Immune System Algorithms to Environmental Exploration of Robot Navigation and Mapping

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Abstract. In real-world applications such as rescue robots, service robots, mobile mining robots, and mine searching robots, an autonomous mobile robot needs to reach multiple targets with the shortest path. This paper proposes an Immune System algorithm (ISA) for real-time map building and path planning for multi-target applications. Once a global route is planned by the ISA, a foraging-enabled trail is created to guide the robot to the multiple targets. A histogram-based local navigation algorithm is used to navigate the robot along a collision-free global route. The proposed ISA models aim to generate a path while a mobile robot explores through terrain with map building in unknown environments. In this paper, we explore the ISA algorithm with simulation studies to demonstrate the capability of the proposed ISA in achieving a global route with minimized overall distance. Simulation studies demonstrate that the real-time concurrent mapping and multi-target navigation of an autonomous robot is successfully performed under unknown environments.

Keywords: Immune system algorithm · ISA · Multi-target navigation · Autonomous navigation · Path planning

1 Introduction

Autonomous robots are robots that perform tasks without human interference for any corrective measures. Autonomous robots accomplish tasks by using their sensors to gather information about their surroundings. There are many applications for autonomous robots in the real world; these include but not limited to service robots, agricultural robots, mining robots, mine searching robots, and rescue robots. In all the above applications, the fundamental requirement for the autonomous operation of these robots includes path planning and mapping. Path planning and mapping of autonomous robots is a crucial issue that needs addressing before developing a completely autonomous exploring robot.

There has been considerable research in this area due to its real-world applications. Multi-target motion planning is very crucial for an autonomous robot. The multi-target path planning seeks a collision-free route to visit a sequence of targets with the minimized total distance under unknown environments. Let us consider a case in Fig. 1. There are nine points that must be visited by a robot. Let us consider Spot 1 as the starting point and Spot 9 as its final destination. There are multiple paths that could be traversed to reach Spot 9 but only a few passes through Spot 2–8 also some of the spots are longer than the others. The first stage would be to determine the best order to reach Spot 9 with Spots 2–8 in its path. The main optimization criteria are the length of the path and the cost of the travel. The second stage is focused on path planning; this stage is to ensure collision-free traversal of the global route based on the map information. Then, the robot moves to the next waypoint/target according to the global path. It may encounter some new obstacles, which is an unexpected obstacle on the map. The algorithm replans the necessary changes to avoid the obstacles and achieve the target based on the input sensor data. In this stage, there are multiple concurrent sub-steps for robot motion planning and map building. Robot motion can be controlled with a servo motor with a motion controller which obtains its input from the path planner. Also, feedback from the sensor array, which may be a combination of LIDAR, RADAR, SONAR, Optical Camera would be useful in navigation, obstacle detection, and map building.
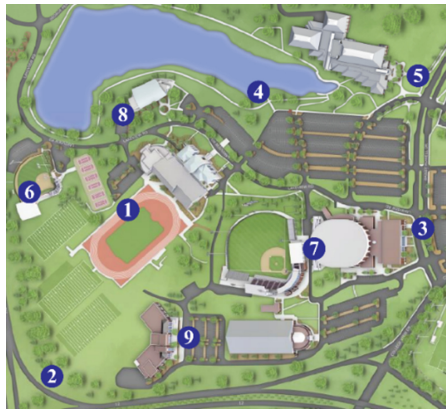
Fig. 1. Aerial cartoon of a multi-target navigation.

Many approaches have been proposed, which achieve reliable autonomous robot motion planning [1–7, 14, 15]. Gu *et al.* [1] proposed a motion planning model based on the elastic band method where tunability and stability are focused on automated passenger vehicle navigation. Raja *et al.* [2] proposed an algorithm-based Genetic Algorithm (GA) by introducing a potential field method for motion planning for a 6-wheel rover. Davies *et al.* [3] developed a GA path planner to guide an autonomous robot to reach specified multiple targets, free of collision. The main downside for this algorithm is given that artificial waypoints may need to be added to avoid deadlock scenarios due to local minima, which is computationally expensive. Luo and Yang [4, 5] developed a bio-inspired neural network model that performs both mapping and path planning.

Luo *et al.* [6] proposed a biologically inspired neural network approach to real-time collision-free motion planning of multiple mobile robots in unknown environments. However, multi-target navigation studies have not been performed much for intelligent robot systems. Faigl and Macak [7] developed a self-organizing map-based method with an artificial potential field navigation function to generate an optimal path of a mobile robot to visit multiple targets. Gopalakrishnan and Ramakrishnan [11] implemented a multi-target navigation model of an autonomous robot modeled as a point robot without map building capability. Santos *et al.* [9] implemented a Max-Min Ant system algorithm based on how ants navigate the terrain with higher efficiency in comparison with the GA and A* algorithm but it lacks map building capabilities. Serres *et al.* [10] proposed optic flow-based motion planning which imitates navigation of insects in the presence of obstacles. However, this effort lacks multi-target and map building capabilities.

In this paper, a real-time concurrent multi-target motion planning and map building approach of an autonomous robot in completely unknown environments is proposed. The global route is generated by Immune System Algorithm (ISA) from the provided multiple targets/waypoints. The sensory information obtained by onboard sensors mounted on the robot is utilized for its real-time concurrent multi-target navigation and map building in unknown sceneries. The rest of this paper is organized as follows. The ISA global path planner is proposed in Sect. 2, which first obtains the multi-target access sequence from ISA, and then obtains the collision-free trajectory with obstacle avoidance from ISA. In Sect. 3, the real-time concurrent map building and collision-free multi-target navigation of the autonomous robot are introduced. Afterward, the simulation and comparison studies of multi-target navigation and map building of the autonomous robot in various unknown environments are described in Sect. 4. Finally, several important properties of the proposed approach are concluded in Sect. 5.

2   Immune System Algorithm Based Multi-target Navigation

Immune System Algorithm (ISA) is a swarm-based bio-inspired algorithm based on the human immune system. A human body is often subjected to harm due to various pathogens such as bacteria or viruses. Thanks to the highly developed and effective immune system, most of these pathogens are targeted and destroyed, keeping our bodies healthy. The different stages taken by our immune system to protect our bodies can be described as follows. When pathogens attack our bodies, the antigen proteins on the surface of the pathogen provoke an immune system response. If this is the first attack by this pathogen the immune system mass produces antibodies tailored to detect this pathogen and destroys them this is known as a primary response. During the initial response, the produced antibody is propagated by cloning during which somatic hyper-mutation occurs. Thus, produced antibody may have a better affinity to the pathogen (optimization) and hence better detect the pathogen differentiating from other cells and destroying it with T-cells. As the process of propagation and mutation continues some B cells differentiate memory B-cells with a high affinity toward the antigen of the attacking pathogen. The memory B-cells considerably im-prove immune system response time on future pathogen infection as it is optimized to detect, seek, and destroy this particular pathogen. The immune system inspired ISA follows the same iterative approach in opti-mizing the objective function because of this ISA can easily be used to solve different

types of optimization problems often encountered in engineering, such as multi-target navigation problems.

2.1 Multi-target Access Order

Algorithm 1: Calculate distance between targets

N = Number of targets

$W = W_{i=1}^N, D = D_{i,j=1}^N$

$D \leftarrow \text{Distance}(W,N)$

Require $N > 1$

Initialize: $i = 1; j = 1$

while $(i \leq N)$ **do**

    while $(j \leq N)$ **do**

        $\text{Distance}, D_{ij} = \sqrt{(X_i - X_j)^2 + ((Y_i - Y_j))^2}$

        $j = j + 1$

    end

end

Return D

Fig. 2. Objective of the multi-target access order. Given the coordinates of the target point and optimize the access sequence according to the distance.

In the practical applications of multi-target navigation and mapping, multiple targets are provided by GPS coordinates. These targets are a series of waypoints and the relative cost of traveling between each target. The target is to search for the route of all waypoints that pass all waypoints at once and find the shortest overall journey. For example, in a rescue robot application, the robots start from a designated waypoint, visit each other, and then end at the initial waypoint. The traveling salesman problem (TSP) is an optimization problem that minimizes the travel distance in a limited number of cities while the travel cost between each city is known. The classic TSP is used to deal with the problem of multi-target access, in which a series of targets are visited, thereby minimizing the total planned length of the route. The goal of this TSP with respect to multi-objective navigation is to search for an ordered set of all waypoints so that autonomous robots can access it, thereby minimizing costs. For TSP, each waypoint and the distance or cost between them must be listed. Therefore, the target is a waypoint, where the GPS coordinates of the targets are in latitude and longitude.

The multi-target access order problem has practical applications in certain areas, such as the transportation planning problem that needs to be delivered and the problem of minimizing fuel costs and time. This specific problem is very similar to our multi-target path planning problem for autonomous robotic applications, especially for search and rescue robots. The pseudocode for the implemented ISA is explained in Algorithm 1, 2, and 3, as shown in Fig. 2 and Fig. 3. The objective of the algorithm is to minimize total path length P when n number of Cartesian coordinates (X_n, Y_n) of waypoints are given.

Algorithm 2: Calculate the minimum path

N = Number of targets

NP = Number of paths

$P = P_{i=1,j=1}^{N,NP}, D = D_{i,j=1}^{N}$

$(minpath, minlen) \leftarrow Pathlength(P, D, NP, N)$

Require $N > 1$ and $NP > 1$

Initialize: $i = 1; j = 1$

while $(j \leq NP)$ **do**

    while $(i \leq N)$ **do**

        $len_j = len_j + D(W(P_{i,j}), W(P_{i+1,j}))$

        $i = i + 1$

    end

    if $len_j \leq minlen$ **then**

        $minlen = len_j$

        $minpathindex = j$

    end

end

while $k \leq N$ **do**

    $minpath_k = P_{k,minpathindex}$

    $k = k + 1$

end

Return minipath, minilen

Algorithm 3: Immune System Algorithm for multi-target access order

NP = Number of immunized individuals

NCL = Number of clone

N = Number of targets

G = Number of generations

$W = W_{i=1}^{N}$ and $W_i = (X_i, Y_i)$

$(minpath, minlen) \leftarrow ISA(W, N, NP, NCL, G)$

Initialize: $np = 1; ncl = 1; g = 1$

D=Distance(W, N)

while $n \leq N$ **do**

    $P_n = n$

end

while $(g \leq G)$ **do**

    while $(np \leq \frac{NP}{2})$ **do**

        P=randompermutation (P)

        while $(ncl \leq NCL)$ **do**

            $P_{(1+N*random(N)),ncl} \leftrightarrow P_{(1+N*random(N)),ncl}$

        end

    end

    minpath2,minlen2=Pathlength(P,D,$\frac{NP}{2}$,N)

    if $minlen2 \leq minlen$ **then**

        minlen=minlen2

   minpath=minpath2

    end

end

(a)   (b)

Fig. 3. Pseudo code of the (a) calculate the minimum path as fitness function (b) ISA for multi-target access order.

2.2 ISA for Path Planning

To plan the global trajectory from one waypoint to another, obstacles in the map need to be considered. We need to find a collision-free trajectory with obstacle avoidance while seeking the shortest distance to reduce energy consumption and improve efficiency. In this paper, we take the local search procedure into account for finding the shortest path in the map with ISA. The proposed method integrates the local search procedure to search and find the short and reasonable trajectory with the ISA.

The first stage of seeking the optimal path is to find a feasible solution since the unfeasible ones are not realistic. In order to improve the performance of finding the optimal path through the ISA algorithm, the path is gradually constructed from the generated random points (all in free space, outside the obstacle). On the basis of Dijkstra's algorithm to find the shortest path in a graph, the path is built from the start point S and the next path point is chosen from the N randomly generated points. The same procedure is taken place for the chosen points until the final target is reached and the edges are their connections in the map. Each point is directly connected to all other points. When its connection passes an obstacle and becomes an unfeasible solution, the distance between its nodes is set to infinite to ensure that only a feasible solution can be found as the shortest path. The benefit of the local search procedure is to filter out unfeasible connections

with infinite length among the nodes. The point-to-point navigation result is shown in Fig. 4(a) and the proposed algorithm for path planning is given in Algorithm 4 as shown in Fig. 4(b).
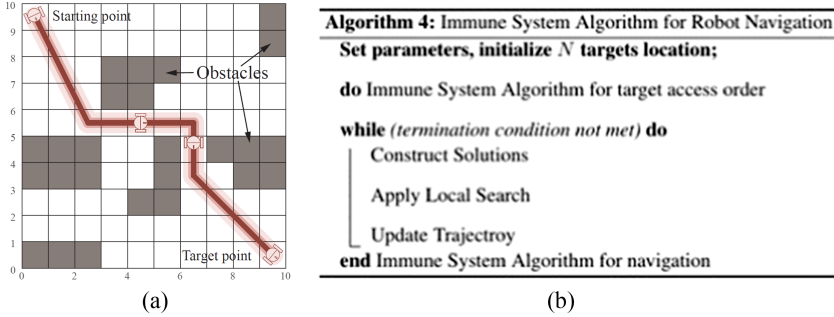
Fig. 4. (a) Illustration of ISA point-to-point navigation. (b) ISA algorithm for path planning.

3   Real-Time Concurrent Mapping and Multi-target Navigation

Concurrent map construction and navigation are the keys to successful robot navigation in unknown environments. In order to achieve a high degree of autonomy and robustness in robot navigation, map construction is a basic task, which enables autonomous robots to make decisions while avoiding obstacles. Therefore, in terms of robot navigation, when a mobile robot is walking in an unknown environment, a two-dimensional map will be constructed, which is filled with cells of equal size (marked as "occupied" or "free").

In our navigation system, it is divided into two layers, one layer is the ISA global path planner described in Sect. 2, and the other layer is the local navigator based on the histogram. Efficiency and flexibility make ISA adapt to the motion planning and map building of autonomous robots. Local navigation aims to create speed commands for autonomous mobile robots to move towards the target. A series of markers are included in the motion plan, which decomposes the global route generated by the ISA global planner into a series of fragments, making the model particularly effective for working areas that are densely filled with obstacles. Ulrich and Borenstein [12] developed a Vector Field Histogram (VFH) based robot reactive navigation method based on the histogram. In this paper, we use VFH as a local reactive navigator based on LIDAR for obstacle avoidance.

Concurrent map building and navigation are the essences of successful multi-target navigation under unknown environments. Map building is a fundamental task in order to achieve high levels of autonomy and robustness in multi-target navigation that makes it possible for autonomous robots to make decisions in positioning with obstacle avoidance. It is especially beneficial for autonomous robots to implement robust multi-target navigation in unknown terrains, given the fact that it facilitates the utilization of path planning algorithms to determine the optimal trajectory among waypoints as multiple

targets. A precise estimate of the robot pose is demanded by map building so that accurate registration of the local map on the global map is capable of being carried out. The polar histogram of obstacles in the workspace with VFH is shown in Fig. 5(a). In our navigation system, the histogram-based local navigator senses obstacles through a vehicle-mounted 270º LIDAR with a radius of 2.5.
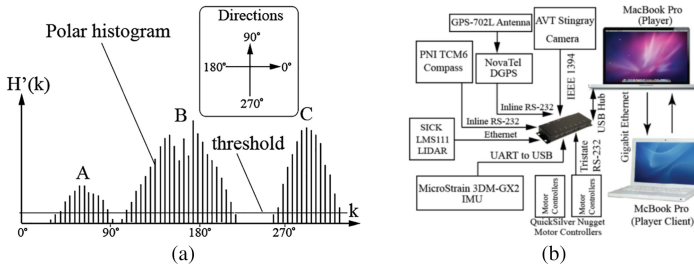
Fig. 5. (a) Polar histogram of obstacles in workspace with VFH method (redrawn from [12]). (b) The sensor configuration for multi-target navigation and mapping.

4 Simulation and Comparison Studies

In this section, simulations and comparison studies are used to verify the effectiveness and efficiency of the proposed ISA multi-target autonomous robot navigation and mapping. A 270º SICK LMS111 LIDAR is configured for the obstacle detection illustrated in Fig. 5(b). This LIDAR unit obtains data over a 270° field-of-view with 0.25° resolution, a maximum range of 20 m, and a 25 Hz scanning rate. The sensor configuration of the robot for multi-target navigation and mapping is illustrated in Fig. 5(b). The ISA based multi-target global path planning and VFH local navigator are simulated and tested in multi-target navigation with obstacle avoidance.

4.1 Comparison of the Proposed ISA Model for Path Planning with ACO

Table 1. Comparison of path length (Fig. 15 case 4 in [13])

| Models	Minimum length	Mean length	Improvement from proposed model
Proposed ISA model	**35.47**	**36.17**	—
ACO [13]	38.80	40.97	11.71%
Improved ACO [13]	38.14	40.16	9.93%

The proposed ISA path planning method, as stated in Sect. 2.2, is first applied to a test scenario with populated obstacles in comparison of the test scenario identical as Fig. 15

case 4 of [13] shown in Fig. 6 in this context. The trajectories of robot motion planning are illustrated about the proposed ISA model, ACO and improved ACO, respectively, in Fig. 6. The workspace has a size of 35 × 30, which is topologically organized as a grid-based map. The starting point is (5, 3) and the target point is (23, 29). In Table 1, comparative data may be found that our proposed model is much better than the models of ACO and improved ACO, respectively, in the minimum trajectory length, and mean trajectory length. The comparison results show that the trajectory length by our proposed model is 8.58% shorter than ACO, 7.00% shorter than improved ACO, respectively. The mean trajectory length by our proposed model is 11.71% shorter than ACO, 9.93% shorter than improved ACO, respectively. The trajectory planned by our proposed ISA model is shown in Fig. 6(c).
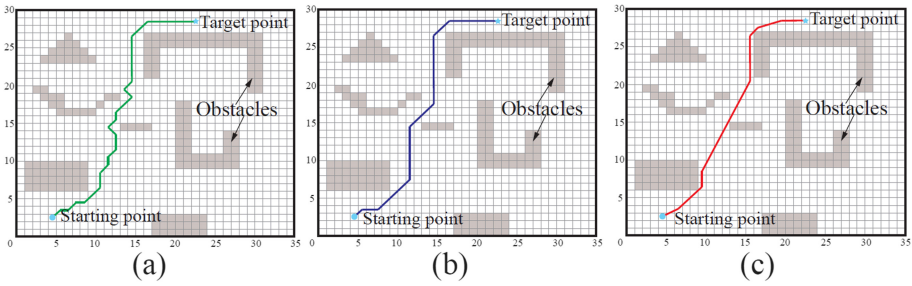
Fig. 6. Illustration of robot navigation with various models. (a) ACO model [13]; (b) improved ACO model [13]; (c) the proposed model.

## 4.2 Simulation of Proposed ISA Model for Multi-target Path Planning
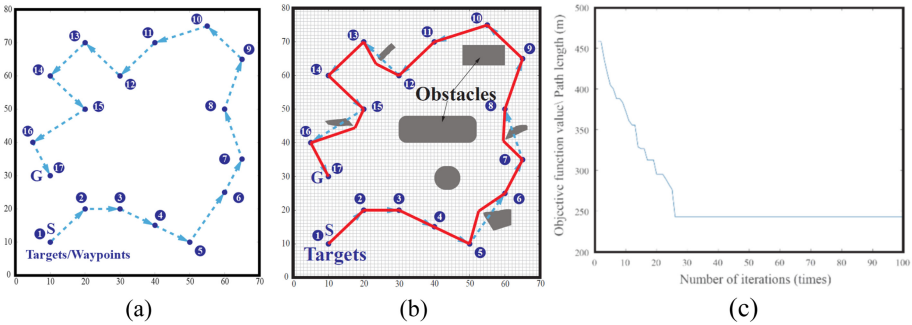
Fig. 7. Illustration of multi-target path determined by proposed ISA mode. (a) ISA algorithm for TSP applied in a 17-target workspace; (b) final trajectory of the proposed ISA model (c) the fitness value over iterations.

The proposed ISA associated with VFH local navigation is applied to the multi-target navigation application as shown in Fig. 7 and Fig. 8. Luo *et al.* [8] proposed a hybrid PSO approaches to resolve multi-target robot motion planning issues. However, their

model has not considered the obstacles in the environment in global path planning which is necessary for autonomous robot navigation systems. The workspace has a size of 70 × 80, which is topologically organized as a grid-based map. There are 17 targets in the workspace and a service mobile robot is needed to reach each target. Initially, the starting point of the robot is at S (10, 10), which is also considered to be the target point 1. After executing this ISA-based TSP algorithm with only the coordinates of the 17 targets, the access order of the targets with the smallest total length of the route is obtained as shown in Fig. 7(a). The fitness value of iteration in terms of the ISA is shown in Fig. 7(c). Then in the light of the whole environment information, such as obstacles, the final *trajectory* planned by the proposed ISA model regarding the multi-target access order is shown in Fig. 7(b).

The robot is able to traverse from the initial point to plan a reasonable collision-free route to reach the final designation. The robot moves based on the planned global trajectory while it constructs the map with 270º LIDAR. The trajectory generated by the robot is shown in Fig. 8(a) whereas the map built is illustrated in Fig. 8(b) at the end of the travel of the robot.
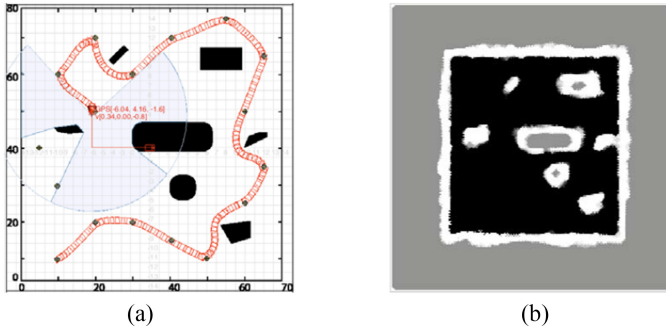

Fig. 8. Illustration of ISA based multi-targets robot navigation and mapping model (a) trajectory generated in the middle stage; (b) map built at the end of stage.

4.3 Comparison of the Proposed ISA Multi-target Path Planning Model with Genetic Algorithm

The proposed model is then applied to a test scenario with populated obstacles in comparison with the test scenario identical as Fig. 2 of [3] shown in Fig. 9(a) in this context. The workspace has a size of 20 × 30, which is topologically organized as a grid-based map. Initially, the starting point is located at S (0, 0). The trajectory planned when using our proposed ISA model is illustrated in Fig. 9(b). The generated trajectory length completed by the robot is listed in Table 2 in comparison with Davies's model [3]. The shorter trajectory is generated by our ISA model illustrated in Fig. 9(b). It is observed that our model outperforms over theirs in terms of the trajectory length.

With VFH-based local navigator, the built map from the initial position S (0, 0) and the final trajectory planned is illustrated in Fig. 9(c), and final map built exactly when
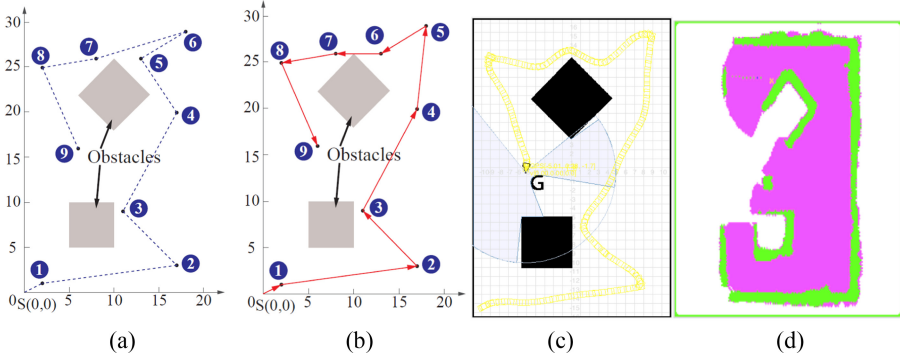
Fig. 9. Comparison studies with Davies's model [3]. (a) planned trajectory by Davies's model (redrawn from [3]); (b) planned trajectory by our ISA model; (c) illustration of robot trajectory generated at the end; (d) illustration of map built at the end.

the robot reaches the final target are illustrated in Fig. 9(d). The green fields indicate detected obstacles, and the pink portion of the image represents explored zones by the 270° LIDAR scans.

Table 2. Comparison of path length (Fig. 2 in [3])

Models	Minimum length	Improvement from proposed model
Proposed ISA model	**74.202**	—
GA [3]	77.798	4.6%

To demonstrate its efficiency in determining the path length. Figure 10 shows a plot of iterations required to reach an ideal solution in comparison with other orders of algorithms like log-linear and exponential algorithms. The ISA is run with a varying number of points and the results show the algorithm performs better than a quadratic algorithm $O(n^2)$ but worse than Log-linear algorithm $O(nlog(n))$ which is much better than the brute force method of solving which is an $O(n!)$ algorithm.
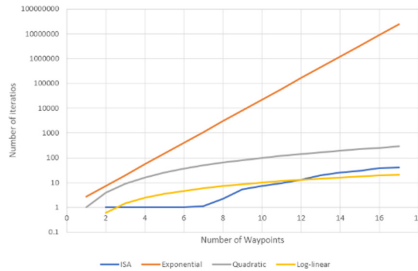
Fig. 10. Approximate estimation of the order of the algorithm with different number of targets.

5 Conclusion

The ISA based path planning algorithm was developed in this paper. ISA is first utilized to solve multi-target access order by solving the traveling salesman problem, then ISA is applied with the map information to obtain a collision-free global path. A LIDAR-based local navigator algorithm has been implemented for local navigation and obstacle avoidance. In addition to the multi-target ISA based navigation, grid-based map representations are imposed for real-time autonomous robot navigation. Simulation and comparison studies have demonstrated the effectiveness of the proposed real-time multi-target ISA approach of an autonomous mobile robot.

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