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Fuzzy Logic-Ant Colony Optimization for Explorer-Follower Robot with Global Optimal Path Planning

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ABSTRACT

Path planning is an essential task for the mobile robot navigation. However, such a task is difficult to solve, due to the optimal path needs to be rerouted in real-time when a new obstacle appears. It produces a sub-optimal path and the robot can be trapped in local minima. To overcome the problem the Ant Colony Optimization (ACO) is combined with Fuzzy Logic Approach to make a globally optimal path. The Fuzzy-ACO algorithm is selected because the fuzzy logic has good performance in imprecision and uncertain environment and the ACO produce simple optimization with an ability to find the globally optimal path. Moreover, many optimization algorithms addressed only at the simulation level. In this research, the real experiment is conducted with the low-cost Explorer-Follower robot. The results show that the proposed algorithm, enables them to successfully identify the shortest path without collision and stack in "local minima".

Keywords: Fuzzy-Ant Optimization, Global Optimal, Path-planning, Explorer-follower Robot

1. INTRODUCTION

Swarm robot navigation can be defined as a network of mobile robots, moving in a dynamic environment to perform certain cooperative tasks for reaching the targets while avoiding obstacles [1]. Basically, there are four components in the navigation process such as perception, localization, path planning and motion control. Within this context, each individual robot in the swarm is considered as a dynamic agent. There is no direct mechanical link between pairs of robot agents within the swarm, but rather some wireless sensing and communication links between certain assigned pairs. The main purpose of using this robot is to collectively reach the targets that are difficult to achieve by an individual robot system [1][2]. One kind of swarm robotics system is the Explorer-Follower robot. They work on the group and communication by using wireless sensing. However, it is desirable for the rest of the robot team to automatically follow the best path, without necessarily maintaining visual contact with each other. A wide variety of algorithms has been investigated to control the operation of swarm robots. Some of these algorithms, are bio-inspired by nature and try to mimic the evolutionary behavior of living colonies, called swarm intelligent [3]. However, many swarm algorithms have been presented and tested on simulation, only a few of them have been actually implemented on the real robot. The swarm robotics systems performing a cooperative task has become a challenging research field. The control algorithm ensuring that swarm robots can uphold a specific formation while traversing a trajectory, avoiding collisions simultaneously and achieving the target. One of the cooperative tasks is path planning, it is a key step in mobile robot control, and the quality of path influences the efficiency of the mobile robot. Hence, designing an efficient path planning algorithm is essential.

Currently, many algorithms for solving the problem in path planning, such as Artificial Potential Field [4], Fuzzy Logic [5], Neural Networks [6], Genetic Algorithm [7][8], Particle Swarm Optimization [9][10] and others. However, such algorithms can't reach an ideal solution separately in a complex dynamic environment, the methods are inefficient when the target is a long distance away or the environment is cluttered. Artificial potential field easily gets traps into local minima. Fuzzy logic offers a possibility to mimic expert human knowledge, however, the computational expensive when the input increases. Neural network has the capability to learn from existing knowledge, unfortunately, the learning process needs more time to converge. Genetic Algorithm is an evolutionary algorithm, is able to resolve composition optimization problems. However, it updates the good individuals entirely and doesn't have exploited the characteristics of the path solution space. Particle swarm optimization is suitable for the optimization problem but only sub-optimal, and it can get trap in local minima. Many intelligent autonomous systems for exploring their environment require estimating the positions of surrounding objects as precisely as possible. Due to the real-world optimization problems are dynamic, regarding the objective function, decision variables, problem instance, constraints, and it changes stochastically over time [10]. To track the optimal solution over time with the environmental changes is desirable. Previous research shows that the interest in ant-based algorithm meta-heuristics is growing in mobile robotics system [11][12][13][14]. The ant colony optimization (ACO) algorithm is one of the prominent algorithms in the robotic fields. The idea is to find the optimal path from the nest to where the food is a graph based on the behavior of food seeking ants [15][16][17]. Unfortunately, the implementation introduces a number of practical challenges and issues that are not encountered, and it addressed only at the simulation level.

In this research, the ACO algorithm is selected due to the process of path planning need the optimization approach. However, the main drawback of ACO algorithm, it can't be applied in a dynamic environment and it can't reach the global optimal [18], to overcome the ACO drawback, fuzzy logic is combined with it. Due to, fuzzy logic produces a good performance in imprecision condition and uncertain environment. Normally, the combination of both methods is advised to enhance their advantages and eliminates some of their weaknesses. The proposed hybrid algorithm will be run in a different task. For steering control in a dynamic environment and for determining the optimal path. Hence, the combination of the above algorithm is desirable to produce a good solution for path planning application. The rest of the paper are organized as follows: section 2 briefly discusses the original ACO algorithm while section 3 describes our proposed algorithm. Section 4 presents the explorer-follower robot, the experimental setup, and Fuzzy-ACO performance and finally, the paper is concluded with the conclusion and future work in section 5.

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2. ANT COLONY OPTIMIZATION ALGORITHM

The ACO algorithm is bio-inspired by the behavior of ants exploring several possible paths between a source and a destination. Each of these ants will start by traveling on one of these paths. The ants have no global awareness of the different paths and have no means to measure the length of the traveler. When searching for food, the ants show the complex social behavior is based on deposit hormones, which called pheromones. Pheromones guide another ant walk in a path that has been granted with a special characteristic of the food source. More pheromones are released when more ants walk along the path. It makes a conclusion that such path is the shortest way to get to the food source. The shortest path toward the food produces the most pheromones because more ants can travel it in less amount of time [16]. On the other hand, the pheromone levels on the shortest path remain high because the pheromone deposit speed is faster than its evaporation speed. For reducing the ants change the path, the pheromone in a long path will evaporate over time. This situation is built to avoid ants trapped in local minima and produce a sub-optimal path [15]. Consequently, the ACO is more suitable for problems where source and destination are clearly predefined and specific. The main procedure to find the optimal solution of ACO algorithm divided into five stages such as, generate artificial ants, make an iteration/loop for each ant until complete scheduling of tasks, deposit the pheromone on visited states, daemon activities and evaporate pheromone. All the process can be described by Equation (1) to Equation (5) as follow,

i) An ant will move from node *i* to node *j* with probability

The weight of pheromone is used to determine the probability of ants motion to move from one point (i) to another point (j) on each iteration. Every each of iteration process will occur updates on the movement of the ants to get another point that already exists ants else and find another point that no ants. The robot will leave pheromone of T which will add value to the density of pheromone or grades gray level at the left point. If the ants do not move, then the ants will not leave a trail pheromone. The existence of the ants can be expressed by the ant position r and orientation θ. Because the response at a given time assumed to be independent of individual circumstances before, it is sufficient to determine the probability of transition from one place (r, θ) to the next (r^*, θ^*). Response function can be effectively brought into the two parameters of the transition rules between the points using a weighting function pheromone which is denoted by the symbol $\tau_{i,j}$. Where τ is the density of pheromone that is the number of pheromones contained at the point where the robot, β Osmotropotaxic reflect the sensitivity which is one type of information processing devices that regulate the tendency to follow pheromone. In addition to the weight of pheromones, there is also a weighting factor $\eta_{i,j}$ where η is the change in direction every step. Weighting factor measures the difference in direction in the previous direction, the last time the robot occupies. Therefore that the probability and the robot transition from node *i* to node *j* as follow [17],

$$\rho_{i,j} = \frac{(\tau_{i,j}^{\alpha})(\eta_{i,j}^{\beta})}{\sum(\tau_{i,j}^{\alpha})(\eta_{i,j}^{\beta})} \quad (1)$$

where,

$\tau_{i,j}$ is the amount of pheromone on edge i;α is a parameter to control the influence of $\tau_{i,j}$; $\eta_{i,j}$ is the desirability of edge i,j; and β is a parameter to control the influence.

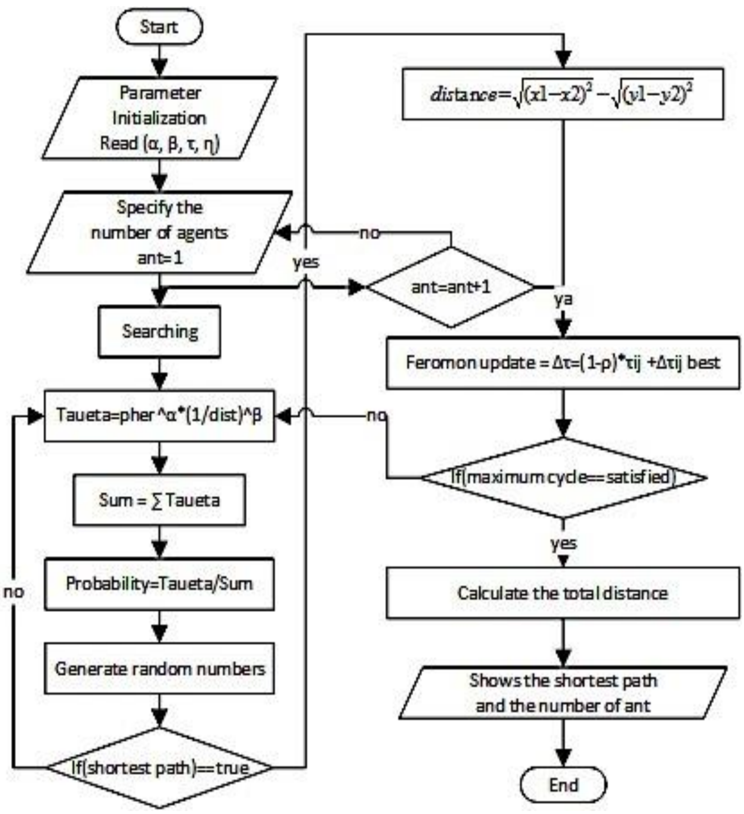

FIGURE 1. ACO flowchart

ii) Calculating the pheromone update $\eta_{i,j}$,

The pheromone update of the path (from node i to j),

$$\tau_{ij}(t+1) = (1-\rho) * \tau_{ij}(t) + \Delta\tau_{ij}(t) \quad (2)$$

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with ρ is a rate of pheromone evaporation and $\Delta\tau_{ij}$ is the amount of pheromone deposited. After pheromone evaporation occurs, the new pheromone levels are updated. It levels are updated with the additional pheromone at the path,

$$\Delta\tau_{ij}(t) = \sum_{k-1}^{m} \Delta\tau_{ij}^{k}(t) \tag{3}$$

$$\Delta\tau_{ij}^{k}(t) = \begin{cases} \frac{1}{L_k}, e(i,j) \in L_k \\ 0 \end{cases} \tag{4}$$

where L_k is the associated cost or reward of ant k for choosing this path.

iii) Calculating the distance

After the path is created, then the ants make the new path. To calculate the distance for each distance, the Eq. (5) is used,

$$d = \sqrt[4]{((x_1 - x_2)^2 - (y_1 - y_2)^2)} \tag{5}$$

The optimal route is obtained through evaluation of the number of pheromones deposited by ants on the paths. This characteristic of biological ant colonies is inherited in ACO algorithm to solve discrete optimization problems. From the Equation (1) to Equation (5), the ACO computational flow chart is shown in Figure 1.

3. RESEARCH METHOD

3.1. FUZZY-ACO PROCESS

In this research, the combination algorithm of the Ant Colony Optimization and Fuzzy Logic for robot path planning is investigated. The goal is to find the shortest and collision-free route (if exists) between a starting point and a destination point in a grid network. In designing of the Fuzzy-ACO algorithm consists of three scheme such as (i) obstacle avoidance and wall following algorithm for all robots to ensure collision-free route, (ii) search algorithm for explorer robot to find the target, and (iii) trail algorithm for follower robot on the globally optimal path. The experiments are conducted by using two low-cost robots as Explorer and Follower with 3 infra-red sensors for avoiding the obstacles, 1 photodiode sensor for search the target and 1 camera sensor for pheromone deposit/evaporate. The microcontroller is used for processing the decision control of Fuzzy-ACO algorithm. Communication between the robots by utilizing X-Bee/Zig-bee equipment. The infra-red sensors are used to control the steering of the mobile robot. To make simplicity only two input membership function create, near and far. Linguistic ‘Near’ if the obstacle closes the robot about 30 cm and ‘Far’ if the obstacle about 50 cm from the robot. The output of the sensor as an input to the Fuzzy controller, and become speed this experiment.

In this experiment 8 rules are created based on Sugeno approach as shown in Table 1. It creates a simple algorithm, due to only low- cost robot with simple processor and sensor. In this experiment to process Fuzzy-ACO algorithm, 8 bits AT-Mega 16 microcontroller only has 16 Kbytes of RAM and 512 of ROM is utilized (See Figure. 2). For finding the target photodiode sensor is placed at the bottom of the robot. The robot will follow the black dot from photo diode because it reflection of the food of ants. If the food is found, then the Explorer will send the signals via the X-Bee to the Follower. The Fuzzy-ACO algorithm divided into two processes for all environmental situations. First, the fuzzy logic algorithm is activated for avoiding the obstacle and second, the ACO algorithm in the explorer robot active for finding the target and to determine the optimal path. The Fuzzy-ACO algorithm in the follower robot only active, when the communication signal from the X-Bee is high or “1”, it’s mean the target have found.

TABLE 1.
Fuzzy rule bases

Rule	Input (sensor)			Output (speed)	
	Left	Front	Right	Motor 1	Motor 2
1	Near	Near	Near	Slow* condition	Fast * condition
2	Near	Near	Far	Fast	Slow
3	Near	Far	Near	Slow	Slow
4	Near	Far	Far	Medium	Slow
5	Far	Near	Near	Slow	Fast
6	Far	Near	Far	Fast	Slow
7	Far	Far	Near	Fast	Medium
8	Far	Far	Far	Fast	Fast

Initially, the ACO algorithm has to define all the parameters, in terms of the number of robots, the number of iterations (cycles) that the maximum that can be done, the intensity of trail pheromones, pheromone evaporation coefficient, and other parameters in accordance with the wishes of the user. Furthermore, the iterative process carried out until the desired stopping criteria.

3.2 DIGITAL PHEROMONE USING HSV SEGMENTATION

Explorer robot during a journey to find the point of food will make a trail path in the form of the path with a different color. These colors will be recorded with a camera sensor. The output from the color sensor as a digital pheromone to give the guidance to the follower on a path toward food information. The Color Weight in the RGB value will be used as the weight of the digital Pheromone which is a variable in Ant Colony Algorithm. Each color has its own RGB value which can be seen in Table 2. Each pixel is processed by using the Hue, Saturation, Value or HSV segmentation method. HSV is a color model that describes colors (hue or tint) in terms of their shade (saturation or amount of gray) and their brightness (value or luminance) (Figure 3).

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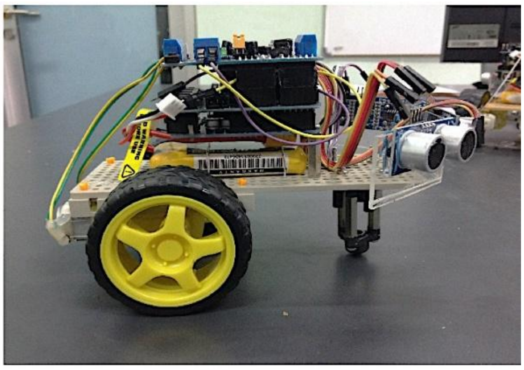

FIGURE 2. Simple explorer robot

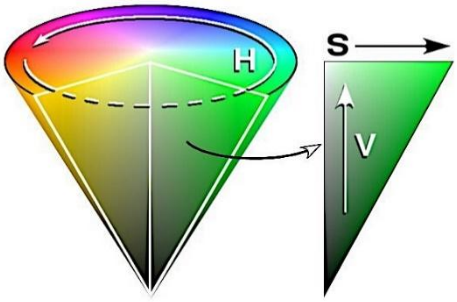

FIGURE 3. HSV colour space

Red, Green, Blue (RGB) color model from camera sensor describes the color in terms of the amount of light of red, green, and blue in it. Five values of white, red, green, blue and black in range value from 0 to 255, with white defined is (255, 255, 255), red color is (255, 0, 0), green color (0, 255, 0), blue color (0, 0, 255), and black color is (0, 0, 0). All values are determined as a threshold. Based on the RGB value is transformed into HSV value. The purpose of using this method for separating color from the camera sensor with another color in the environment [19]. Basically, the HSV method has five stages to process every color become a pixel including gray scale, thresholding, edge detection, hue circle and direction detection. The table 2, present the sample of threshold color in RGB to HSV in pixel value. Such process for testing the function of camera sensor to meets the tolerance value with 0% of error. From the Table 2, show the HSV segmentation to decompose an image into meaningful parts for further analysis, resulting in a higher-level representation of the image pixels like the foreground objects and the background.

Based on the HSV process, the object with the color red, green and blue produce white color output. Such color dominant than the black color output. For red color object, the number of white pixels is detected from 55.873 to 56.108. For an object in green color, the number of white pixels is detected from 57.436 to 57.611. For objects in blue color, white pixel number detected from 62.037 to 62.104. This shows that the HSV color segmentation algorithm successfully detects red, green and blue. Every pixel value from the HSV process are assigned as weighted in the ACO process. All values of pixel weight are transformed as a digital pheromone (see Figure 4).

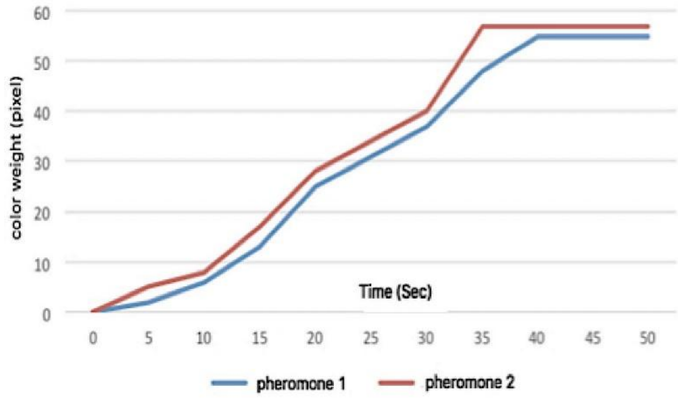

FIGURE 4. Digital pheromone visualization

All stages can be described in Figure 5 below. By using such approach the optimal path can be selected. After the optimal path is selected, then the trail of pheromone from start to the target is sent to the follower robot.

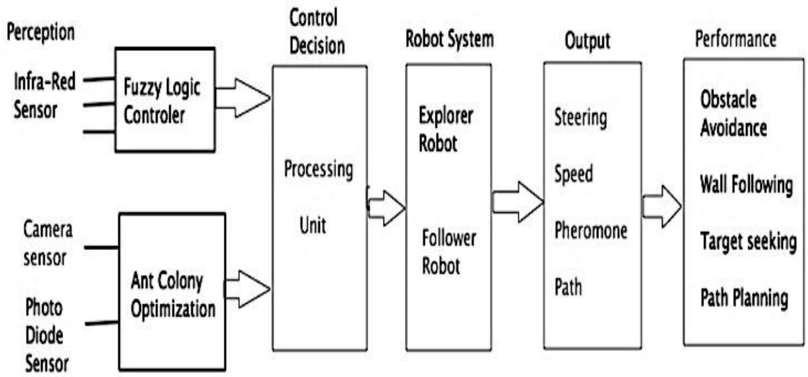

FIGURE 5. Path planning scheme

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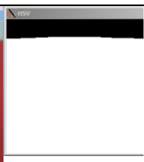
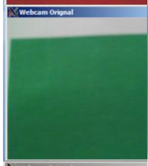
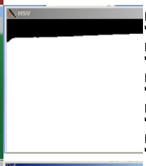
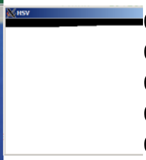
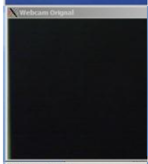
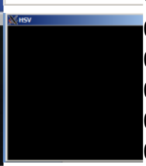
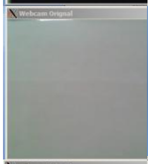
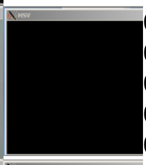
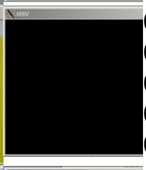
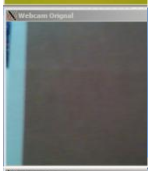
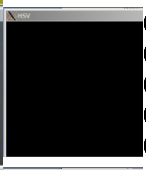
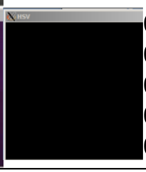
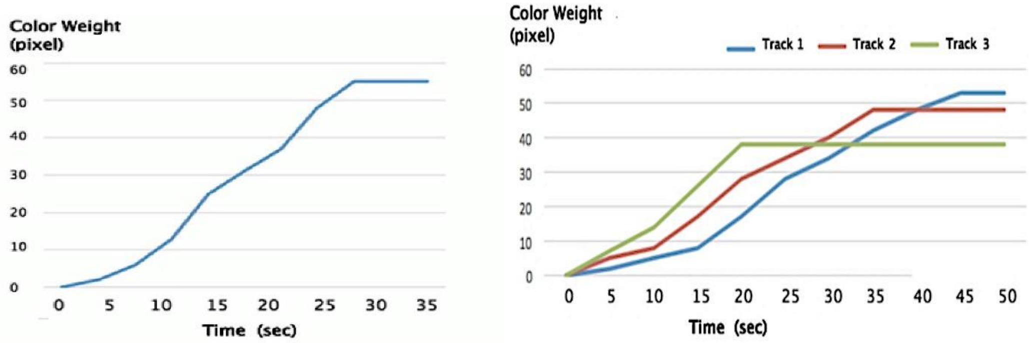
TABLE 2.
The sample of threshold from RGB (hexadecimal) to HSV (pixel)

Colour	RGB Hex	Source (320 x 240) pixel	HSV (320 x 240) pixel	Number of Pixel in white colour
Red	#FF0 000			55.986 56.073 55.873 55.977 56.108
Green	#00F F00			57.611 57.608 57.611 57.452 57.436
Blue	#000 0FF			62.037 62.043 62.053 62.077 62.104
Black	#000 000			0 0 0 0 0
White	#FFF FFF			0 0 0 0 0
Yellow	#FFF F00			0 0 0 0 0
Brown	#B97 A57			0 0 0 0 0
Purple	#A34 9A4			0 0 0 0 0

3. EXPERIMENTAL RESULTS

Since the robots can neither deposit chemicals nor sense their concentrations, the chemical pheromone was replaced by digital pheromone or electromagnetic signals. In digital pheromone, rather than laying down the chemical on the traveled path, explorer and follower robot communicated via the color sensor to a home base. The home base recorded the number of times each path had been completed. It was critical that this home base was stationary and located near the origin because in a scaled-up application, with a larger number of robots, it may not be possible to establish communication between the robots. The home base was situated near the origin because that would be where a robot needs to report a completed path and acquire the updated data for the next trip.

In this research, three experiments are created. (i) the case only one path in the environment, (ii) the case three paths are generated, and optimal the path is selected, and (iii) three paths are generated but with moving obstacle and the optimal path is selected. The three conditions are presented in Figure 7 to Figure 9. To validate the proposed Fuzzy-ACO algorithm in the dynamic environment, some obstacles are placed in the environment but only experiment 3 use the moving obstacle. In experiment 1, the Fuzzy-ACO only create one path. In this situation, the proposed algorithm produce past response for finding the target without collision and the follower robot has the ability to follow the pheromone trail (Figure 7 (a), Figure. 8(a) and Figure 9(a)). The digital pheromone update for every node when the robot moves (from *i* to *j*) as shown in Figure 6 (a) and Figure 6 (b).



(a) Single path (b) Three paths

FIGURE 6. Digital pheromone up-dates

The pheromone update as weight values obtained from the color sensor in the edge can be seen in Figure 7. In such experiment, to obtain the quality of color, due to its reflection a pheromone, the color from the sensor is separated with domain color in a testing environment by using HSV method. The ACO algorithm must be called again in order to find the shortest path in this new network with obstacles. From Figure 8, the Explorer robot makes three path. Each path generates the different value of pheromone. The more pheromone on a robot path, the more possibility that the follower robot will take the path. Then the probability only depends on the pheromone levels. The node that is the closest one to the target has the highest probability of being selected.

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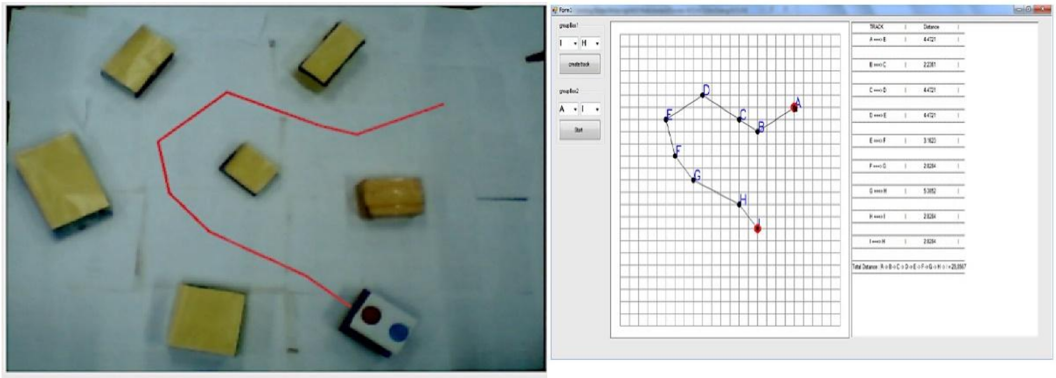
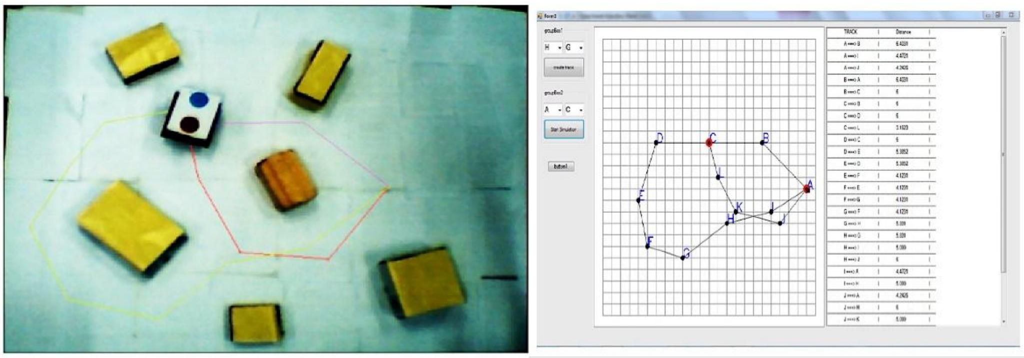


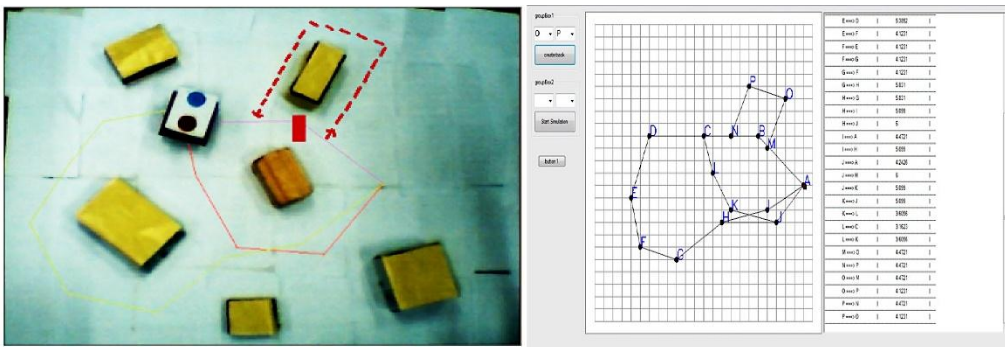
(a) Real experiment (b) Path created by the robot

FIGURE 7. Experiment 1 with one path created



(a) Real experiment (b) Path created by the robot

FIGURE 8. Determine the optimal path of experiment 2



(a) Real experiment (b) Path created by the robot

FIGURE 9. Experiment 3 with moving obstacles

In the experiment 3, when moving obstacle is placed in the path, the follower robot still finds the target with optimal value, without collision. The probability near with experiment 2 with a static obstacle (Figure 9).

TABLE 3.
Fuzzy-ACO performances

Exp	Path	Distance(div)	Pheromone	Probability	Optimal Path
1	1	29,8567	55	100%	Path 1 (100%)
	1	35,335	53	11,2%	
2	2	16,2895	48	42,6%	Path 3 (46,5%)
	3	12,4031	38	46,5%	
	1	29,8567	53	11,2%	
3	2	16,2895	48	42,6%	Path 3 (46,1%)
	3	25,4704	38	46,1%	

All the experimental results are resumed in Table 3. Artificial ants as a digital pheromone for path planning robot implement in randomize construction heuristic which makes the probabilistic decision. From all experiments, the Fuzzy-ACO produce a good performance for finding the target, success planning the path to the final position, move without collision and it has the globally optimal without stack in “local minima” when the robot move in clutter environment by using moving obstacle. When follower robot is active, it receives two signals from two sensors such as (i) active signal “1” from photodiode sensor and (ii) color weight from camera sensor as a digital pheromone. Two signals are selected only from optimal path. The follower only follows the trail of digital pheromone on the path. However, it produces the target position error when it moves, due to the follower doesn’t use fuzzy to avoid the obstacle based on the infra-red sensor. The target direction based on the pheromone on the path. The target position error from the follower robot is shown in Table 4.

TABLE 4.
Error position of follower robot to find the target

No	Target position error	
	X	Y
Experiment1	2,81%	1,19%
Experiment2	2,81%	1,19%
	0,40%	1,76%
	0,13%	1,16%
Experiment3	2,81%	1,19%
	0,40%	1,76%
	0,58%	3,49%
Error rate	1,59%	1,73%
Percentage of success	98,41%	98,27%

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4. CONCLUSION AND FUTURE WORKS

This paper presents a combination of meta-heuristic Fuzzy-ACO algorithm to find a globally optimal path planning method for the explorer-follower robot and also discusses the measures utilized to overcome the other challenges. It was implemented to simplify for making a decision control and reduce the computing workload without compromising the performance of the proposed algorithm. The validation of algorithm is tested by using experimental results with the real robot. The result found that the proposed algorithm is effective. The search time needed for generating the globally optimal path is just 20 second (experiment 3), which indicates that the proposed algorithm can be used in the real-time path planning. The algorithm produces less computational resource only 1 Kbytes. Moreover, the other performance obtained with a good result in terms of the robot move in the environmental without collision, and capable of finding the optimal path in a short time. In the future the ACO algorithm would be useful to find optimal paths within the mesh network, using frequency analysis rather than strict distances. We plan the real experiment with several robots and the results will be verified with other optimization method.

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