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A Novel Method for Path Planning of Mobile Robots via Fuzzy Logic and ant Colony Algorithem in Complex Daynamic Environments

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Abstract— **Researches on mobile robot path planning with meta-heuristic methods to improve classical approaches have grown dramatically in the recent 35 years. Because routing is one of the NP-hard problems, an ant colony algorithm that is a meta-heuristic method has had no table success in this area. In this paper, a new approach for solving mobile robot navigation in dynamic environments, based on the heuristic feature of an optimized ant colony algorithm is proposed. Decision-making influenced by the distances between the origin and destination points and the angle variance to the nearest obstacles. Ideal paths are selected by the fuzzy logic. The proposed ant colony algorithm will optimize the fuzzy rules' parameters that have been using to On-line (instant) path planning in dynamic environments. This paper presents a new method that can plan local routs all over the area and to guide the moving robot toward the final track. Using this algorithm, mobile robots can move along the ideal path to the target based on the optimal fuzzy control systems in different environments, especially in dynamic and unknown environments.**

Keywords- Ants colony algorithm, fuzzy logic, path planning, mobile robot.

I. INTRODUCTION

Robots are essential elements in today's society. The term robot is used for a wide range of mechanical machines, which have mobility [1]. In the case of mobile robots, path planning is a major challenge. Path Planning for a mobile robot which is in an environment with various obstacles, is finding a path without obstacles from the starting point to the destination. In this regard Issue such as shortness and Simplicity of route are important criteria affecting on the optimality of selected routes [2].Today finding suitable algorithms for mobile robot navigation is one of the hot scientific topics. Mobile robots have been used extensively in various fields such as space research, nuclear industries and mines. In these applications, finding a safe route for the robot is a prerequisite for success. So finding a suitable routing algorithm for the robot to move from the starting point toward the target, without collision with obstacles in the environment is an important issue in robotics. By considering the length of the path traveled by the robot, and energy consumption and its performance time, we need to follow an algorithm that finds the shortest possible route [3], [4].

After 30 years of research in this field, we can classify Investigations into classic and heuristic researches. Classical methods for over 20 years in the field of change or combination are including: possible road map [5], map [6], and cell decomposition [7] which are based on mathematical programming. The second methods are heuristic. When the classical method of solving routing problems that have Np-hard nature, For robot motion planning encountered different difficulties, Heuristic methods inspired by nature were introduced [8]. In the exploratory classification, potential field method [9], and soft computing are including: Neural Networks, Genetic algorithm [8], [10], the Simulated Annealing algorithm [3], the Ant Colony Optimization algorithm [11], Particle Swarm Optimizer algorithm [3], [8] and fuzzy logic [11]. According to [12], [13] using Meta heuristics algorithm for routing in mobile robots is increasing. To achieve optimal path recognized environments the best option is to use evolutionary algorithms [14], [13]. In this regard, the usage of the Ant Colony Algorithm due to its discrete nature and also its relationship for efficient routing issues is very significant [12], [15]. Ant Colony Algorithm for routing needs a detailed and preset map so it cannot be used in unknown environments. Another problem in the use of the evolutionary algorithm for mobile robot navigation is that the optimization process should be done before the robot moves (off-line), and then the robot will move on the path [14]. Thus, using this algorithm (in spite of good ability in the route optimization) is not possible in many practical applications. So for mobile robot navigation in unknown environments with fixed and moving obstacles, without knowing the position and movement of the obstacles, On-line (instant) routing methods must be used. Fuzzy logic has a very good performance in an on-line node to node path planning for robots [14], [16]. In this paper, to determine the optimal path of mobile robots in an unknown environment, a new method based on determination of fuzzy rule table, which has a very important impact on a fuzzy logic system performance, have been provided. Because the routing issue is a kind of Np-hard problem, here ACO algorithm is used to determine the optimum fuzzy rule table. The main objective of this paper is to provide a new method that can plan local paths around the environment routes and guide the moving robot toward the final track. This goal is achieved by optimization of fuzzy rules table for the mobile robot motion by utilizing the ant colony algorithms. In the rest of the paper: The second section presents the proposed fuzzy-colony algorithm, and then robot's work place environments, which are fairly simple to highly sophisticated will design. In

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the third section, the simulation results in terms of path length and the time spent in different environments with varying complexities are presented. Furthermore, in this part examples of considered parameters for the ant colony algorithm in different environments are presented. The proposed algorithm has been discussed in Section IV. The fifth section discusses about the efficiency and effectiveness of the proposed algorithm.

II. METHOD

In [15], Routing of mobile robots has been considered in known dynamic environments in three workspaces, including relatively simple, moderately complex, and complex. Considering strengths and weaknesses of evolutionary algorithms, to improve the optimality criteria for dynamic unknown environment, three workspaces listed in [15] were used. In the proposed method, the Ant Colony Algorithm will determine the optimized elements of the fuzzy rule table. For this purpose, a number of initial and final points have been considered in different workspaces. In each iteration, each ant based on the probability relationship in the ant colony algorithm will determine an output for each of fuzzy rules and finally, a solution is produced. According to the fuzzy control system, based on the produced schedule for each ant, for all pairs of initial and final considered points, routing takes place. Finally, criteria for evaluating the solution generated by the ants are the average length of the path traveled by the moving robot for each pair of points. Overall process of the proposed method is presented as follows:

A. producing Appropriate solutions by ants

In proposed method, each ant for producing a solution for each fuzzy rule considers a membership function according to selection probability law in the ant colony algorithm, shown in Fig. 1, complete their route and finally, a solution is achieved. This choice is done according to (1), the selection probability equation.

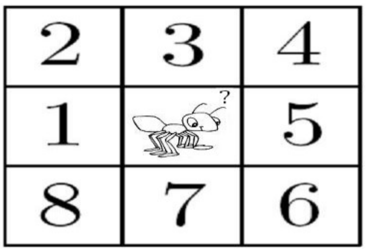

Fig. 1 Order of adjacent numbered squares

$$P_{ij}^{k}\left(t\right)=\frac{\tau_{ij}^{\alpha}\left(t\right)\times \eta_{ij}^{\beta}}{\sum_{i=1}^{n}\tau_{ij}^{\alpha}\left(t\right)\times \eta_{ij}^{\beta}} \quad (1)$$

Where τ_{ij} is the amount of pheromone in membership function for the i^{th} output for j^{th} rule. η_{ij} is heuristics data of i^{th} membership function for j^{th} rule. P_{ij} (t) is the selection probability of i^{th} membership function for j^{th} rule in iteration t. α and β are two constant parameters that indicate the amount of influence of pheromone and heuristics data in selecting the output membership functions for each rule. In This paper to speed up the convergence of the algorithm, according to (2) the table is set manually in [16] is considered as heuristics data in selection of ants. Using this relationship, selection probability of membership functions in the rules table will increase in order of 2^{β}which results in speeding up the convergence of the algorithm.

$$n_{ij}=\begin{cases}2 & if\ j^{th}\,MF\ G\\ 1 & Otherwise\end{cases} \quad (2)$$

B. Evaluation of the produced solutions

In each iteration, after all ants have developed their own solutions, they are evaluated according to (3), and the best ant will select.

$$Cost_{k}^{t}=\frac{\sum_{i=1}^{N}L_{i}^{k}}{N} \quad (3)$$

Where, N is the number of paths considered in different workspaces, and L_i^k is the path length for the i^{th} workspace (i^{th} initial and final point's pair) which is obtained by routing phase using the rules table for the k^{th} ant.

C. Pheromone update for all routes

After all ants have developed their own solutions and their eligibility was evaluated, general pheromone update is done according to (4). Pheromone matrix considered in this issue is a two-dimensional matrix with n rows, which are the number of output membership functions and m columns that is the number of fuzzy rules. The pheromone change for each element is updated according to (5).

$$\tau_{ij}\left(t+1\right)=\tau_{ij}\left(t\right)+\Delta\tau_{ij} \quad (4)$$

$$\Delta\tau_{ij}=-\lambda\tau_{ij}\left(t\right)+\begin{cases}\frac{Q}{num} & for\ nodes\ of\ the\ best\ ant\\ 0 & otherwise\end{cases} \quad (5)$$

Where $\tau_{ij}\left(t\right)$ is pheromones corresponding to i^{th} membership function for j^{th} fuzzy rule in previous iteration and $\tau_{ij}\left(t+1\right)$ is pheromones corresponding to i^{th} membership function for j^{th} fuzzy rule in current iteration. In addition, Q is the amount of pheromone secreted, and "num" is the number of ant priority among pheromones secreted candidate. λ is the pheromone evaporation coefficient which is a number between zero and one. Fig. 2 presents general flowchart of the proposed algorithm.

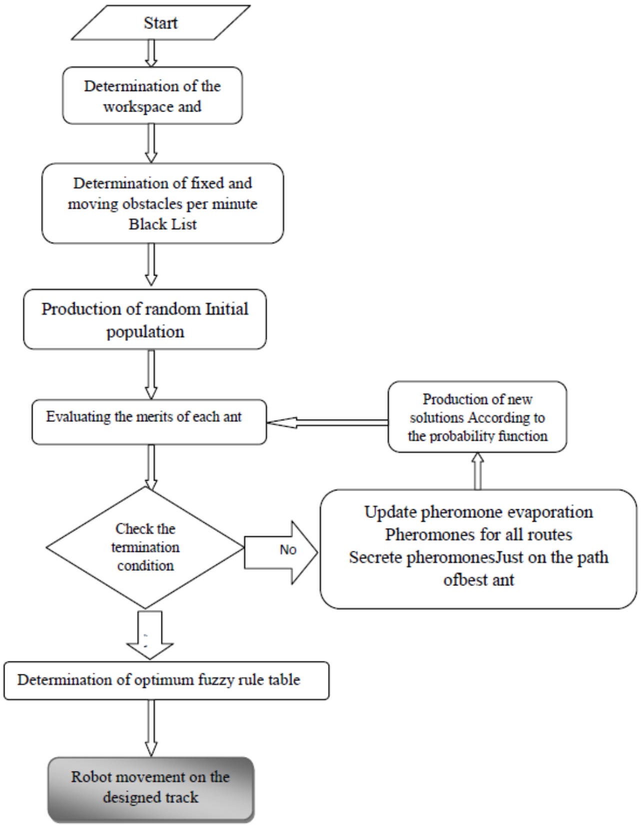

Fig. 2 Overall flowchart of the proposed algorithm.

III. THE SIMULATION RESULTS

Production of random population means each ant considers one output for each fuzzy rule then evaluation merits of each ant by considering the fuzzy rules table obtained by each ant, results in optimal routes for sets of initial and final points. The average path length for different paths is considered as a criterion for suitability evaluation of ants. It should be noted that in proposed method based on the combination of fuzzy and ant colony algorithms, routing is done only once in off-line mode, which results in optimization of parameters in fuzzy rules table. Run-time using a laptop computer with Intel Dual core processor with a processing speed of 3GHz and 4GB RAM, with Windows 7, by Matlab R2011 software, was 417 minutes, But then for routing for each specific input and output modes, Based on fuzzy logic routing is performed using the optimized rules table. In fact, with this method, the ant colony algorithm will determine the optimal elements of fuzzy rule table, with the aim to reduce the robot's path. In this paper for the simulation, three workspaces (different) with four different states (four initial and final points) are assumed. As a result, for the solution of each ant, 12 different paths are achieved by using fuzzy logic. Average length of the path found by each ant in 12 different path is considered as a criterion for suitability evaluation of each ant. Notably, then, routing based on fuzzy logic for each point in the workspace and initial and final desired points is done by utilizing the optimized rules table. As a result, the time required to implement the proposed routing algorithm based on the combination ant colony, and fuzzy algorithms is very similar to routing run-time with fuzzy logic method (manually setting the table). However, here the length of the path traveled by the robot is much shorter than the path traveled with fuzzy logic [16]. The optimal table by ant colony is according to Table1.

Table1. Table of optimized fuzzy rules obtained by Ant Colony Algorithm.

Output: priority of the next node selection	**Input 2: Angle difference with respect to target**	**Input 1: Distance to the nearest obstacle**
Very low	Very low	Very low
Very low	low	Very low
Very low	Medium	Very low
Very low	High	Very low
Very low	Very high	Very low
Medium	Very low	low
Very low	low	low
low	Medium	low
low	High	low
Very low	Very high	low
low	Very low	Medium
Medium	low	Medium
low	Medium	Medium
low	High	Medium
Very low	Very high	Medium
Very high	Very low	High
High	low	High
Medium	Medium	High
low	High	High
Very low	Very high	High
Very high	Very low	Very high
Very high	Low	Very high
High	Medium	Very high
Medium	High	Very high
Low	Very high	Very high

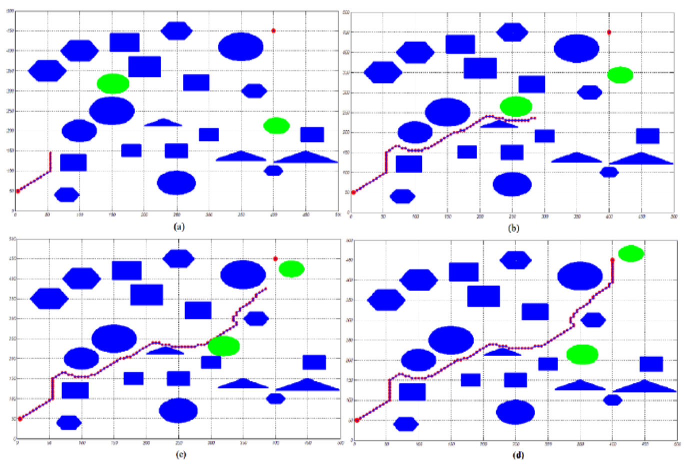

Fig. 3 Routing with the proposed method in relatively complex environments start at (50, 5) and end at (450,400), 916.24 cm path length.

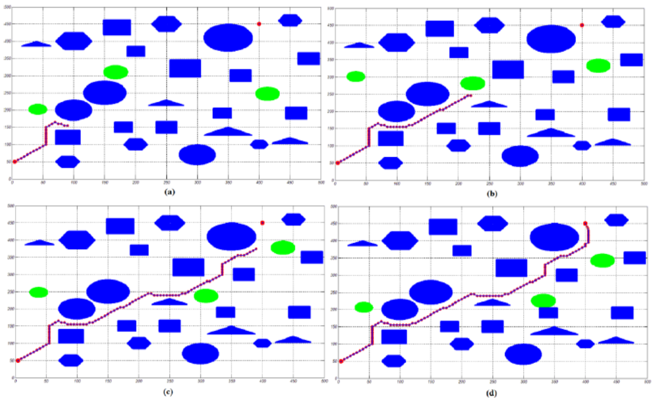

Fig. 4 Routing with the proposed method in quite complicated environment start at (50, 5) and end at (450,400), 927.18 cm path length.

In quite complicated and relatively complex workspaces in the mentioned simulated environment, the proposed algorithm improved fuzzy rules table in [16] with the evolutionary characteristics of the ant colony algorithm so that the walking robot can select the optimal path in any situation without any collision with obstacles, which may be at any speed, direction, and shape in front of robots. Table2 compares the performance of the proposed fuzzy-colony algorithm with the proposed fuzzy algorithm in [16]. In different environments path length found by the proposed fuzzy - Colony algorithm is far less than the optimal fuzzy algorithm proposed in [16]. This is due to optimization of fuzzy rules table in [16] by a sophisticated expert with evolutionary ACO algorithm. The path length is expressed in cm.

Table 2. Performance of the proposed algorithm in different environments.

workspaces complexity	Starting Point	Target Point	Fuzzy	ACO_Fuzzy optimization
Relatively simple workspaces	(50,5)	(450,400)	620.9	616.19
Relatively simple workspaces	(20,55)	(460,455)	660.52	658.69
Relatively simple workspaces	(30,65)	(465,460)	656.8	655.61
Relatively complicated workspaces	(50,5)	(450,400)	965.4	927.18
Relatively complicated workspaces	(20,55)	(460,455)	725.10	718.61
Relatively complicated workspaces	(30,65)	(465,460)	727.9	711.33
Quite complicated workspaces	(50,5)	(450,400)	924.4	916.24
Quite complicated workspaces	(20,55)	(460,455)	726.4	720.74
Quite complicated workspaces	(30,65)	(465,460)	709.6	706.75

Fig. 5 illustrates the comparison of the routes traveled by moving robots for Real-Time (on-line) fuzzy logic and optimized fuzzy algorithm with the ant colony. The improvement of the fuzzy rules table is quite evident by the ant colony algorithm. To avoid repetition, only the result of the third workspace which is quite complicated is offered.

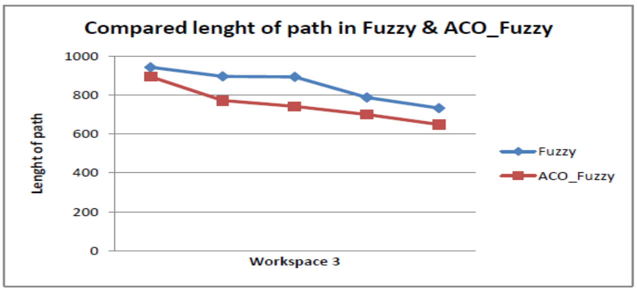

Fig. 5 Comparison of path length in quite complicated workspace by the proposed fuzzy-ant colony and fuzzy algorithms.

According to Fig. 6, it follows that for every 5 points in quite complicated environment with variable origin and target points, the ant colony offers the shortest path due to off-line search. But since all the information is not fully available to the robot, fuzzy logic approach has been proposed and by considering the length of the paths obtained, this method has the greatest distance traveled by the mobile robot. When the fuzzy rules table optimized with the evolutionary ant colony algorithm, as is also evident in figure below, The result shows that the Distance traveled by the proposed fuzzy -colony algorithm in an unknown environment is very close to the traveled distance introduced by evolutionary algorithms in [15].It should be noted that evolutionary algorithms due to prior knowledge of the environment, choose the shortest path, but in the real-world, robots are facing the unknown environment and obstacles and the proposed colony – fuzzy algorithm in such unknown environments will find short paths with respect to optimality criteria (length, distance and elapsed time). The length of these paths is close to the length of the path traveled by evolutionary algorithms that obtained from adequate and accurate information from their environment.

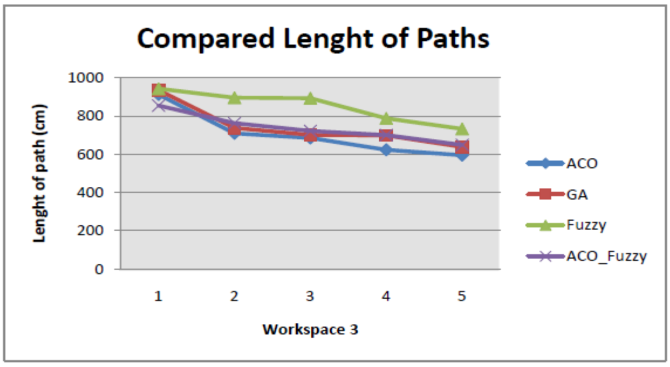

Fig. 6 Comparison of path length in quite complicated workspace by the proposed algorithms.

IV. DISCUSSION

Routing and location identifications are considered as the most important task of a mobile robot. With respect to working environment of mobile robot, different algorithms and various methods have been used. Among them for a known environment with fixed obstacles, ants routing algorithm have better performance. There are a great number of investigations in this field, but most work environments for mobile robots are areas with fixed and moving obstacles in a different direction and speed that are famous as the dynamic complicated known environments, and there is less study in this field. So in unknown dynamic environment due to lack of mapping and also shortage of mobility functions of barriers, Ant Colony Algorithm alone is not working. Because in mentioned algorithm, it is necessary to have detailed information about the environment and mobility functions of obstacles, in these cases, real-time methods must be utilized. In the meantime, fuzzy logic with fuzzy rules table plays an important role in robot's navigation in complex environments. Fuzzy rules table is usually set by an expert. On the other hand, manually setting the table cannot be fully optimized. Therefore, to optimize the parameters of fuzzy table, the evolutionary ant colony algorithm has been used in this research. In other words, the ant colony algorithm with respect to optimality criteria, affects the fuzzy table which has been set by an expert, and offers efficient routing of mobile robots. So with this method in every unknown environment a robot can find its way with the optimality criteria. In other words, in each iteration, each ant according to the selection probability relationship in ant colony algorithm, for each of the fuzzy rules, determine an output, and eventually produce a solution. Then According to fuzzy control systems based on the table produced for each ant, for all pairs of considered initial and final points routing is done.

V. CONCLUSIONS

For routing in an environment similar to the real environments on-line methods are needed. Among these methods, fuzzy logic is a good choice for solving this kind of problem, due to on-the-spot node to node routing for mobile robots and has been regarded by Researchers. Basis of fuzzy logic is determination of fuzzy rules table, which is determined by an expert. However, such a table cannot be completely optimized if it is determined manually. Therefore, considering that determining the fuzzy rules table is a kind of NP problem, using evolutionary algorithms and especially ant colony algorithm with respect to its discrete nature is very beneficial. Ant colony algorithm improves fuzzy rules table that is determined by a qualified person according to optimality criteria, which are including the length, the time and the smoothness of the path in this article and finally optimizes elements of table. As a result, the proposed hybrid algorithm enables the mobile robot to pass the optimal path at the right time to achieve the goal in every unknown environment with any obstacle.

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