Path distances between frontiers are calculated by using cost_map provided by the move_base package. The path distance is equivalent to the edge’s weight. In general, the number of possible solutions for the created graph can be calculated as follows. Given there is V number of vertices, the number of edges E can be calculated as in (1).

\[ E = \frac{V(V-1)}{2} \]  

(1)

Thus, the number of possible solutions S can be found as in (2).

\[ S = \frac{(V-1)!}{2} \]  

(2)

The factorial in (2) shows that the number of possible solutions grows very large with the increase of the number of vertices V. In this case, using Brute-force approach to evaluate all possible solutions will be infeasible as robotic exploration requires a real-time decision. Alternatively, an intelligent approach that may heuristically evaluate few significant possible solutions to consistently produce a near-optimal solution is required. The application of GA on such problem is more feasible as it applies heuristic search method based on Darwinian natural selection theory to find the best solution. In this work, the proposed global search target-assignment using GA is calculated as in Figure 3.

In this frontier strategy, the target-assignment sub-module is called periodically at a fixed frequency F set by the user. The frontier detector sub-module will pass a list of detected frontiers (vertices) and all path distance information between frontiers (edges’ weights) to the target-assignment sub-module. GA starts the process by generating an initial population of random chromosomes with size P. Each chromosome represents a sequence of frontiers to be visited as in Figure 4. The total path distance of the frontiers sequence is calculated by using path distance between frontiers information received by the GA.

A fitness function is designed to evaluate the quality of a candidate solution in terms of the total path distance length of frontiers’ sequence in a chromosome as in (3).

\[ f(c) = d_{rt_1} + \sum_{i=1}^{T-1} d_{t_it_{i+1}} \]  

(3)

where \( d_{rt_1} \) is the path length between robot and frontier \( t_1 \), \( d_{t_it_{i+1}} \) is the path length between frontier \( t_i \) and frontier \( t_{i+1} \). Each frontier sequence is represented by a 2-tuple contains \((C, f)\) where \( C \) is its corresponding chromosome and \( f \) is the fitness of the frontier sequence.

After all chromosomes have been evaluated with (3), GA performs evolution operators with a common sequence of selection, crossover and mutation operations. In this work, Roulette wheel selection, Order1 crossover and Order1 mutation are applied in the GA configuration. A new population of offspring produced from the operations replaces the initial population, and the processes are repeated until the maximum generation G set by the user is reached. At the end of the process, the frontier sequence with the highest fitness is selected. From the selected frontier sequence, the first frontier in the sequence is chosen as the next best target location.
Figure 3 The flowchart of the processes implemented by the proposed GA-based global search target-assignment

Figure 4 The configuration of a chromosome

4. Results
The system configuration as explained in section 3 was configured in a desktop equipped with an Intel Core i5 CPU 1.8GHz 8GB RAM and installed with Ubuntu 16.04 and ROS Kinetic. Experiments to investigate the effectiveness of the proposed method were conducted via computer simulation. Using the Gazebo simulator, two simulated bounded areas with different geometrical information were constructed. Table 1 shows the visualisation of the areas with their geometrical information. The two different areas
were used to observe the functionality of the proposed method in various types of environments.

In each experiment run, the robot was initially placed at a fixed location colored with a hollow red circle in Table 1. It is assumed that the robot has no prior information or an environmental map before performing the exploration. When the robot exploration program turned on, the software operation as mentioned in section 3.1 was executed. When the target-assignment module is called, the target selection task was activated performing processes as depicted in section 3.2. The robot will move to the target location as suggested by the frontier strategy. The experiment run stops when the robot completely exploring all possible spaces.

Table 2 presents the configuration of the GA-based global search target-assignment used in this experiment. The selection of 100 maximum generations and 10 chromosomes in each population was done heuristically with the main aim to balance between achieving real-time processing and getting near-optimal solutions in every target-assignment cycle.

For exploration performance comparison, the proposed global search target-assignment was compared with the canonical local search target-assignment that uses the greedy approach in determining the next target location. Hereafter the proposed approach is called GA-TA, and the canonical approach as CAN-TA. For each exploration area in Table 1, the total of ten (10) exploration run was conducted for statistical analysis purpose. The first five (5) runs were configured with the robot implements GA-TA, while the latter five (5) runs were performed with the robot set to used CAN-TA.
The results clearly show that GA-TA outperforms CAN-TA in terms of the total path cost to complete the exploration mission for both indoor and construction areas. The improvement made by GA-TA in terms of median path cost is about 50.4% and 31.8% for the indoor area and the construction area, respectively. It can also be observed that the standard deviation of GA-TA is smaller compared to CAN-TA. This result shows GA-TA has a consistent exploration path cost compared to CAN-TA that has a wider standard deviation in both exploration areas.

![Boxplots of exploration performance for GA-TA and CAN-TA target-assignments on the indoor and construction areas](image)

**Figure 5** Boxplots of exploration performance for GA-TA and CAN-TA target-assignments on the indoor and construction areas, respectively

**Table 3** Statistical information of the exploration performance for GA-TA and CAN-TA target assignments

<table>
<thead>
<tr>
<th>Area</th>
<th>Indoor</th>
<th>Construction</th>
</tr>
</thead>
<tbody>
<tr>
<td>Parameter</td>
<td>GA-TA</td>
<td>CAN-TA</td>
</tr>
<tr>
<td>Median</td>
<td>6201.0</td>
<td>12,493.0</td>
</tr>
<tr>
<td>Standard deviation</td>
<td>25.1</td>
<td>933.4</td>
</tr>
<tr>
<td></td>
<td>GA-TA</td>
<td>CAN-TA</td>
</tr>
<tr>
<td>Median</td>
<td>28,711.0</td>
<td>42,080.0</td>
</tr>
<tr>
<td>Standard deviation</td>
<td>1,375.2</td>
<td>3,671.8</td>
</tr>
</tbody>
</table>

**5. Discussion**

The quantitative results in section 4 can deduce that GA-TA yields better exploration performance from CAN-TA. To have a better insight into the factor that contributes to the improvement, a qualitative observation was performed on few target-assignment decisions. Table 4 compares the decision made by GA-TA and CAN-TA when exploring the construction area. The table tabulates whether the deployed GA-TA target-assignment chooses the nearest frontier to the robot location or not at each important cycle.

**Table 4** Comparison of decision made by GA-TA and CAN-TA in selecting the nearest frontier as the next best target location at each important cycle

<table>
<thead>
<tr>
<th>Cycle, T</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
<th>8</th>
<th>9</th>
<th>10</th>
<th>11</th>
<th>12</th>
<th>13</th>
</tr>
</thead>
<tbody>
<tr>
<td>GA-TA</td>
<td>X</td>
<td>✓</td>
<td>X</td>
<td>✓</td>
<td>X</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>CAN-TA</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
</tr>
</tbody>
</table>

✓ The nearest frontier X Not the nearest frontier
Significant different decisions can be seen in the first few cycles of GA-TA when the potential target locations are vast and spread over the map. In most cycles, GA-TA tends to choose a target location that may produce the shortest total travelling path that not necessarily the nearest frontier to the robot location. Meanwhile, the later cycles may force GA-TA to choose the nearest frontier as the target location that at the same time produces the shortest total travelling path. This is because most of the parts of the map have been explored and the number of frontiers reduces proportionally. Figure 6 shows the corresponding target selection by GA-TA in the first four (4) cycles for observation.

![Figure 6](image)

**Figure 6** The corresponding target selection by GA-TA in the first four (4) cycles of Table 4

### 6. Conclusion and future work

This paper presents an enhanced frontier strategy of autonomous robotic exploration with GA-based global search target assignment approach. Simulation results have shown that implementing the global search target-assignment of the frontier strategy can increase exploration performance in terms of robot’s travelling path cost. Based on the experiments, exploration performance increases about 31% to 50% from the canonical frontier strategy that uses the local search target-assignment paradigm. For future works, the proposed approach can be tested on real robots and various geometrical environments to investigate the generality of the proposed approach. Furthermore, the theoretical calculation of computational resources required can be studied to optimise the appropriate parameter setting of the deployed GA.

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### Conflicts of interest

The authors have no conflicts of interest to declare.

### References


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