A Novel Knowledge-Based Genetic Algorithm for Robot Path Planning in Complex Environments

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Abstract—In this paper, a novel knowledge-based genetic algorithm for path planning of a mobile robot in unstructured complex environments is proposed, where five problem-specific operators are developed for efficient robot path planning. The proposed genetic algorithm incorporates the domain knowledge of robot path planning into its specialized operators, some of which also combine a local search technique. A unique and simple representation of the robot path is proposed and a simple but effective path evaluation method is developed, where the collisions can be accurately detected and the quality of a robot path is well reflected. The proposed algorithm is capable of finding a near-optimal robot path in both static and dynamic complex environments. The effectiveness and efficiency of the proposed algorithm are demonstrated by simulation studies. The irreplaceable role of the specialized genetic operators in the proposed genetic algorithm for solving the robot path planning problem is demonstrated through a comparison study.

Index Terms—Genetic algorithm, mobile robot, path planning, domain knowledge, problem-specific operator, obstacle avoidance

I. INTRODUCTION

Path planning is a fundamentally important issue in mobile robotics. A mobile robot needs to carry out a series of tasks in order to navigate in an environment. First, the mobile robot needs to sense the environment to obtain knowledge about the target and obstacles and to localize itself in the environment. Then a path planner is needed to construct a suitable collision-free path for the robot to move from the start location to the target location. Very often it is desirable that the robot path is optimal or near-optimal with respect to time, distance or energy. Distance is a commonly adopted criterion. After a suitable path is available, a path tracking algorithm makes the mobile robot to follow the path and reach the target. Although each task involved in mobile robot navigation has different challenges, when the environment information is already available, path planning becomes the primary task for the mobile robot. This paper assumes that the environment information is completely known in static environments and the new environment information is already updated in dynamic environments. Therefore, it is basically path planning for global navigation. The algorithm deals with path planning problem only, and does not involve localization and path tracking. When the environment information is partially known or only short-range information of the environment can be obtained during robot’s navigation, it is called local navigation. Path planning for local navigation usually cannot be separated from other tasks such as localization and path tracking, and algorithms for navigation instead of just path planning are required. Markov Decision Process (MDP) is widely used for this task [1]–[4]. MDP is mainly used for indoor robot’s navigation, especially for corridor or office environments. MDP-based approaches are able to deal with some uncertainty, which makes it can be used in realistic applications. However, MDP also usually requires the structure of the environment to be known, and it usually deals with environments with simple (rectangular or block) obstacles. Besides, the path planned by MDP approaches are usually not intended to be optimal, but feasible. The path planning in this paper falls out of the category of MDP-based path planning. It emphasises on its ability to plan optimal or near optimal path among complicated obstacles.

Robot Path planning has been an active research area, and many methods have been developed to tackle this problem [5], such as global configuration-space methods [6], [7], potential field methods [8], [9], and neural networks based approaches [10]–[13]. Each method has its own strength over others on certain aspects. Generally, the main difficulties for path planning problem are computational complexity, local optimum, and adaptability. Researchers have always been seeking alternative and more efficient ways to solve the problem.

There is no doubt that path planning can be viewed as an optimization problem (e.g., the shortest distance) under certain constraints (e.g., obstacle avoidance). Since the appearance of genetic algorithms (GAs) around before 1975 [14], GAs have been used for solving various optimization problems successfully, particularly very complex problems where conventional searching approaches would fail. GAs are advanced stochastic search techniques analogous to natural evolution based on the principle of “survival of the fittest” [15], [16]. Potential solutions of a problem are encoded as chromosomes, which form a population. Each individual of the population is evaluated by a fitness function. A selection mechanism based on the fitness is applied to the population and the individuals strive for survival. The fitter ones have more chance to be selected and to reproduce offspring by means of genetic transformations such as crossover and mutation. The process is repeated and the population is evolved generation by generation. After many generations, the population converges to solutions of good quality, and the best individual has a good chance to be the optimal or near-optimal solution. The feature of parallel search and the ability of quickly locating high performance region [15] contribute to the success of GAs.
on many applications. It is not surprising that many researchers have applied GAs to path planning of mobile robots (e.g., [17]–[21]). However, like most early GA applications, most of those methods adopt classical GAs that use fixed-length binary strings and two basic genetic operators (crossover and mutation), while few modifications were made to the algorithms. Sughira et al. [17]–[19] proposed a genetic algorithm for robot path planning with fixed-length binary string chromosomes based on cell representation of the mobile robot environment. A workspace is divided into grids, in which a mobile robot can only move from one cell to the adjacent one. The grids occupied by obstacles are assigned with more weight so that a path intersecting with an obstacle has more cost. At each cell, there are eight possible directions to move. A path is represented by a sequence of moving directions starting from the start point. In a chromosome, a gene is a relative direction, and what it represents can only be interpreted from all the previous genes. Since the number of moving steps to reach the target is uncertain, variable-length chromosome comes very naturally. However, in order to use the fixed-length chromosomes and the basic genetic operators, the robot path is limited to be $x$-monotone or $y$-monotone, which means that the projection of the path on $x$-axis or $y$-axis is non-decreasing. Obviously, this monotone approach puts some restriction on path-planning solutions and makes it unsuitable for complex environments. Another disadvantage of the fixed-length GA approach is its biased encoding. The entire path is represented by a sequence of relative directions and distances. A small change at the beginning of a binary string may dramatically affect the entire path while changes at the end part of the binary string have only minor effects. Moreover, besides the infeasible robot path that intersects with obstacles, this encoding suffers from the problem of other invalid paths: after crossover or mutation the new path may go beyond the environment; and there is no guarantee that a path reaches the target because the generated sequence of directions may not necessarily lead the robot path to reach the target. With too many invalid chromosomes, the performance of the genetic algorithm would be highly affected. The approach of using standard GAs with an inefficient binary encoding and by limiting the path planning seems not very effective. Although Tu and Yang [22] improved this approach by using variable-length chromosomes instead of fixed-length chromosomes, the efficiency of the approach is still not improved and it would take hours to evolve a solution because of the biased and inefficient encoding.

The classical GAs use binary strings and two basic genetic operators. After encoding solutions to a problem, the classical GAs are more like “blind” search. They perform well when no or very little prior knowledge is available. However, GAs do not have to be “blind” search when additional knowledge about the problem is available. The available knowledge could be incorporated into GAs to improve the efficiency of GAs [16], [23]. There are many ways to incorporate additional knowledge into GAs. First, problem-specific knowledge can be used in a more natural way of chromosome representation of potential solutions to a problem instead of binary strings. Second, genetic operators can be modified to use the knowl-
edge in the operation and to fit the problem more. In addition, heuristic methods (e.g., local search) can be combined into the genetic operators. Furthermore, problem-specific knowledge can be used to guide construction of initial population. One or more of the above techniques were experienced by some researchers in various applications, and obtained satisfactory results [24]–[35].

Robot path planning is such a complex problem that the incorporation of domain knowledge into the GAs would significantly improve the efficiency in obtaining the solution. Graph technique is a traditional way of representing the environment where a mobile robot moves around in a workspace. Shibata et al. [36], [37] proposed a genetic algorithm based on MAKLINK graph environment representation [38]. The MAKLINK uses a free-link concept to construct the available free space between obstacles within an environment in terms of free convex areas. The free-link is a line connecting the corners of two polygonal obstacles (the working space boundary is treated as obstacles too), and should not intersect with any of the edges of the obstacles. Free-convex area is formed by free-links and edges of obstacles. The midpoint of each free-link is used as a node in the graph. Each node is numbered and a path is encoded as a sequence of these nodes with variable length. To make sure the path is valid (collision free), adjacent genes must be the numbers that are connected with a free-link in the graph. In this genetic algorithm, orderly based and variable-length chromosomes are used, which is much more natural than fix-length binary chromosomes. This graph-based method needs to form a configuration space before applying the genetic algorithm. The forming of the configuration space could be very time consuming, and it is only suitable for static environments because a slight change of the environment would cause the re-computation of the graph. Besides, a robot path can only visit the fixed nodes pre-determined by the graph, not everywhere in the workspace. Such a robot path can only be sub-optimal and lack flexibility. One advantage of this method is that every possible path is feasible because the graph is generated under the consideration of collision avoidance. This makes the evaluation of a chromosome relatively simple and fast.

More effective path-planning methods can be found in [39] and [40]–[43], which deviate from standard GAs. In [40], a multi-path planning algorithm that can be applied to up to six degrees of freedom was proposed. The algorithm is based on an iterative multi-resolution path representation. A path is represented by a hierarchically ordered set of vectors that define path vertices generated by a modified Gram-Schmidt orthogonalization process. A multiple population steady-state GA with fitness sharing is developed for multiple robot path planning. It uses minimal representation size criterion and cluster analysis to formulate evolutionary speculations. Xiao et al. [40]–[43] proposed an evolutionary path planner for both on-line and off-line planning, which uses a continuous coordinate representation and eight problem-specific genetic operators. This approach uses two different fitness functions to evaluate feasible paths and infeasible paths. Both approaches above use problem-specific chromosome structures and non-standard genetic operators, and show better results.
over the early approaches using standard GAs. However, both approaches are relatively complicated on the problem representation, solution evaluation, or GA structure. In [39], a binary tree for path representation is needed, which is obtained by iteratively using a special method. Also, the multipopulation approach makes its GA structure more complex than a simple GA. Besides, they only deal with static environments, although in [40], a suddenly appeared obstacle is considered.

In this paper, a novel knowledge-based genetic algorithm is proposed. It incorporates problem-specific knowledge into many aspects of the algorithm: encoding, evaluation, and genetic operator. This is different from the above introduced GA approaches to path planning that only incorporate additional knowledge into one element of the GA. It uses a simple yet effective path representation that combines grids and coordinates representations. The environment including obstacles and end-points (starting point and target point) are represented by their natural coordinates in a continuous workspace. Grids are only applied to the nodes of paths to round off the coordinates of the nodes to integers according to a certain resolution. Unlike other grid methods, the grids adopted here do not limit the movement of the robot path, but simplify the chromosome structure and genetic operation. This approach makes it possible to have one number for each gene and to use integer numbers instead of real numbers in chromosomes. The proposed GA has five knowledge-based genetic operators. Problem-specific genetic operators are not only designed with the domain knowledge of robot path planning, but also incorporate small-scale local search that improves efficiency of the operators. A relatively simple but effective evaluation method is applied to both feasible and infeasible solutions to detect collision and reflect solution quality. The collision detection developed here is suitable for arbitrarily shaped obstacles. No commercial or already-made packages are used. The proposed GA is suitable for both static and dynamic environments. In dynamic environments, the robot is capable of avoiding the moving obstacles, while moving toward the target. The effectiveness and efficiency of the proposed knowledge-based GA for mobile robot path planning are demonstrated by simulation and comparison studies.

This paper is organized as follows. The proposed knowledge-based genetic algorithm for path planning for a mobile robot is presented in Section II, including the problem representation, solution evaluation, and five genetic operators specifically designed for robot path planning. Section III presents the simulation results for both static and dynamic environments. The effectiveness of the specially developed genetic operators for robot path planning and the complexity of the proposed algorithm are discussed in Section IV. Finally, some concluding remarks and future work are briefly outlined in Section V.

II. THE PROPOSED KNOWLEDGE BASED GA FOR PATH PLANNING

The proposed genetic algorithm features its simple and unique problem presentation, its effective evaluation method and its knowledge-based genetic operators specifically designed for robot path planning. In this section, the problem presentation is first provided. Then the evaluation method is presented. After that, five problem-specific genetic operators are given. The outline of the proposed knowledge-based GA is finally presented.

A. Problem Representation

Problem representation is a key issue in the applications of GAs. The proposed GA uses a simple yet effective path representation. The mobile robot environment is represented by a 2-dimensional (2D) continuous workspace, where obstacles are represented by the coordinates of their vertices. The boundary of obstacles is formed by their actual boundary plus a minimum safety distance with consideration of the size of the mobile robot, which makes it possible to treat the mobile robot a point in the environment. According to a certain resolution, the grids assigned with integer numbers are applied to the workspace. Fig. 1 gives an example of an environment and path representation. Such a grid representation is different from the one that usually uses grids to discretize the whole environment and to limit the robot movement to one of its eight adjacent cells, and also different from the one that uses relative directions to represent a path [17]. The grids here are not to discretize the whole environment and do not affect obstacle representation. As shown in Fig. 1, the grids have no effects on obstacles, start point and target. The grids here are to form the intermediate nodes of a path. A potential robot path is formed by several line segments connecting the start point $S$, intermediate nodes, and the target point $T$, where $S$ and $T$ are represented by their natural coordinates. An intermediate node is a node falling on one of the grids applied on the workspace and is represented by its associated number. For instance, in Fig. 1, Node 88 is an intermediate node.

In fact the grids here indicate the resolution that only affects the intermediate nodes, and at the same time make it possible to use integers to represent a node instead of real-valued coordinates. Therefore, the chromosome structure and the genetic operations are simplified, and thus speed up the computation. Using grid numbers to represent intermediate nodes is acceptable as long as the resolution is high enough for the environment in question. An example of path encoding is shown in Fig. 2. A feasible robot path is a collision-free path, i.e., no nodes fall on any obstacle, and none of the line segments intersect any obstacles. The length of a chromosome is variable, between the minimum of 2 and the maximum length $N_{\text{max}}$.

B. Evaluation

A robot path generated by the GA can be either a feasible (collision free) path or an infeasible path where at least a line segment intersects an obstacle. The evaluation should be able to distinguish feasible and infeasible paths and tell the difference of path qualities within either category. In addition, it is very important to differentiate the qualities of infeasible paths because the GA would evolve feasible solutions from those infeasible solutions. It requires that those infeasible
solutions with better qualities should be easier to be evolved by the GA. Therefore, the evaluation method should first detect collision. Secondly, if the path collides with obstacles, it should tell how deep it intersects, i.e., how difficult the path can escape from the obstacles so that new solutions can be more-easily evolved from those easier-to-escape solutions. If the path is collision free, its quality is simply indicated by the path length. In this study, the evaluation function is defined as

\[ F_{\text{cont}} = \sum_{i=1}^{N} (d_i + \beta_i C), \]  

where \( N \) is the number of line segments of a path, \( d_i \) is the Euclidean distance of the two nodes forming the line segment, and \( C \) is a constant. Variable \( \beta_i \) is the coefficient denoting the depth of collision, which is defined as

\[ \beta_i = \begin{cases} 0 & \text{if the } i\text{th line segment is feasible} \\ \sum_{j=1}^{M} \alpha_j & \text{if the line segment intersects obstacle(s)} \end{cases}, \]

where \( M \) is the number of obstacles intersecting the line segment, and \( \alpha_j \) is determined by considering how deep a line segment intersects an obstacle \( j \). It is defined as the shortest moving distance for escaping the intersecting obstacle. Fig. 3 explains the definition of \( \alpha_j \). In Fig. 3(a), \( \alpha_1 \) is treated as the shortest distance to move the line out of the obstacle. In Fig. 3(b), \( \gamma \) is the shortest distance, but it is not enough to move the path away from the obstacle, therefore, instead \( \alpha_1 \) is assigned to \( \beta_i \). In Fig. 3(c), the obstacle is connected to the wall and is treated as a dead-end. The line can only escape from the other side of the obstacle. Thus \( \beta_i \) is assigned as \( \alpha_1 \).

Fig. 3(d) shows the situation that the line segment intersects two obstacles, it is considered to be more difficult for the path to move away from both, so the sum of \( \alpha_1 \) and \( \alpha_2 \) is used for \( \beta_1 \).

Accurate collision detection plays an essential role in the evaluation. Collision detection itself is a hard topic that interests many researchers. Here an effective algorithm is developed to detect collision between a straight line and arbitrarily shaped obstacles in a 2D environment. The obstacle can be rectangular, convex or concave. The method for checking if a line intersects a convex obstacle is simple and was described by Pavlidis [46]. For an arbitrarily shaped obstacle, collision detection is much more difficult. Some algorithms and packages are available, such as [47]. Considering the specific requirements needed in the proposed GA on collision detection between a straight line segment and an obstacle as well as on quality assessment, we developed an algorithm for both collision detection and quality evaluation. An arbitrarily shaped obstacle is treated as a group of convex obstacles connected to each other. The number of convex obstacles and information regarding connection between them are obtained. Besides, a Min-Max box of the Group (MMG) is calculated indicating its minimal and maximal coordinates \( x \) and \( y \) of the group. Similarly, a Min-Max box of Obstacle (MBO) is also obtained for each convex obstacle in the group. If a line does not intersect any MMG, then it is collision free. Otherwise, check each MMO of the intersected group. The line intersects the group if and only if it collides at least one convex obstacle of the group. Meanwhile, the depth of intersection is calculated with the consideration of related vertices in the group and connection information. The use of min-max box decreases the computation time.

The proposed evaluation method gives a penalty to infeasible paths, but still keeps them in the population pool because they might become good feasible solutions after certain genetic transformations. Importantly, this evaluation may allow some overlap between fitnesses of feasible and infeasible solutions by adjusting \( C \). It would be beneficial to give more chance to some good infeasible solutions that would be easily to be evolved to good solutions. During the evaluation, some
information obtained by the evaluation needs to be recorded so that later it can be used by some specialized genetic operators as heuristic knowledge without re-calculation in order to save computation time. The information includes feasibility (feasible or infeasible), number of infeasible line segments, and which obstacles intersected by which line segments of a path.

C. Genetic Operators

Those two commonly-used basic genetic operators, crossover and mutation, are not applicable for the robot path-planning problem here. They have to be tailored to suit for the problem and the adopted problem representation. In addition, to make the genetic algorithm more effective, three more specialized operators are designed to make use of available problem-specific knowledge, including knowledge of the environment (e.g., numbers and positions of obstacles) and the path (e.g., feasibility and quality of a path). Some of the operators combine a small-scale local search technique. These five operators are illustrated in Fig. 4.

**Crossover** is the operator that randomly choose a node from Parent 1 and the other node from Parent 2. Exchange the part after these two nodes. Check these two offspring, and delete the part between two same nodes if it happens. The traditional 1-point or 2-point crossover cannot be used here because the length of a chromosome is variable. The choice of different crossover sites in different parents can increase the variability of chromosome length, which benefits exploration of the solution space.

**Mutation** is to randomly choose a node and replace it with a node that is not included in the path. Mutation is served as a key role to diversify the solution population. Therefore, it is not necessary that a solution is better after it is mutated.

**Repair** is to repair an infeasible line segment by inserting a suitable node between the two nodes of the segment. To locate the best node available, a local search is applied in the neighboring grids of the intersected obstacle.

**Deletion** is applicable for both feasible and infeasible path. Randomly choose one node, check its two adjacent nodes and connected segments, if the deletion of the chosen node is beneficial (turn the infeasible to the feasible, or reduce the cost), delete the node.

**Improvement** is designed for feasible solutions. Randomly chose one node, do a local search in the neighboring grids of the node, move to a better location. This operator is used for fine tuning of a feasible solution.

These operators are necessary to evolve feasible and good quality solutions. The firing of these operators depends on two criteria: probability and heuristic knowledge (e.g., if feasible then improvement). In an environment with many obstacles, the portion of feasible solutions in the initial population is small. **Crossover** and **mutation** operators are far from adequate to evolve good solutions. It is desirable to have these operators specially designed for robot path planning, such as **repair** and **deletion**, to evolve feasible solutions from the infeasible ones. The important role of these problem-specific operators is discussed in details in Section IV.

D. Outline of the Proposed Knowledge-based Genetic Algorithm

An outline of the proposed knowledge-based genetic algorithm is given in Fig. 5. Initial solutions are generated randomly and are evaluated by the fitness function in Eqn. (1). The best solution from the initial population $P$ is selected and assigned to $best_{sofar}$. Two parents are selected according to some selection mechanism. Here, tournament selection is used. Then one or more genetic operators are selected and applied to the two parents according to some probabilities and heuristic knowledge and reproduce two children. The selection and reproduction are applied to the whole population. The old population consisting of parents is called parent population $P$, and the new population consisting of children is called child population. The whole parent population $P$ will be replaced by child population with elitism after application of selection and reproduction to the whole parent population $P$. Elitism is realized by replacing the worst individual in the child population with the best individual in the parent population $P$. In this way, when replacing the parent population with the child population, the ‘elite’ from the parent population $P$ won’t be lost. After replacing the whole population, the child population becomes the parent population $P$ for the next generation.

The best solution so far ($best_{sofar}$) is updated in each generation, and it will be the final solution when a stop criterion is satisfied. The stop criterion can either be that the preset maximum generation is exceeded, or that the best solution remains unchanged for certain number of generations.

![Fig. 4. Five specialized genetic operators that incorporates specific knowledge of robot path planning.](image-url)
The proposed algorithm is also suitable for robot path planning in a dynamic environment. It checks the sensed environmental information either every several generations or after a predetermined period. If the environment is changed, the algorithm will re-evaluate the current population according to the new environment. At the time of change, the algorithm has gone through many generations, the diversity of the population is relatively low, which may make it more difficult for the GA to evolve new solutions. To increase diversity so as to deal with the new environment, mutation with high mutation rate is applied to the population. From now on it starts the process to evolve a new solution for the new environment. The proposed algorithm is computationally efficient and would be fast enough to evolve a feasible (if not near optimal yet) robot path from the current robot location to the target, if the environment is not changing too fast. In a very complicated dynamic environment, the robot may have to wait for a feasible path evolved.

### III. Simulation Results

To demonstrate the effectiveness of the proposed knowledge-based genetic algorithm, several simulations were conducted. In the simulations, parameters for the proposed genetic algorithm are set as: population size is 50, probability for mutation per chromosome is 0.2, and 0.9 for all the other operators. Tournament selection and elitism are applied. The proposed GA can deal with different resolutions as shown later in the discussion section. For simplicity, in all simulations in this section, 100 units × 100 units grids is used to the nodes of paths unless it is otherwise stated. The simulation results also show that 100 × 100 resolution is high enough for the environments studied in this section. All simulations are conducted on a Pentium III PC (933 MHz) with Windows 2000 Operating System.

#### A. Path Planning in Unstructured Environments

The proposed knowledge-based GA is first applied to an unstructured environment with many arbitrarily shaped obstacles. Fig. 6 shows one typical run. The algorithm first randomly generates the initial population as shown in Fig. 6(a). Fig. 6(b) displays the best solution in the initial population, which is even infeasible and has the cost of 1043.25. Starting from this initial population, after selection and genetic operations, generation by generation, the population is evolved better and better. Fig. 6(c) shows the best solutions obtained from several different generations. It shows that the best solution first becomes feasible, and then the genetic algorithm starts to improve the quality of solutions in each generation. The best solution in the population after certain number of generations is obtained as the final solution. Fig. 6(d) shows the final solution obtained at generation 46. The cost is 117.56 and the computation time is 6.09 seconds. To test the robustness of the proposed GA, it has been run for many times. For 20 runs, the average cost is 117.91 with the standard deviation of 1.43, and the average computation time is 7.81 seconds with 2.58 standard deviation, and the average generations needed is 51 with 16 standard deviation.

#### B. Path Planning in Complex Environments

The proposed genetic algorithm can be easily applied to robot path planning in complicated environment, such as U-shaped or maze-like environment, where some potential based path planning approaches and local path planning approaches may be trapped [10], [12]. Fig. 7 gives an example to show the ability of the genetic algorithm to solve maze-like problem. For the environment in Fig. 7 the proposed model is capable of obtaining the near-optimal solutions in an average of 43 generations for 20 runs, where the average cost of 418.65 (with 4.11 standard deviation) and computation time of 15.95
Fig. 6. One typical run of robot path planning in an unstructured environment. (a) The randomly generated initial paths; (b) The best path in the initial population; (c) The best paths from different generations; (d) The final solution path.

seconds (with 2.72 standard deviation). A typical run is shown in Fig. 7 where Fig. 7(a) shows the initial solutions. The best solution (with a cost of 176.96) in the initial population is shown in Fig. 7(b), which is an infeasible path. Fig. 7(c) displays the evolving best solutions from different generations in evolution process. The final solution is obtained at generation 44 with the cost of 411.67 and has taken 17.13 seconds. Figures 8 and 9 show two other examples of zig-zag environment and a environment with U-shaped obstacles. The simulation shows that the proposed GA is able to deal with them easily. Fig. 8 shows a zig-zag environment, where Fig. 8(a) shows the evolving solutions, and Fig. 8(b) shows the final result with cost of 155.89 obtained at generation 60 that takes 3.43 seconds. The average cost for 20 runs is 156.31 with 1.99 standard deviation, the average generation needed is 52 with 12 standard deviation, and the average time taken is 2.94 seconds with 1.37 standard deviation. Fig. 9 shows the simulation result in an environment with double U-shaped obstacles. Fig. 9(a) shows the results in the evolution process while Fig. 9(b) displays the final path obtained at generation 49 and with cost 152.01. The average cost for 20 runs for this environment is 152.44, the average generation needed is 56, and the average time taken is 9.91 seconds.

C. Path Planning in a Clustered Environment

In this simulation, the proposed genetic algorithm is applied to a clustered environment with many arbitrarily shaped obstacles. Even for obstacles with very complicated shapes, the GA can still accurately detect collision and evolve near-optimal solutions. In a very complicated environment, it is possible that the GA obtains different solutions in different runs because of the randomness involved in genetic algorithms. However, near-optimal solutions are guaranteed. Fig. 10 shows four near-optimal solutions from four different runs. Their costs are 160.50 (a), 160.93 (b), 163.95 (c) and 170.53 (d), respectively, which are slightly different, but they are all good solution paths to this complex environment. The average computation time for the four runs is 20.83 seconds.

D. Path Planning in a Dynamic Environment with Moving Obstacles

The proposed genetic algorithm can not only deal with complex static environment, but also be suitable for dynamic environments with moving obstacles while the mobile robot is moving at a certain speed. A simulation is presented to show the adaptability of the proposed genetic algorithm to a changing environment with on-line planning. In Fig. 11
initially the slash-shaded obstacle is on the left side, which closed the left channel for the robot. It moves from the left to the right like a door opening the left side to shut the right channel at the speed of 1 unit/second (with 100 unit×100 unit grids applied). The robot moves at the speed of 2 units/second. The environment information as well as the robot position are updated every two seconds. Fig.s 11(a)-(g) show the snapshots of the obtained path solutions after updating the environment information at each time instance. The dots indicate the robot positions at the time of each update. The white line shows the the trajectory of the robot in the past, and the black line is the current path solution according to the last updated environment information (including the positions of the moving obstacle and the robot). Fig. 11(a) displays the obstacle original position, the start point of the robot, and the obtained path solution. In Fig. 11(b) and (c), the moving obstacle moves to new positions, but the movement of the obstacle has not actual impact onto the current solution. However, the algorithm adjusts the path slightly because of changes in the robot position (new start point). Starting from Fig. 11(d), the moving obstacle has actual impact on the obtained best path solution. The genetic algorithm is able to evolve a new path to avoid collision with the moving obstacle while trying to have the shortest path. As shown in Fig. 11(d)-(h), the best path solutions remain between the gap while the door is shutting because they are the shortest paths with regard to robot positions at the moment. When the door is shut totally, as shown in Fig. 11(i), the algorithm obtains a complete new path immediately to escape the deadlock. When the door is shut, the moving obstacle stops over the right side, but the robot position is still updated periodically, and the genetic algorithm obtains the best paths according to the new start points. Obviously, only slight adjustment is needed when necessary.

The simulation shows that the genetic algorithm is able to successfully obtain collision free and good quality solutions soon according to the last updated environment information. Occasionally, the robot might be trapped into a certain location when the moving of the obstacle and moving of the robot make the robot switch directions along a same path. However, this should happen rarely because it needs the right timing of moving of the obstacle and the robot. Also, randomness involved in the genetic algorithm will reduce the likeliness of
repeating the same path so as to reduce the chance of being trapped. The overall quality of solutions in very complicated environment may possibly increase when the interval between environmental information updates increases because the algorithm will have more time to refine the solution. For example, Fig. 12(a) displays the path obtained when the update interval is 1 second instead of 2 seconds in Fig. 11 at the stage of Fig. 11(i), where the quality of the path is better. Obviously, when the moving speeds of the obstacle and the robot are different, different path planning results will be expected. Fig. 12(b) shows the path planning when the moving obstacle moves faster at the speed of is 2.5 units/second while the robot moves at the same speed as in Fig. 11 In Fig. 12(c) and (d), the robot moves faster (5 units/second), so the robot is able to pass through the right opening before it is closed by the moving obstacle.

**E. Path Planning in a Dynamic Environment with Unknown Obstacles**

In this simulation, the algorithm is applied to an environment with unknown obstacles. At the first, the robot environment is partially known. Unknown obstacles are sensed when the robot is moving toward the target along the current planned path. Robot environment with suddenly appearing obstacles is one of the dynamic environments need to be handled by path planning task. Fig. 13 shows such a dynamic robot environment and the snapshots of the path planning results of one typical run. Fig. 13(a) shows the partially known environment at the beginning of path planning, and the planned path with the current environment. When the robot moves to location p along the current path, obstacle A is detected and the environment information is updated accordingly. Once the genetic algorithm senses the change, it re-evaluates the population, and the current best path is not feasible any more. A new path shown in Fig. 13(b) is obtained in as short as 1.10 seconds. The robot now follows the new path and may adjust the path if necessary according to every new start point. When the robot moves to location q, obstacle B is detected. The newly detected obstacle has no actual impact to the best solution even though it has some impacts to some other solutions in the population. Therefore, the robot continues moving along the unchanged path (Fig. 13(c)) until it comes to location r, where obstacle C is removed (Fig. 13(d) and(e)). With the new environment information, a new best path is evolved immediately (0.08 seconds). Fig. 13(f) displays the whole path.

**Fig. 13. Path Planning in a Dynamic Environment with unknown obstacles.**

This simulation demonstrates that the genetic algorithm is able to react to newly sensed obstacles very quickly. When the newly detected obstacle blocks the current path, it is able to avoid the obstacle and obtain a good quality path. When the appearance of the obstacle is irrelevant, the current path is not disturbed. The algorithm also responds to removal of an obstacle. The algorithm updates the start point while it moves towards the target, and the algorithm will update the path if it finds a better path with the current start point.

**IV. DISCUSSION**

The above simulation results demonstrate that the proposed knowledge based GA is capable of evolving satisfactory robot paths in complex environments. This is mainly contributed by the specialized genetic operators that incorporate heuristic knowledge. To show the contribution from these operators, a comparison study between the GA with and without the developed specialized operators is conducted. The comparison is conducted in the same environment as shown in Fig. 8. To see the performance of the GA without the developed specialized operators, we only keep crossover and mutation operators, and shut off all the other operators. As every specialized operator can be viewed as a special mutation operator, simply shutting
off those operators makes the two sides of the comparison have different mutation rates. To minimize the bad effect of this, we first set a best mutation rate for the GA with only crossover and mutation operators. By running the GA for 20 times at different mutation rates, a mutation probability of 0.5 is selected as the best value. Then the GAs with and without specialized operators are run for 20 times respectively. Statistic analysis is shown in Table I.

| Specialized operators | with | without |
|-----------------------|------|---------|
| number of runs        | 20   | 20      |
| Best found path cost  | Mean | 156.31  | 352.35  |
|                       | SD   | 0.47    | 12.36   |
| Number of generations | Mean | 52      | 346     |
|                       | SD   | 13      | 84      |
| time needed           | Mean | 2.94    | 0.84    |
|                       | SD   | 0.77    | 0.94    |

![Fig. 14](image1)

Fig. 14. The path obtained by the GA with only the crossover and mutation operators.

The above simulation was done by shutting off repair, deletion and improve operators, and the simulation result proves the effectiveness of these genetic operators. The next question is: Are those three specialized genetic operators effective enough to evolve good quality solutions? To answer the question, another simulation that shuts off crossover and mutation operators is conducted. First, the simulation is conducted with the same environment as above. Feasible solutions can be obtained, but with much more generations and deteriorated qualities. For 20 runs, the average cost is 251.56 with 24.17 standard deviation, and 174 generations are needed on average. Fig. 15 shows one typical run of this simulation. The path has the cost of 239.63 and is obtained at generation 168. Then the simulation is conducted with the environment shown in Fig. 7 that is much more challenging. It turns out that the algorithm without crossover and mutation operators fails to get a feasible path. The failure is as expected. Although the repair operator is very powerful, yet it is not deterministic and it tries to repair one infeasible line segment at one time. When the path has too many infeasible line segments and the partially repaired paths cost more, the solution is trapped into the low cost infeasible solutions. In this case, the only way to improve the solution is to combine other line segments from other paths by crossover.

![Fig. 15](image2)

Fig. 15. One typical run of the GA without crossover and mutation operators.

The above simulations of shutting off one or more genetic operators demonstrate that every genetic operator contributes to the success of the algorithm, and all the operators work together to deal with different robot environments.

Simulation study also indicates that the proposed knowledge-based genetic algorithm is practically feasible because the required computation time is quite reasonable. As introduced before, grids are used to form the intermediate nodes of a path. Obviously, resolution is a main factor to affect the computation time. However, simulation results show that the computation time does not increase dramatically as the resolution increases. For example, for the environment shown in Fig. 6 when resolution is 100 × 100, the average computation time is 7.81 seconds for 20 runs. When the resolution increases to 200 × 200, the average computation time is 9.03 seconds, and it takes average 12.25 seconds to compute when the resolution is 400 × 400.

Another factor affects the computation time is the number of the obstacles in an environment. Simulation study is also conducted to show the sensitivity of the proposed GA to the
number of obstacles (a concave obstacle is considered as two or more convex obstacles). Fig. 16 shows the environment with different numbers of obstacles: 20, 30 and 40. Accordingly, the average computation time for 20 runs is 5.53, 11.54 and 18.96 seconds, respectively. The simulation results show that the number of obstacles in the environment is the main factor affecting computational time of the algorithm. The reason behind this is that the algorithm needs to check collision with every obstacle. Like other genetic algorithms, evaluation is the bottleneck of the algorithm.

![Image](image)

Fig. 16. Path planning in environments with different numbers of obstacles. (a) 20 obstacles, takes average 5.53 seconds; (b) 30 obstacles, takes average 11.54 seconds; (c) 40 obstacles, takes average 18.96 seconds.

V. CONCLUSION

In this paper, a knowledge-based genetic algorithm for path planning of mobile robots is proposed. The GA uses a simple and unique path representation that uses natural coordinates to represent environment and grids to form the intermediate nodes of paths. The classical crossover and mutation genetic operators are tailored to the path planning problem. The proposed genetic algorithm also incorporates domain knowledge into its three problem-specific genetic operators for robot path planning. These operators also adopt small-scale local search based on some heuristic knowledge. The effectiveness of these knowledge-based operators is demonstrated by simulation studies. The simulation results also show that the proposed genetic algorithm is applicable for both static and dynamic environments. The developed GA also features its one fitness function for both feasible and infeasible solutions. This evaluation method accurately detects collision between obstacles and paths, and effectively distinguishes quality of both feasible and infeasible solutions, which is critical for the GA to evolve better solutions. The capability of the proposed genetic algorithm of dealing with moving obstacles and the efficiency in computation time make the proposed knowledge-based genetic algorithm able to be applied to real applications.

Knowledge incorporation into GAs is desirable when GAs are applied to specific problems. In the proposed GA, domain knowledge is incorporated into its genetic operators. There are many other ways to utilize additional knowledge besides designing specialized genetic operators. Constructing beneficial initial population is one area that domain knowledge could be used as guidance. In the initial population generated randomly for robot path planning in a complex environment with many obstacles, there are only few or no feasible solutions. If we use domain knowledge to generate more feasible solutions for initial populations, the GA would work better. This would be a future work. Besides, the genetic algorithm includes more genetic operators, firing of which depends on their respective probability. On-line tuning of these probabilities would be much desirable, which would another important future work.

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