Research Article

International Journal of Advanced Technology and Engineering Exploration, Vol 8(75)
ISSN (Print): 2394-5443 ISSN (Online): 2394-7454
http://dx.doi.org/10.19101/IJATEE.2020.762170

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

Mohd Faisal Ibrahim*, Aqilah Baseri Huddin, Mohd Hairi Mohd Zaman, Aini Hussain and Siti Nurhafizah Anual
Department of Electrical, Electronic and Systems Engineering, Universiti Kebangsaan Malaysia, Malaysia

Received: 27-September-2020; Revised: 18-February-2021; Accepted: 19-February-2021

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 requires for the robot 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

*Author for correspondence
This work was supported in part by the Ministry of Higher Education Malaysia and Universiti Kebangsaan Malaysia under grants FRGS/1/2017/TK04/UKM/02/10 and GGPM-2016-003.

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 considered 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.

3.1System 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.

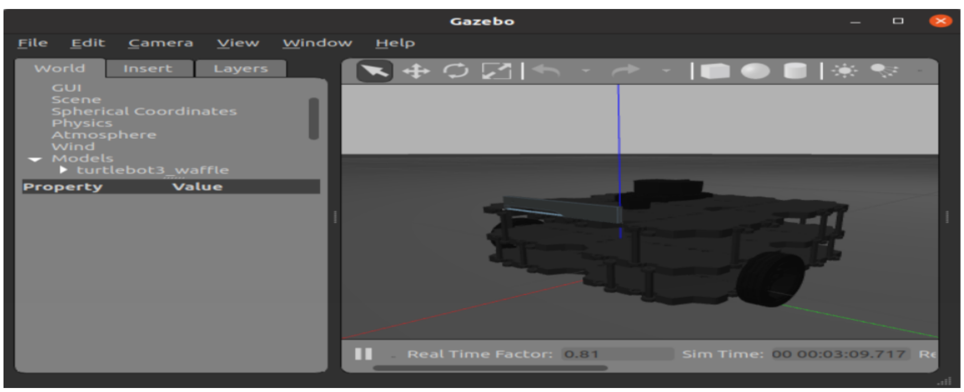


Figure 1 Gazebo simulator interface with simulated Turtlebot 3 waffle

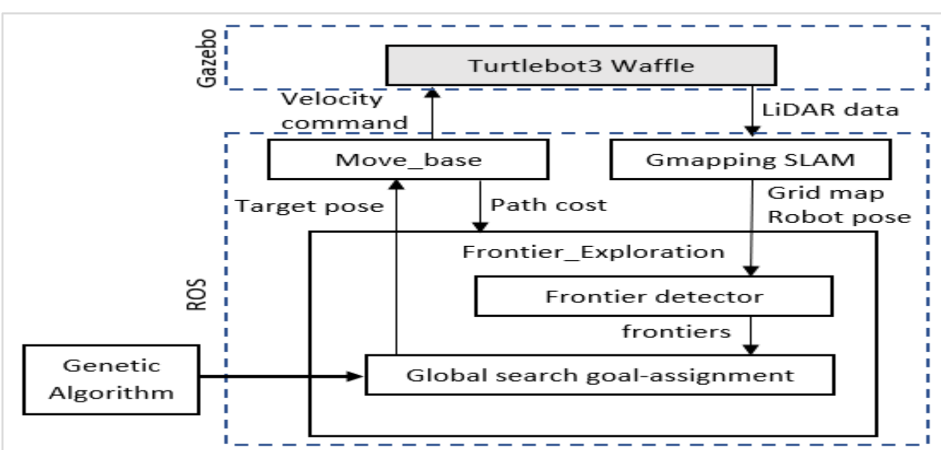


Figure 2 Overall dataflow on the autonomous robotic exploration system

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).

$$E = \frac{V(V-1)}{2} \qquad (1)$$

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

$$S = \frac{(V-1)!}{2} \qquad (2)$$

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).

$$f(c) = d_{rt_1} + \sum_{i=1}^{T-1} d_{t_i t_{i+1}} \qquad (3)$$

where d_{rt_1} is the path length between robot and frontier t_1, $d_{t_i t_{i+1}}$ 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.

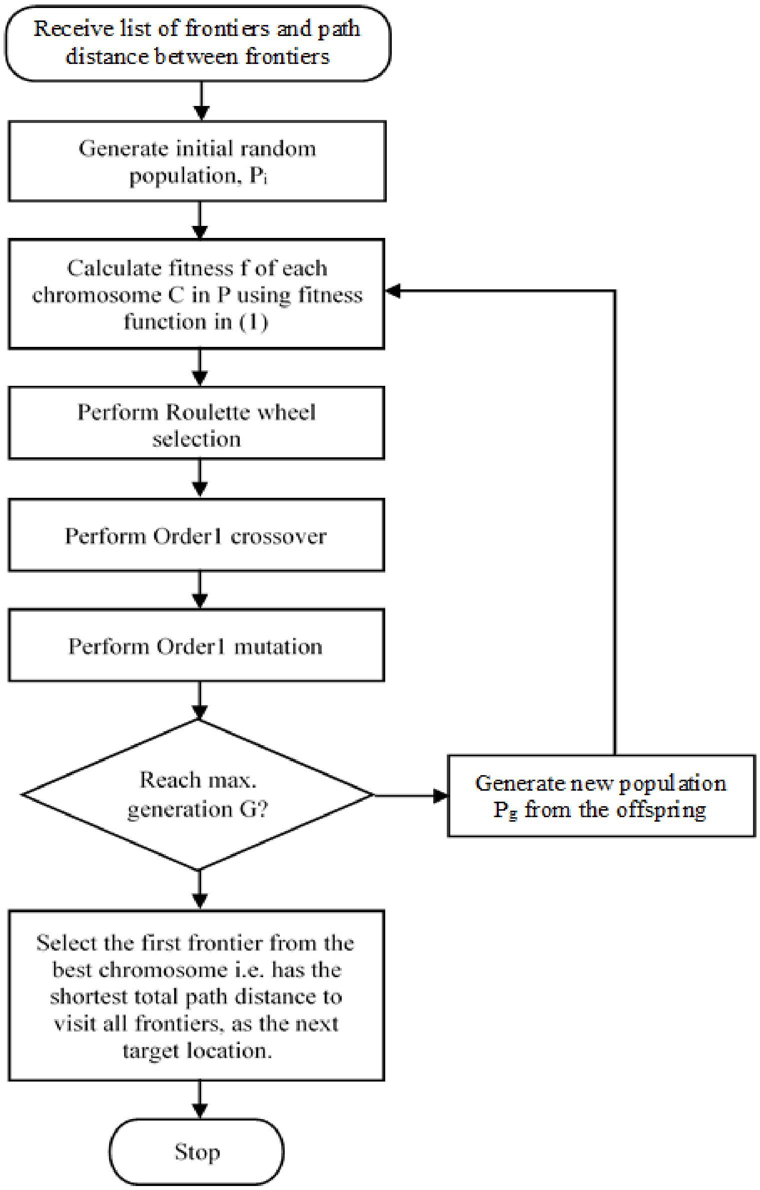
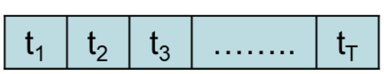


Figure 3 The flowchart of the processes implemented by the proposed GA-based global search target-assignment



t_i : frontier i, where $1 \ll i \ll T$
T : total number of frontiers

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 1.8HGz 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.

Table 1 Simulated bounded areas constructed in Gazebo simulator

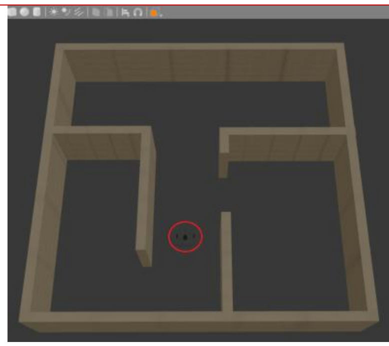
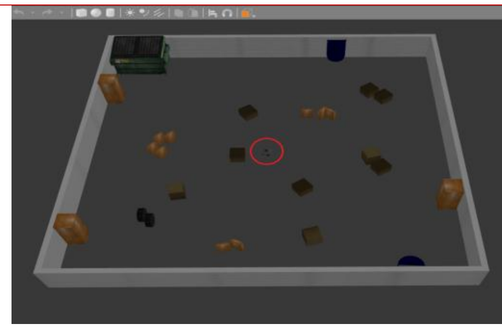
Area name	**Indoor area**	**Construction area**
Bounded area		
Initial robot position	Fixed at location O	Fixed at location O
Area size	5m x 5m	10m x 10m
Geometrical type	Indoor area with a corridor and three empty rooms separated by walls.	Construction site with scattered obstacles like garbage bin, piles and other construction materials.

Table 2 The configuration of GA-based target-assignment

Parameter	**Value**
Frequency of being called, F	1 Hz
No. of generation, G	100 generations
Population size, P	10 chromosomes
Probability of crossover	1.0
Probability of mutation	0.1
Termination criteria	Fixed number of generations

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.

Figure 5 presents the boxplot of exploration performance for GA-TA and CAN-TA. The performance is compared in terms of the total path cost taking by both target-assignment approaches. The path cost is calculated based on the gradient descent of the navigational potential field algorithm represents efforts taking by the robot to move to a location on a grid map. The lower the path cost the better the exploration performance. From the boxplot, the mean and the standard deviation of the exploration performance were calculated as in *Table 3*.

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.

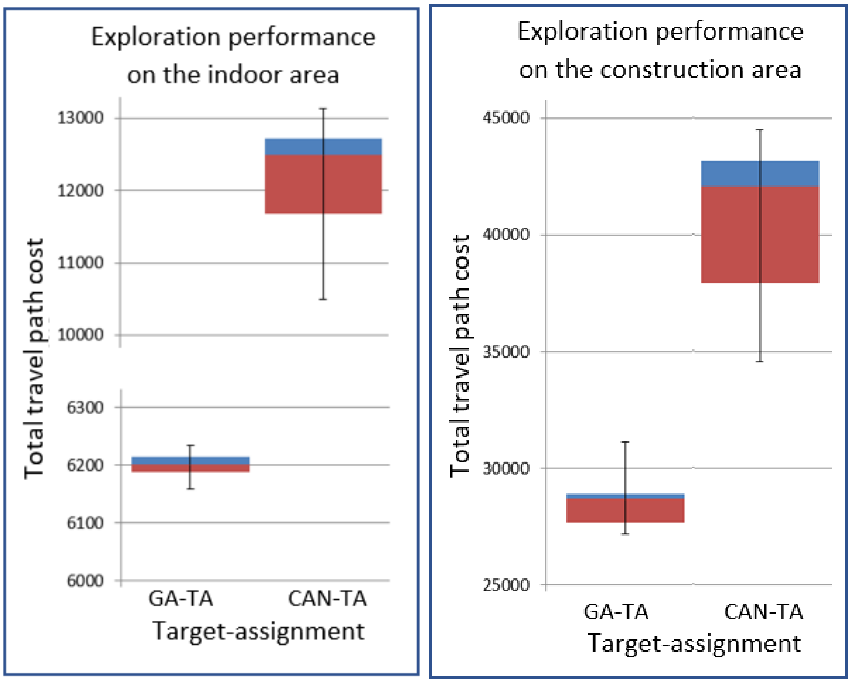


Figure 5 Boxplots of exploration performance for GA-TA and CAN-TA target-assignments on the indoor and construction areas, respectively

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

Area	**Indoor**		**Construction**	
Parameter	**GA-TA**	**CAN-TA**	**GA-TA**	**CAN-TA**
Median	6201.0	12,493.0	28,711.0	42,080.0
Standard deviation	25.1	933.4	1,375.2	3,671.8

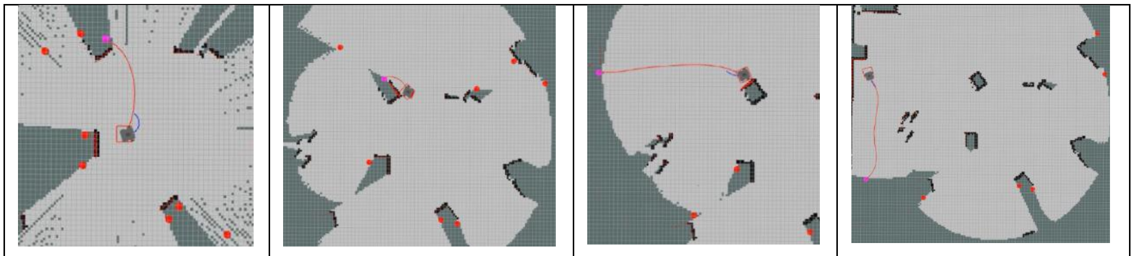
5.Discussion

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

Cycle, T	1	2	3	4	5	6	7	8	9	10	11	12	13
GA-TA	X	✓	X	✓	X	X	✓	✓	✓	-	-	-	-
CAN-TA	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
	✓	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.



T=1	T=2	T=3	T=4

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.

Acknowledgment

This research is funded by Ministry of Higher Education Malaysia and Universiti Kebangsaan Malaysia under grants FRGS/1/2017/TK04/UKM/02/10 and GGPM-2016-003.

Conflicts of interest

The authors have no conflicts of interest to declare.

References

[1] Amanatiadis AA, Chatzichristofis SA, Charalampous K, Doitsidis L, Kosmatopoulos EB, Tsalides P, et al. A multi-objective exploration strategy for mobile robots under operational constraints. IEEE Access. 2013; 1:691-702.

[2] Yamauchi B. Decentralized coordination for multirobot exploration. Robotics and Autonomous Systems. 1999; 29(2-3):111-8.

[3] Doroodgar B, Liu Y, Nejat G. A learning-based semi-autonomous controller for robotic exploration of unknown disaster scenes while searching for victims. IEEE Transactions on Cybernetics. 2014; 44(12):2719-32.

[4] Sirasanagandla S, Pachipulusu M, Jayaraman R. Development of surveillance robot to monitor the work performance in hazardous area. In international conference on communication and signal processing 2020 (pp. 1559-62). IEEE.

[5] Dang T, Mascarich F, Khattak S, Papachristos C, Alexis K. Graph-based path planning for autonomous robotic exploration in subterranean environments. In IEEE/RSJ international conference on intelligent robots and systems (IROS) 2019 (pp. 3105-12). IEEE.

[6] Vidal E, Hernández JD, Palomeras N, Carreras M. Online robotic exploration for autonomous underwater vehicles in unstructured environments. In OCEANS-MTS/IEEE Kobe Techno-Oceans (OTO) 2018 (pp. 1-4). IEEE.

[7] Fang B, Ding J, Wang Z. Autonomous robotic exploration based on frontier point optimization and multistep path planning. IEEE Access. 2019; 7:46104-13.

[8] Gomez C, Hernandez AC, Barber R. Topological frontier-based exploration and map-building using semantic information. Sensors. 2019; 19(20):1-20.

[9] Ryu H. Graph search-based exploration method using a frontier-graph structure for mobile robots. Sensors. 2020; 20(21):1-23.

[10] Gao W, Booker M, Wang J. Self-exploration in complex unknown environments using hybrid map representation. arXiv preprint arXiv:2004.08535. 2020.

[11] Faria M, Maza I, Viguria A. Applying frontier cells based exploration and lazy theta* path planning over single grid-based world representation for autonomous inspection of large 3D structures with an UAS. Journal of Intelligent & Robotic Systems. 2019; 93(1):113-33.
[12] Lu L, Redondo C, Campoy P. Optimal frontier-based autonomous exploration in unconstructed environment using RGB-D sensor. Sensors. 2020; 20(22):1-16.
[13] Shankar A, Shivakumar M, Prakash KR. A survey on frontier based strategies for multi robot exploration. International Research Journal of Engineering and Technology (IRJET). 2020; 7:532-8.

Mohd Faisal Ibrahim received B.Eng. and M.Eng. degrees in electrical and electronic engineering from Universiti Teknologi Malaysia, in 2002 and 2006, respectively, and the Ph.D. degree from the University of Adelaide in 2015. Currently, he is a senior lecturer in the Department of Electrical, Electronic and Systems Engineering, Universiti Kebangsaan Malaysia (UKM). His research interests are in Intelligence Systems, Evolutionary Robotics and Optimisation. Since joining UKM since 2007, he has conducted various research works, led few research grant projects and appointed as an industrial consultant.
Email: faisal.ibrahim@ukm.edu.my

Aqilah Baseri Huddin received her BEng (First Class Hons) in Electrical and Electronics Engineering and her PhD in Electrical and Electronics Engineering from the University of Adelaide, Australia in 2007 and 2015, respectively. She is currently a senior lecturer in the Department of Electrical, Electronics and System Engineering in Universiti Kebangsaan Malaysia, UKM. Her research interests are mainly in the field of Image Processing and Artificial Intelligence.
Email: aqilah@ukm.edu.my

Mohd Hairi Mohd Zaman received the B.Eng. degree in Electrical and Electronic Engineering from Universiti Teknologi Malaysia in 2002, and, M.Sc. and Ph.D. degrees in Electrical, Electronic and Systems Engineering from Universiti Kebangsaan Malaysia, in 2012 and 2019, respectively. He is currently a senior lecturer in the Department of Electrical, Electronic and Systems Engineering, UKM. His research interests are in Fault Diagnosis, Artificial Intelligence and Robotics.
Email: hairizaman@ukm.edu.my

Aini Hussain received the B.Sc. degree in electrical engineering from Louisiana State University, USA, the M.Sc. degree in systems and control from the University of Manchester Institute of Science and Technology (UMIST), U.K., and the Ph.D. degree in electrical and electronics engineering from Universiti Kebangsaan Malaysia (UKM), Bangi, Malaysia. She is currently a Professor with the Department of Electrical, Electronic and Systems Engineering, Faculty of Engineering and Built Environment, UKM. Her research interests include AI, intelligent systems, machine learning, and signal and image processing. In the big data era, she is also looking into research involving Predictive Analytics, Cloud Computing, Iot Applications, and so on.
Email: draini@ukm.edu.my

Siti Nurhafizah Anual received the B.Eng and M.Eng. degrees in electrical and electronic engineering from Universiti Tun Hussein Onn Malaysia in 2012 and 2014, respectively. She is currently in her final year of the doctoral study at Universiti Kebangsaan Malaysia. Her research interests are in Intelligence Systems, Evolutionary Robotics and Optimisation.
Email: P93213@siswa.ukm.edu.my