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Chen-Chien Hsu
Department of Electrical Engineering, National Taiwan Normal University, Taipei, Taiwan, R.O.C., jhsu@ntnu.edu.tw

Wei-Yen Wang
Department of Electrical Engineering, National Taiwan Normal University, Taipei, Taiwan, R.O.C

Yi-Hsing Chien
Department of Electrical Engineering, National Taiwan Normal University, Taipei, Taiwan, R.O.C.

Ru-Yu Hou
Department of Electrical Engineering, National Taiwan Normal University, Taipei, Taiwan, R.O.C.

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Chen-Chien Hsu, Wei-Yen Wang, Yi-Hsing Chien, and Ru-Yu Hou

Key words: ant colony optimization (ACO), pheromone diffusion mechanism, global path planning, field-programmable gate array (FPGA).

ABSTRACT

An improved ant colony optimization (ACO) algorithm is proposed in this paper for improving the accuracy of path planning. The main idea of this paper is to avoid local minima by continuously tuning a setting parameter and the establishment of novel mechanisms by means of partial pheromone updating and opposite pheromone updating. As a result, the global search of the proposed ACO algorithm can be significantly enhanced to derive an optimal path compared to the conventional ACO algorithm. The simulation results of the proposed approach perform better in terms of the short distance, mean distance, and success rate towards optimal paths. To further reduce the computation time, the proposed ACO algorithm for path planning is realized on a FPGA chip to verify its practicalities. Experimental results indicate that the efficiency of the path planning is considerably improved by the hardware design for embedded applications.

I. INTRODUCTION

Path planning is an important topic with navigation (Velagic et al., 2006; Lu et al., 2012; Lee et al., 2014) which has attracted much attention in recent years. In general, path planning can be formulated as: according to a given start node and a desired destination in known/unknown environments, a collision-free path is obtained. The path planning can be broadly divided into two categories: one is global path planning (Chesi and Hung, 2007; Tsai et al., 2011; Hsu et al., 2013; Azimirad and Shorakael, 2014; Hou, 2014; Hsu et al., 2016) which determines a feasible path in a global environment; the other is local path planning (Chu et al., 2012; Yu et al., 2013; Su et al., 2014) which uses sensors to detect obstacles and finds a local collisionfree path.

The researchers had developed several path planning methods, including A* algorithm (Bennewitz et al., 2002; Seo et al., 2009; Wang et al., 2015), D* algorithm (Ferguson & Stentz, 2005; Ferguson & Stentz, 2006; Guo et al., 2009), potential field method (Barraquand et al., 1992; Ge & Cui, 2002; Sahin Conkur, 2005), and swarm intelligence technique (Huang et al., 2014). The A* algorithm is a simple and efficient approach. However, the path built by A* algorithm may be too close to obstacles, and the robot might probably collide with obstacles in practical aspect. The D* algorithm not only provides the shortest path, but also recovers itself immediately when the environment changes. However, it results in heavy computational time. The potential field algorithm pre-processes the map and obtains the vector fields based on the directions to the destination. However, there exists a local minimal problem when it comes to concave obstacles. The swarm intelligence technique was originally inspired in social behavior in nature. It is suitable and popular for solving optimization problems. C. A. Sierakowski et al. (Sierakowski et al., 2005) proposed two case studies of swarm intelligence techniques to solve the problem of optimization of path planning in mobile robotics. In (Huang et al., 2014), a hybrid Taguchi deoxyribonucleic acid (DNA) swarm intelligence was developed for solving the inverse kinematics redundancy problem of six degree-of-freedom (DOF) humanoid robot arms.

The ACO algorithm is a member of the swarm intelligence algorithm family and is developed from observations of a social behavior of ants in nature. Recently, various researches (Wen et al., 2005; Tan et al., 2007; Shi et al., 2008; Porta Garcia et al., 2009; Cai et al., 2010; Tseng, 2015) combined intelligent methods with the ACO algorithm to build the globally optimal path. Porta Garcia et al. (Porta Garcia et al., 2009) presented a proposal to solve the problem of path planning for mobile robots. The selection of the optimal path relies in the criterion of ant colony optimization and fuzzy cost function evaluation. Wen

Paper submitted 07/19/16; revised 12/04/17; accepted 12/19/17. Author for correspondence: Chen-Chien Hsu (e-mail address: jhsu@ntnu.edu.tw).
Department of Electrical Engineering, National Taiwan Normal University, Taipei, Taiwan, R.O.C.

et al. (Wen et al., 2005) proposed an improved ant colony algorithm for low altitude penetration aircraft path planning. Tan et al. (Tan et al., 2007) used the MAKLINK graph theory, the Dijkstra algorithm, and the ant colony system to generate the globally optimal path of mobile robots. In (Tseng, 2015), an enhanced ant colony optimization (EACO) algorithm was proposed to improve the deadlock caused by the cliffs, insufficient exploration rates, and slower convergence rates in the three-dimensional map. In (Cai et al., 2010), a dynamic path planning algorithm based on biphasic ACO with fuzzy control in the environment was introduced. In (Shi et al., 2008), an ACO-PSO hybrid algorithm was demonstrated to resolve the path planning problem for deep-sea mining robots. However, the above methods fail to solve the local minimal problem.

To address the mentioned problem, this paper proposes an improved ACO algorithm for path planning, and the ability of global searching of the improved ACO algorithm can be significantly enhanced in building an optimal path. Simulation results reveal the proposed method performs excellently in path planning. Moreover, we realize the hardware circuit design for path planning based on the improved ACO algorithm on FPGA and build a human-machine interface by the LCD touch module (LTM) to complete an embedded system.

The rest of this paper is organized as follows: Section 2 describes the path planning using a conventional ACO algorithm. Section 3 exhibits the global optimal path search method based on improved ACO algorithm. The FPGA implementation of improved ACO algorithm is suggested in Section 4. The simulation and experimental results of the proposed method are offered in Section 5. Finally, conclusions are drawn in Section 6.

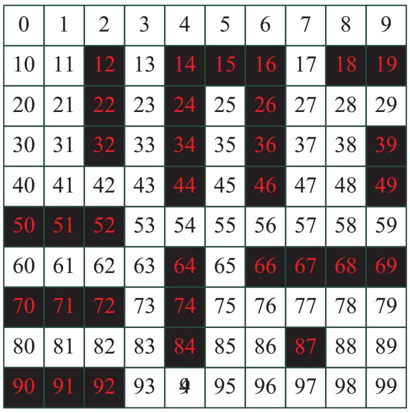


Fig. 1. A grid map example.

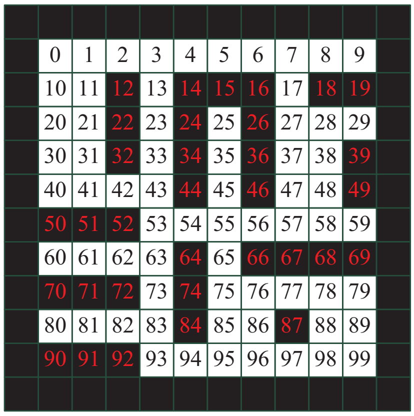


Fig. 2. Diagram of virtual obstacles.

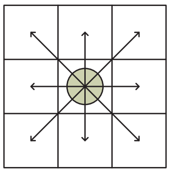


Fig. 3. Valid motion directions.

II. PATH PLANNING USING CONVENTIONAL ANT COLONY OPTIMIZATION (ACO) ALGORITHM

In this paper, the conventional ant colony optimization (ACO) algorithm is applied to detect the shortest and collision-free route. The environment is represented in a 2-D grid map. Firstly, individual ants follow thoughtless paths and achieve poor results. By cooperating with a large number of simulated ants, the superior paths can be found gradually.

1. Environmental Statements

A grid map is a popular medium to represent an environment, where a continuous space is represented by a collection of discrete nodes similar to a bitmap image. Fig. 1 shows a grid map of a dimension of 10×10 nodes representing an environment, where the white areas represent free spaces for a user to move and black ones represent obstacles. To prevent the robot from planning a path by using any node outside of the map, we create a virtual layer of nodes surrounding the original map as shown in Fig. 2, which can be regarded as obstacles during the path planning. When located on the center node, a user can move toward eight potential directions as shown in Fig3.

2. Description of Conventional Ant Colony Optimization (ACO) Algorithm

The conventional ant colony optimization is an algorithm based on the behaviors of ants searching for food, and it is utilized to solve the optimization problem such as the traveling salesman problem (TSP) (Laumond, 1987; Dorigo and Gambardella, 1997; Gong and Ruan, 2004). The ant system (AS) is the first proposed theory in the development of ant algorithm. It is also the basis of other ant models. While walking, ants communicate with each other by a chemical substance called pheromone, which they deposited along the path. The path travelled down by more ants, the more pheromone will be left on the path. The amount of the pheromone on the path is related to how the following ants choose their next step. In other words, the following ants tend to choose nodes with heavier pheromone. In ant system, each ant builds a path according to probabilistic rule at first. Ants tend to move to nodes closer to the destination, which have a greater amount of pheromone. Secondly, after all ants complete their tours, a pheromone updating rule is applied, and it includes two parts: evaporation and deposit. The two processes continue until a given maximal number of iterations is reached.

The ant colony system (ACS) was proposed to improve AS for better performances (Dorigo, 1996; Dorigo and Gambardella, 1997). The AS consists of three different parts, namely, probabilistic transition rule, global pheromone updating, and local pheromone updating. There are two main steps for path planning using ACS, namely choosing node and adjusting pheromone.

1) The Rule of Choosing Node

The ants choose the next node j by a probabilistic state transition rule given by (1).

$$j = \begin{cases} \arg\max_{j \in N_i^k} \left\{ \left(\tau_j\right)^{\alpha} \times \left(\eta_{jD}\right)^{\beta} \right\}, \text{ if } q \le q_0 \\ p_j^k, \, otherwise \end{cases} \tag{1}$$

where q is a random number in [0,1], q_0 is a design parameter which determines preference for exploration and exploitation. η_{jD} is the inverse of the distance between node j and destination D. When the distance is shorter, η_{jD} is larger, which means that node j is likely to be the next for ants to move on. τ_j presents the amount of the pheromone of a node j and will be changed over time. α and β are designed parameters which determine the relative importance between pheromone and the distance. If $\alpha = 0$, then the ants will choose a node which is the closest to the destination as the next node without being affected by pheromone. As well, if $\beta = 0$, a node according to pheromone will be chosen. The values of α and β are determined by trial and error, where β is larger than α in general. Because of the state transition rule, there are two behaviors of the ACS to balance between the exploration of new edges, the exploitation of a priori, and the accumulated knowledge about the problem (Dorigo and Gambardella, 1997).

When q is smaller than q_0, the most attractive node, which has the greatest amount of pheromone, will be decided by ants, and is the closest to the destination as the next node. The behavior for building a path based on a priori and accumulated knowledge from the previous generation is called exploitation.

When q_0 is smaller than q, a node p_j^k is chosen through the state transition rule given by (2), which is the same as the random-proportional rule in ACS.

$$p_j^k = \frac{(\tau_j)^{\alpha} (\eta_{jD})^{\beta}}{\sum_{j \in N_i^k} (\tau_j)^{\alpha} (\eta_{jD})^{\beta}} \tag{2}$$

$$\eta_{jD} = \frac{1}{d_{jD}}, \, d_{jD} = \sqrt{(x_j - x_D)^2 + (y_j - y_D)^2} \tag{3}$$

where p_j^k is the probability of choosing the node j for the next node by an ant k. (x_j, y_j) is the coordinate of the node j, and (x_D, y_D) is the coordinate of the destination D. Obviously, nodes with greater pheromone and shorter distance hold higher probabilities. By doing so, we favor the choice of a node p_j^k with a shorter distance to the destination and a greater amount of pheromone through the probabilistic process, rather than solely choosing the node with the highest probability for the next move. The shortest path called the globally best path L^+ is constructed after all ants finished the tour.

$$L^+ = \min_k \left\{ L^k \right\} \tag{4}$$

where L^k represents the distance of a tour built by ant k. L^+ is the shortest distance of the current generation.

2) The Rule of Adjusting Pheromone

The pheromone updating is performed after all ants arrived at the destination. It includes two main parts: evaporation and deposit.

A fraction of the pheromone evaporates on all nodes according to an evaporation function shown in (5).

$$\tau_i \leftarrow (1-\rho)\tau_i, \, \rho \in (0,1) \tag{5}$$

where ρ is the evaporation rate and τ_i presents the amount of pheromone of the node j. As a result, pheromone over-accumulation and consequent local minima problem can be prevented.

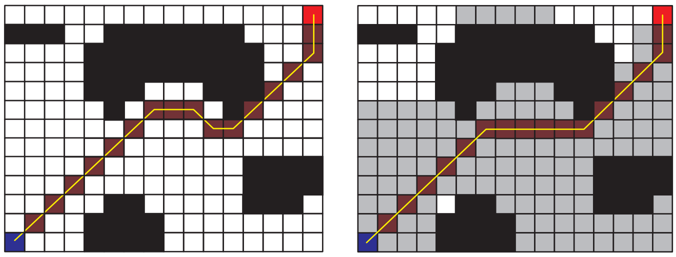
The ACS includes local updating and global updating. The global updating means that pheromone will be deposited on the only global best path. That is, only the ant that has the best performance can deposit pheromone. This helps ants to find the shortest path quickly. Eq. (6) shows the updating function combining evaporation and deposit.

$$\tau_i \leftarrow (1-\rho)\tau_i + \rho \Delta \tau_i^{best} \tag{6}$$

$$\Delta \tau_i^{best} = \frac{Q}{L^+} \tag{7}$$

where Q is a designed parameter that is relative to the speed of convergence. The local updating, on the other hand, is defined as:

$$\tau_i \leftarrow (1-\rho)\tau_i + \rho \tau_0 \tag{8}$$



(a) With local minima problem (b) Without local minima problem

Fig. 4. Path planning.

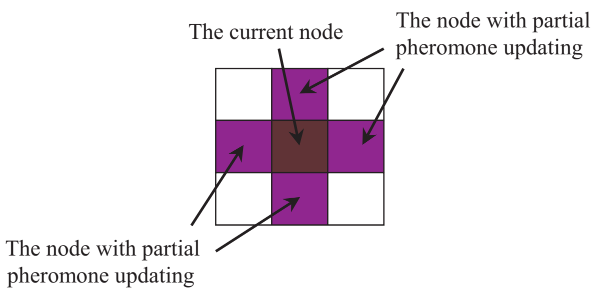


Fig. 5. Diagram of partial pheromone updating.

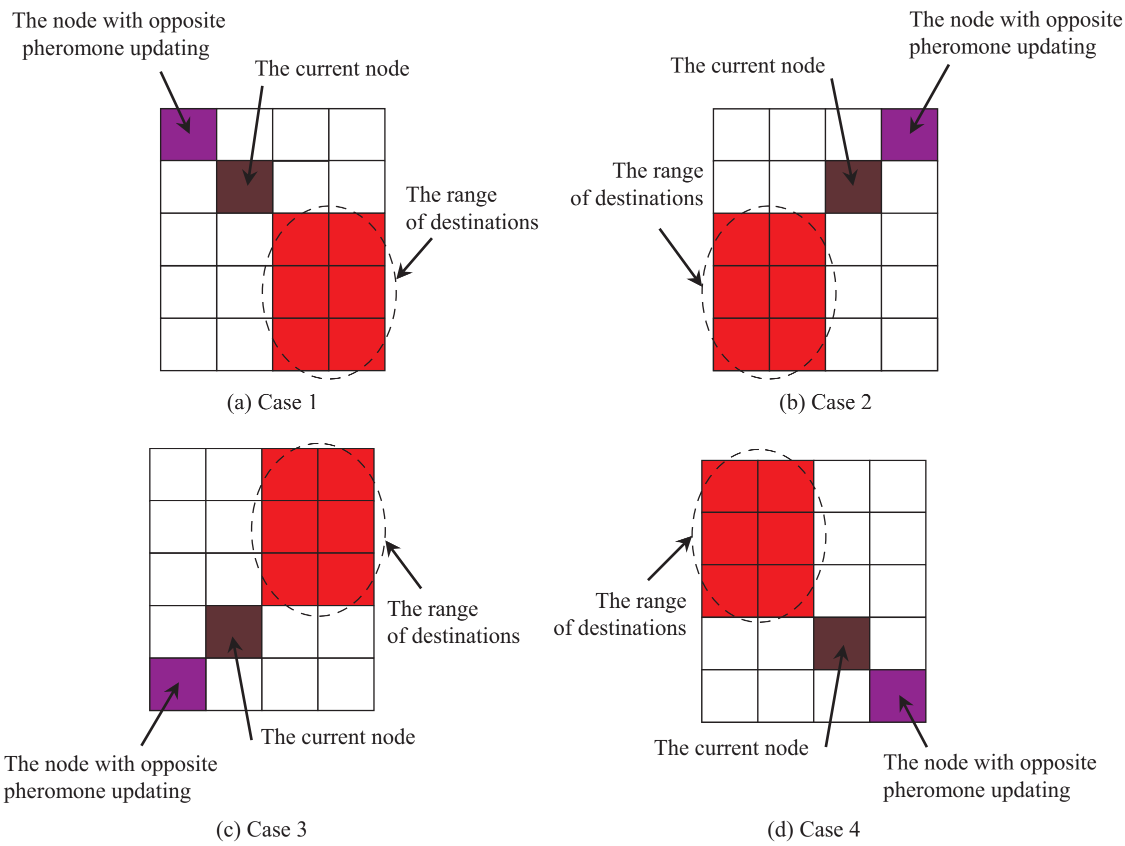


Fig. 6. Diagram of opposite pheromone updating.

where τ_0 is the initial pheromone. In other words, pheromones will be updated every time when ants move to the next node, allowing the ants to explore promising paths and avoid searching for a narrow range of the best previous path.

III. GLOBALLY OPTIMAL PATH SEARCHING METHOD BASED ON IMPROVED ACO ALGORITHM

In conventional ACO algorithm (Dorigo, 1996), the global updating mechanism adversely results in a large difference in the pheromone amount among nodes because the pheromone is deposited only on the global best path. Therefore, an ant might over-follow the globally best ant, leading to a local minimum. Figs. 4(a) and (b) display the path planning with and without the local minima problem, respectively. The blue and red nodes mean the original and destination nodes, and the black nodes reflect the obstacles. The yellow line, made up of the brown nodes, represents the planned path. In this section, we propose an improved ACO algorithm by applying two pheromone updating mechanisms. The first one is to update pheromones for nodes around the globally best path, whereas the other is to update pheromones for nodes on the opposite side to the destination of the globally best path.

1. Partial Pheromone Updating

To address the local minima problem, this paper proposes two pheromone diffusion mechanisms, including partial pheromone updating and opposite pheromone updating. Fig. 5 illustrates the diagram of partial pheromone updating. The brown node means the current node and the pink nodes signify the partial pheromone updating is performed. It should be noted that pheromone updating does not apply to the eight directions of nodes around the globally best path because it can cause over-exploration and result in a local minimum. Therefore, only four directions are utilized for partial pheromone updating.

2. Opposite Pheromone Updating

Besides, an opposite pheromone updating mechanism is utilized to prevent ants from directly choosing the node closest to the destination. Fig. 6 illustrates the opposite pheromone updating rule, composed of four cases. The red nodes represent the range of destinations, brown node is the current node, and the pink nodes imply opposite pheromone updating.

3. Deadlock of Path Planning

To prevent a deadlock from planning path, visited nodes are sequentially recorded in a prohibited list while ants are moving. Ants cannot choose nodes in the list to avoid deadlock led by repeating visiting nodes, as shown in Fig. 7. Although the prohibited list can prevent repeatedly visiting the same nodes, another problem arises in which ants might be trapped in a U-type environment as shown in Fig. 8. To avoid the deadlock, ants need to move backward sequentially until they find a feasible node. For example, an ant is trapped in node 25 and it has nowhere to go forward, as shown in Fig. 8. Then it goes back sequentially via node 35 and node 45. At last, it stops at node 45 when it finds that node 56 is feasible for continuing the tour.

Fig. 9 unveils the flowchart of the improved ACO algorithm for path planning. Given a grid map, we firstly initialize the parameters and place the ants at the start. A number of feasible

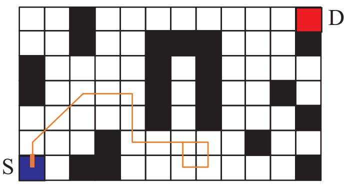


Fig. 7. The loop situation.

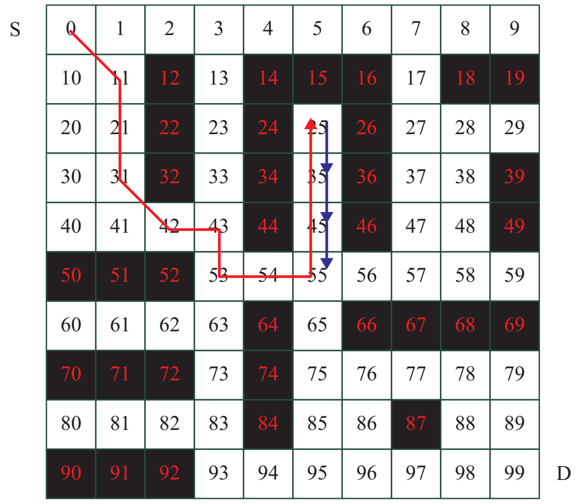


Fig. 8. The deadlock situation in U-type environment.

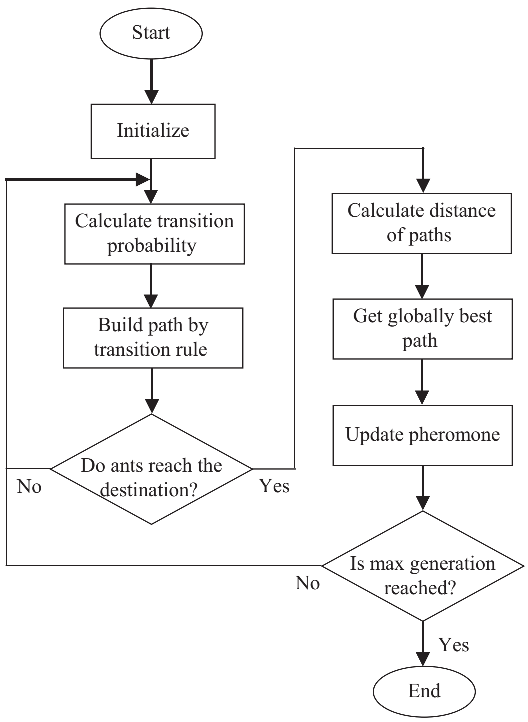


Fig. 9. The flowchart of the improved ACO algorithm for path planning.

nodes are regarded as obstacles for collision avoidance by the obstacle extension mechanism. Ants construct a path through probabilistic state transition rule. The global best path is gener-

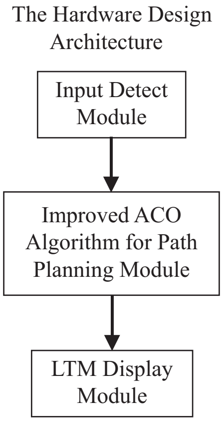


Fig. 10. The hardware design architecture.

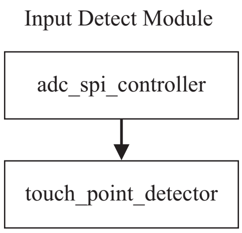


Fig. 11. Input detect module.

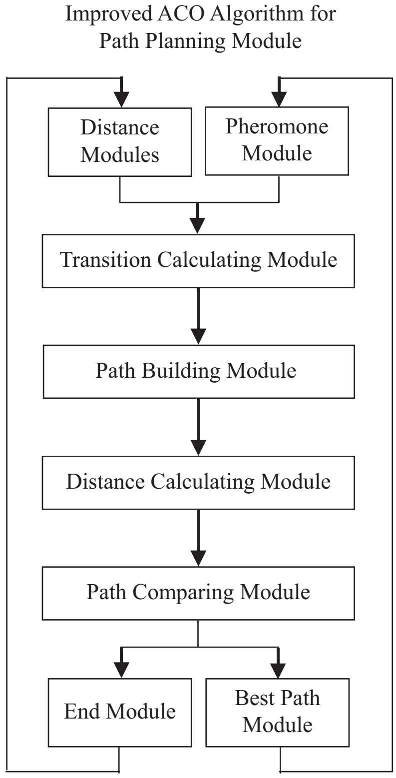


Fig. 12. Improved ACO algorithm for path planning module.

ated when all ants reach the destination. Pheromone updating, including partial and opposite pheromone updating, is performed for the next generation. Ants are placed at the start again. The algorithm then repeats the above process continuously until the maximal number of generations is reached.

IV. HARDWARE DESIGN FOR PATH PLANNING BASED ON IMPROVED ACO ALGORITHM

We implement the proposed algorithm on a DE2-70 development platform combined with a human-machine interface to realize the optimal path planning algorithm. Fig. 10 shows the hardware design, architecture, where the modular design is used to construct the major components, including an input detect module, an improved ACO algorithm for path planning module, and a LTM display module. The input detect module is utilized to detect the positions of the start point and the destination through user touch on the screen. Then the improved ACO algorithm for path planning module begins to plan an optimal path according to the signal from input detect module. The LTM display module is utilized to display the map image and show the results of the path on the LCD screen. More details of these modules will be discussed as follows.

1. Input Detect Module

The input detect module includes adc_spi_controller and touch_point_detector shown in Fig. 11. The main function of adc_spi_controller is to output the information of x and y coordinates of the positions touched by the users on the screen. Then the touch_point_detector will determine the work according to the information from the adc_spi_controller.

2. Improved ACO Algorithm for Path Planning Module

The improved ACO algorithm for path planning module includes distance modules, pheromone module, transition calculating module, path building module, distance calculating module, path comparing module, best path module, and end module. Fig. 12 sets forth the functional blocks of the Improved ACO algorithm for path planning module. The distance module is employed to calculate the distances between each node and destination. Then the distance data is stored in RAM. The pheromone module is applied to store the pheromone of each node on the map to RAM and implement pheromone updating after a generation is finished. The transition calculating module calculates the transition probability after receiving the distance data and pheromone data. The path building module builds the path using the transition probability thereafter. According to the transition rules, the path building module consists of two behaviors: exploitation and exploration. Those two behaviors generate the next node respectively, and the next final node for an ant to go to is chosen by picking a random number. When the next node is produced, the distance calculating module calculates the distance of the path that an ant had walked. Until the ant arrives at the destination, the path comparing module compares the distance of the path to get the optimal path. The best path module is utilized to record the nodes on the optimal path

Table 1. Comparison of shortest distance.

Case	Start/Destination nodes	Using conventional ACO algorithm	Using the proposed ACO algorithm
Case 1	329/962	476.98	464.55
Case 2	329/766	320.77	320.77
Case 3	330/677	455.77	418.49
Case 4	976/61	629.55	617.13
Case 5	976/40	531.83	531.83
Case 6	976/677	460.91	448.49

Table 2. Comparison of mean distance.

Case	Start/Destination nodes	Using conventional ACO algorithm	Using the proposed ACO algorithm
Case 1	329/962	502.15	483.68
Case 2	329/766	326.13	324.28
Case 3	330/677	474.08	438.99
Case 4	976/61	655.58	642.56
Case 5	976/40	543.05	536.10
Case 6	976/677	489.69	459.68

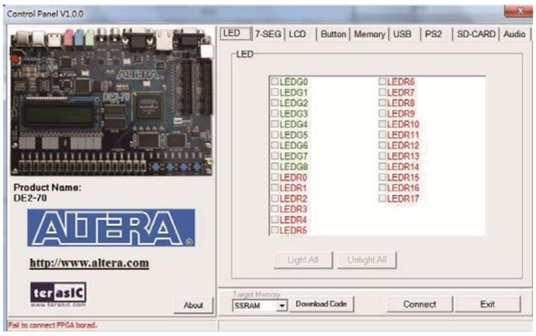


Fig. 13. The control panel.

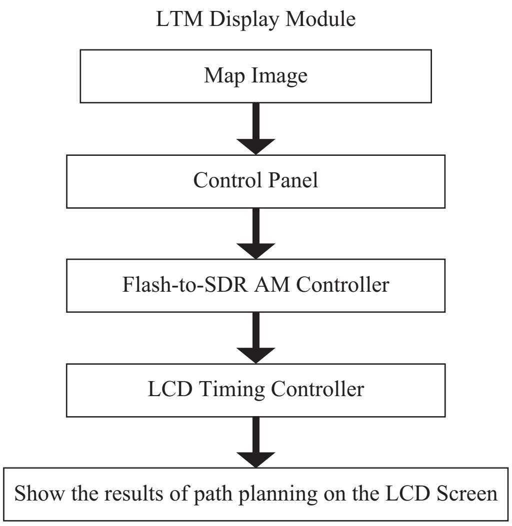


Fig. 14. LTM display module.

for pheromone updating. The end module will send a signal pulse to other modules for initialization when a tour building is accomplished.

3. LTM Display Module

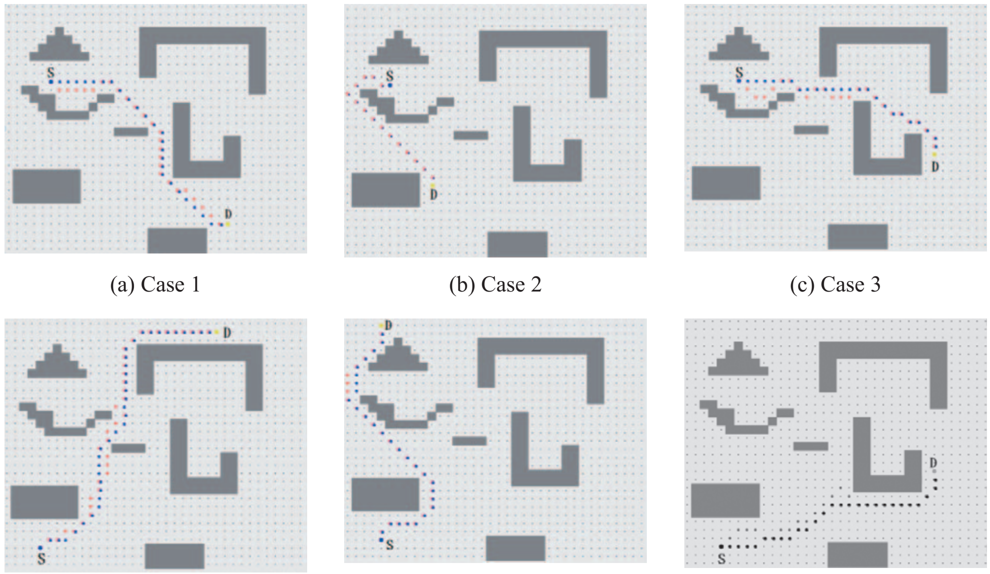
At first, the map image stored in the flash memory is manifested on the control panel, which is an application provided by Altera. It connects the DE2-70 platform with computer. Fig. 13 shows that we can control the component of DE2-70 platform via the interface on the computer. The flash-to-SDRAM controller is utilized to store the data of the map from flash to SDRAM for other modules to use, including head file, RAW data, RGB data etc. The LCD timing controller determines the display timing of image and RGB transformation. Several steps in LTM Display module are demonstrated in Fig.14.

V. SIMULATION AND EXPERIMENTAL RESULTS

In this section, simulation examples include two kinds of comparisons to illustrate the effectiveness and applicability of the proposed method. At first, we compare conventional ACO algorithm with the improved approach in terms of path length. The software environment is Visual Studio 2008 with OpenCV 2.2.1 library. Secondly, to compare the performance gained by the algorithm based on a hardware circuit design, we implement the improved ACO algorithm for path planning with a software design solely written in NIOS II and a hardware design in the Verilog language. Moreover, a DE2-70 development board by Altera is utilized as an experiment platform for evaluating the performance of the design and implementation of the improved ACO algorithm.

1. Comparisons of Path Length between Conventional and Improved ACO Algorithm

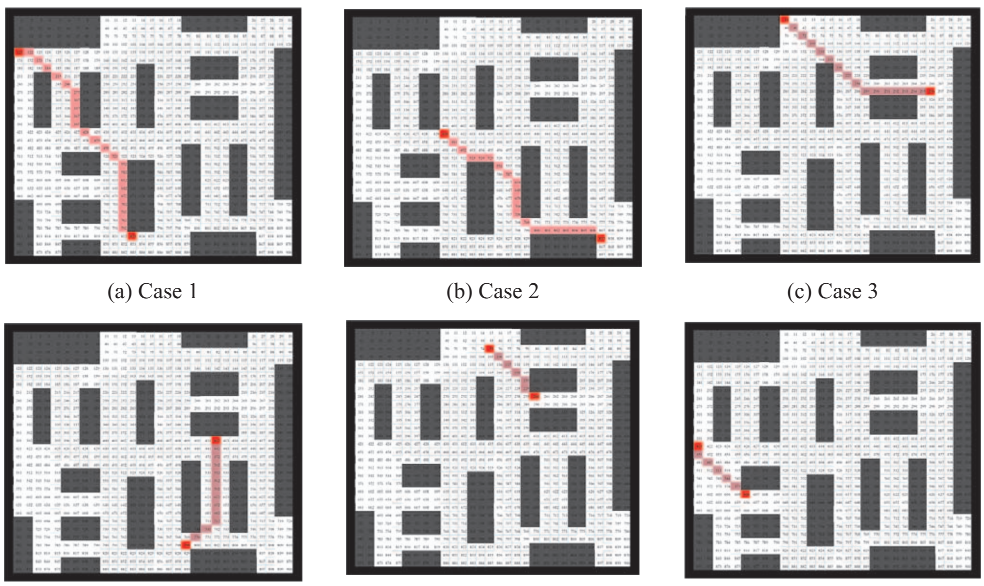
In the simulation, we design a grid map that has a dimen-



(a) Case 1 (b) Case 2 (c) Case 3

(d) Case 4 (e) Case 5 (f) Case 6

Fig. 15. Path planning by conventional and improved ACO algorithm.



(a) Case 1 (b) Case 2 (c) Case 3

(d) Case 4 (e) Case 5 (f) Case 6

Fig. 16. Simulation results of path planning using improved ACO algorithm.

sion of 32 × 36 nodes and 60 ants are utilized in the experiment. α and β are selected as 1.0 and 5.0, respectively. The evaporation rate ρ and the constant Q are selected as 0.5 and 300, respectively. The conventional and improved ACO algorithms both run 1,500 generations. There are six cases for pairs of different starting and destination nodes. All the nodes are evenly distributed on the map and the distance between any two adjacent nodes is normalized to 1 (or 1 unit block). Thus, the path length is represented in terms of the number of unit blocks. The optimal path is the shortest distance from the start node to the destination node. Fig. 15 exhibits the simulation results of path planning by the conventional and improved ACO algorithm for six cases, where *S* and *D* indicate the start and destination, respectively. The red path is generated by the conventional ACO algorithm and the blue one is generated by the proposed approach. It is observed that the desired paths can be obtained by using the proposed approach. Besides, the simulation is executed for forty times to calculate the shortest distance and mean distance. Tables 1 and 2 reveal the simulation results for comparisons between the conventional and improved ACO algorithm.

Table 3. Comparisons of execution time between hardware and software design.

Case	Start/Destination nodes	Software design	Hardware design	Performance improvement
Case 1	121/823	13,377.66 ms	20.39416 ms	655×
Case 2	430/837	9647.545 ms	19.91856 ms	484×
Case 3	10/296	8300.585 ms	18.3741 ms	451×
Case 4	799/412	5236.364 ms	17.89496 ms	292×
Case 5	75/260	3762.713 ms	16.59286 ms	226×
Case 6	421/606	3538.006 ms	16.59035 ms	213×

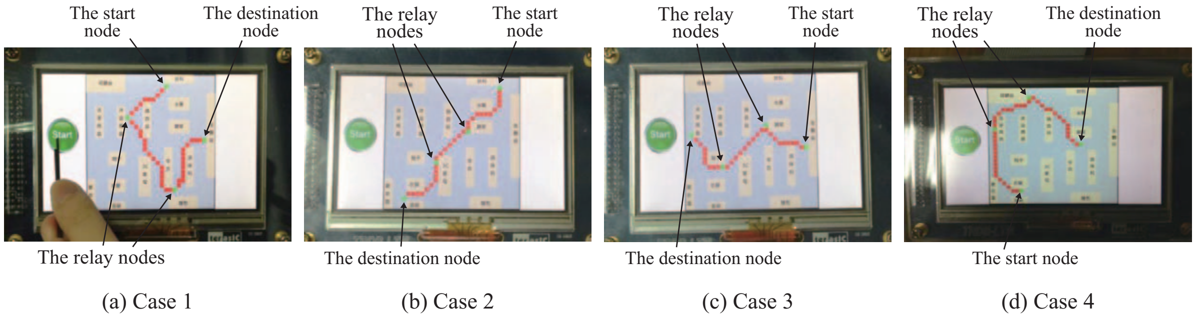


Fig. 17. FPGA implementation of path planning using improved ACO algorithm.

It is noticed the improved ACO algorithm overcomes the problem of local minimum encountered by conventional ACO algorithm. Consequently, the improved ACO algorithm is favorable in terms of shortest and mean distances for cases 1 to 6 through 40 independent simulations.

2. Comparisons of Execution Time between Hardware and Software Design

Secondly, the improved ACO algorithm is utilized to plan a path by pure software design with NIOS II and pure hardware design with Verilog language. There are six cases for pairs of different start and destination nodes. Twenty independent simulations are performed for path planning by pure software design and pure hardware design respectively. Fig. 16 reflects the results of paths planning by the proposed algorithm. Table 3 shows that the consuming time of pure hardware design is much less than the pure software designs. It is proved that the hardware design not only exactly enhances the performance, but also significantly increases the improvement in the longer path planning. That is because the distance of the path is calculated after the ants finish the tours in software flowchart. In hardware, the distance of the path is calculated when ants walk to the next node at the same time. It is evident that the much more time is consumed by pure software design.

3. FPGA Implementation with DE2-70 of Improved ACO Algorithm

In the experiment, we use a market map to illustrate the effectiveness of the proposed ACO-based path planning algorithm and its FPGA implementation with the DE2-70 platform. There are four cases for the different start, relay, and destination nodes shown in Fig. 17. The user can touch the positions they want to visit and then press the "Start" button to search a globally optimal path. The green nodes are the positions touched by the user, and the red nodes represent the globally optimal path. By the experiments, the feasibility of the proposed method is illustrated.

VI. CONCLUSIONS

This paper proposes an improved ant colony optimization (ACO) algorithm for path planning by establishing two pheromone updating mechanisms including partial pheromone updating and opposite pheromone updating. The simulation results of path planning convey that the improved ACO algorithm is qualified to solve the problem of optimizing to a local minimum. To further accelerate the computational speed of the path planning, the improved ACO algorithm is implemented on a FPGA chip. Furthermore, a real-time path planning embedded system with a DE2-70 platform by hardware design is established. Finally, a map mimicking a supermarket floor plan is utilized as an example to implement path planning for solving daily life problem. By touching the positions of merchandise on the screen of DE2-70 platform, users can get the shortest path between the merchandise to avoid wasting time on looking for the objects.

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