Path Planning of the Fire Escaping System Using Active Detection Module

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Article Info

Article history:

Received Oct 19, 2016
Revised Dec 16, 2016
Accepted Jan 2, 2017

Keyword:

A* algorithm
Air-fuel mass ratio
Path planning

ABSTRACT

This article proposes a security system which detects the fire events and plans the moving route. Each robot with several modules owns the shape of cylinder and height, weight and diameter is 18 cm, 1.5 kg and 8 cm. A main controller (STC12C5A60S2) equips robots as a microprocessor. Each robot has the capability to escape from the fire scene. Whenever detecting fires and obstacles using image sensor and reflective IR sensors, robots send the ID code, orientation, and position to the centralized computer and other robots. After other robots have confirmed the fire events, the centralized computer uses the Gaussian probability function to calculate the danger values of the surrounding points near the fire source. And Bayesian estimation method is applied to compute the total estimated value of each point in platform. Furthermore, the total weighted values of all points are shown in a platform and its aim is to enlarge the difference between danger and safety without ambiguity. A* algorithm is used in the escaping routes are planned by a centralized computer. The mobile robot follows the leading of the supervised computer autonomously to escape from dangerous areas. The air-fuel ratio and the rate of increasing in temperature with distance are directly proportional to the danger value. Associating the increasing temperature rate with three-fire sources, it is verified to be an efficient system.

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1. INTRODUCTION

There are multiple sensors for people, i.e., tongue, nose, skin, ears, and eyes, responsible for environmental variation [1]. Inspired from multisensory usefulness, intelligent robots with sensitive sensors of acoustic signal, heat and light will enhance the strength of detecting fire events immediately. Whenever a fire takes place, environmental parameters change, resulting in bringing excessive heat, abnormal acoustic signal, smoke, UV (ultraviolet) intensive light, and so forth. Liu et al. proposed the concept of integrating the fire detection system with multi-function sensors and an alarm system with wireless technology to not only increase fire safety but also reduce false alarms [2]. Sonsale et al. proposed a multi-sensor system with a fire-detection function and a fire-extinguishing function [3]. Zhang and Wang designed an automatic fire alarm system based on a periodical wireless sensor network by measuring the smoke concentration and deploying temperature in the building [4]. Calavia et al. proposed a system designed to minimize video processing and transmission, which can detect abnormal objects and alarming situations by analyzing object movement [5]. In particular, Wang et al. proposed the multisensory system in line with the next generation of fire detection technology [6]. Recently, Yang and Zhuang proposed a behavior control of robot to enhance the capacity of robot especially to avoid obstacles which improved the efficiency of path planning for security system [7]. Apart from IC technology, wireless communication is adopted as another trend.

As for the analysis algorithm of measured data, data fusion is often used in these applications. For data fusion algorithms, there are the Dempster-Shafer evidence method [8], logic filter [9], Bayesian estimation method [10], Neuro network, fuzzy controller, and so on. Further, Neuro fuzzy inference system [11] was widely used to show the efficiency in the related fields of robotics. In this article, the centralized computer keeping tracking of mobile robots is a heavy loading. Radio Frequency Identification (RFID) [12] provided the powerful technique as a remedy to deal with location determination of mobile robots. Guo et al. used the Bayesian estimation method to compute the estimated value of interacting points standing for different levels of danger, found the shortest escaping path, and guided people to escape from the fire scene [10]. But in real cases, such 1-D risk values are not sufficient to determine the distribution of heat of the fire, because the heat decreases from fire center to the surrounding uniformly. As a remedy, the Gaussian 2D discrete mass function is useful to provide enough information about the heat-distribution phenomenon. In light of this, this article develops the heat-distribution model adopting the Gaussian 2D discrete mass function in our system. Furthermore, experimental results are shown to validate the system with better reliability and efficiency.

2. SYSTEM ARCHITECTURE

The system architecture is illustrated in Figure 1, which is composed of a centralized computer, three mobile robots with modules. The communication technology between the centralized computer and the robots is RF transmission technology, eliminating the need of cumbersome cable lines. Robots A and B actively patrol for fire sources autonomously, and robot C follows the command from the centralized computer to leave the fire scene. Robot A detects the left half of the platform and robot B is responsible for the right half at the same time

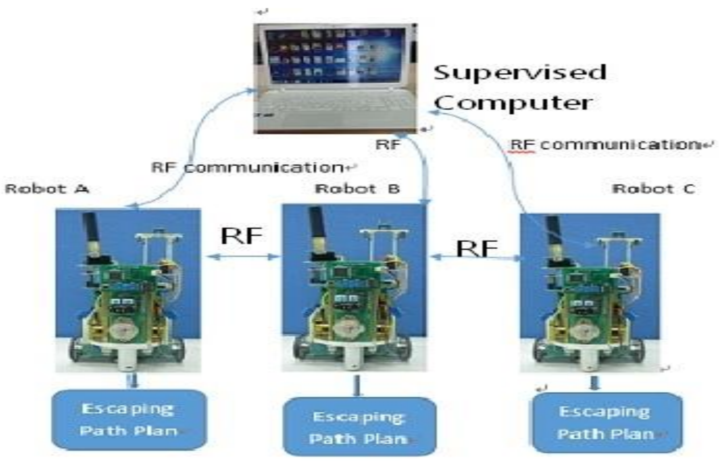


Figure 1. System architecture

All robots with multiple modules which are IR, flame sensor, RF and encoder module is shown in Figure 2. In IR module, there are five CNY70 and three IR sensors embedded in mobile robots to detect obstacles. To make sure it's collision-free in system, we put the three reflective IR sensors with effective detecting length between 10cm and 40cm on the right side, front side and left side to detect obstacles. The image sensor, R2868, is used to detect fire source in flame sensor module.

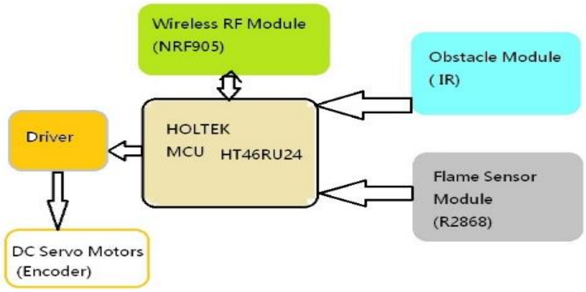
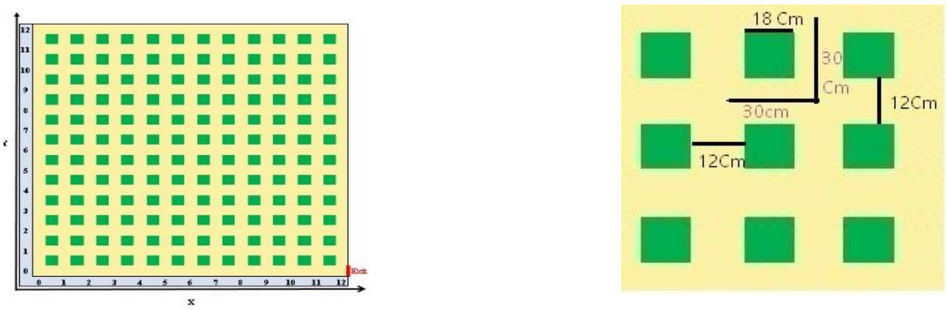


Figure 2. Block diagram of robot

The moving distance on the experimental platform is calculated by the encoder module of the DC servo motor. All the robots patrol the platform autonomously. As soon as a fire event or obstacle is detected, the robot sends real time signals of ID code, location, and orientation to the supervised computer and other robots. Whenever the supervised computer receives a fire alarm signal from the robots, it demands other robots to perform the recheck task and determine whether the fire event is happening or not. The robot search the entire platform as shown in Figure 3 (a) for all the fire sources, which is then used to display the real time status of the shortest escaping path with 13 X13 grids. The format of each grid is shown in Figure 3 (b).



(a) Platform diagram (b) Cell diagram

Figure 3. 2D Experimental platform

3. ALGORITHM ANALYSIS

3.1. Gaussian 2D Discrete Probability Function

The Gaussian function is normal distribution and presents near bell-shaped graph. The Gaussian function is a smoothing operator and belongs to a symmetric function. In the 2 dimensional space, Gaussian probability function is defined as below (1):

$$g(x,y)=\frac{1}{2\pi\sigma^2}e^{-\frac{x^2+y^2}{2\sigma^2}} \tag{1}$$

where : x: the displacement from the origin in horizontal direction
y: the displacement from the origin in vertical direction
σ: standard deviation

The Gaussian 2-D filtering of kernel coefficients are sampled from the Gaussian 2-D discrete mass function. The Gaussian convolution coefficients are sampled from the 2-D Gaussian function as shown in Equation 1. The 5 X 5 kernel coefficients of discrete approximation to Gaussian filter is listed in Table.1 which the value L1 of center is the largest one, L2 is the second, L3, L4… and so on. The danger value decreases from the center to outside surrounding gradually.

The Gaussian filter f(x, y) is part of the spatial filters and is also called spatial convolution. Assuming the source information to be I(x, y), after convoluting, we can get the convoluted information g(x, y). This operation is the convolution presented in Equation (2).

Table.1 Convolution Coefficients of Discrete Approximation to Gaussian Filter

L6	L5	L4	L5	L6
L5	L3	L2	L3	L5
L4	L2	L1	L2	L4
L5	L3	L2	L3	L5
L6	L5	L4	L5	L6

$$p(d) = g(i,j) = \sum_{m=-\frac{M}{2}}^{\frac{M}{2}} \sum_{n=-\frac{M}{2}}^{\frac{M}{2}} I(m,n)\, f(i-m, j-n) \qquad (2)$$

In steading of probability density functions, these discrete variables are the probability mass function which is the probability to represent the dangerous value satisfying the properties of $0 \le p(d) \le 1$

and $\sum_{j=1}^{n}\sum_{i=1}^{n} p(d) = 1$.

Bayesian estimation method provides a rule of formalism to merge sensory information of multiple sensors according the probability theory. The conditional probability, P(Y|X), exists in the range of 0 and 1. Bayes' rule is the basis of Bayesian algorithm (3):

$$P(Y \mid X) = \frac{P(X \mid Y)P(Y)}{P(X)} \qquad (3)$$

where X is the given information, hypothesis Y and we calculate the posterior probability, P (Y|X) according to the X and Y. The posterior probability is computed by multiplying the prior probability associated with Y, P(Y), by the likelihood for P(X|Y) shown in Equation (4) using X and Y.

The redundant information can be merged using likelihood ratio formulation and the odds of Bayes' rule. The information denoted as X_i relating Y from S_i is characterized by P (X_i|Y) and the likelihood P(X_i |-Y) given the negation of Y, or by the likelihood ratio (4):

$$L(X_i \mid Y) = \frac{P(X_i \mid Y)}{P(X_i \mid -Y)} \qquad (4)$$

Defining the prior odds on Y as below (5):

$$O(Y) = \frac{P(Y)}{P(-\mathrm{Y})} \qquad (5)$$

Each sensor is independent mutually to the other sensors. From the information X1, X2….Xn of the n sensors, the posterior odds on Y given by the product of likelihood shown as below (6):

$$O(Y \mid X_1, X_2 ... X_n) = O(Y)\prod_{i=1}^{n} L(X_i \mid Y) \qquad (6)$$

The posterior odds are related to the posterior probability by (7):

$$\mathrm{P(Y|X_1}, X_2.....X_n) = \frac{O(Y \mid X_1, \mathrm{X}_2 ... X_n)}{1 + O(Y \mid \mathrm{X}_1, X_2 ... X_n)} \qquad (7)$$

We take an example to compute the danger value of all point for fire event Y. The fire event is happened as two fire sources defined X_1 and X_2. We compute the danger probability values of point for two fires sources as P (X_1|Y) = 0.75 and P (X_2|Y)=0.25. We calculate the posterior odds and posterior probability of the point (8-9),

$$O(Y \mid X_1, X_2) = \frac{P(X_1 \mid Y)}{P(X_1 \mid -Y)} \frac{P(X_2 \mid Y)}{P(X_2 \mid -Y)} \tag{8}$$

= (0.75/0.25) (0.25/0.75)=1

$$\mathrm{P}(\mathrm{Y}|\mathrm{X}_1, X_2) = \frac{O(Y \mid X_1, \mathrm{X}_2)}{1 + O(Y \mid \mathrm{X}_1, X_2)} \tag{9}$$

$$= \frac{1}{1+1} = 0.5$$

The posterior probability value is 0.5 for the point. And we need to calculate the values of posterior probability for the rest points of platform.The increasing temperature (△T) with distance variance (△X), $\frac{\Delta T}{\Delta X}$, and the air-fuel mass ratio are directly proportional to the danger values. The lower the value of $\frac{\Delta T}{\Delta X}$ is, the safer it is. An increase in the value of △T, change in temperature, means it is closing in on the fire source. If $\frac{\Delta T}{\Delta X} < 0$ it is safe, otherwise, it is dangerous-closing in on the fire source.

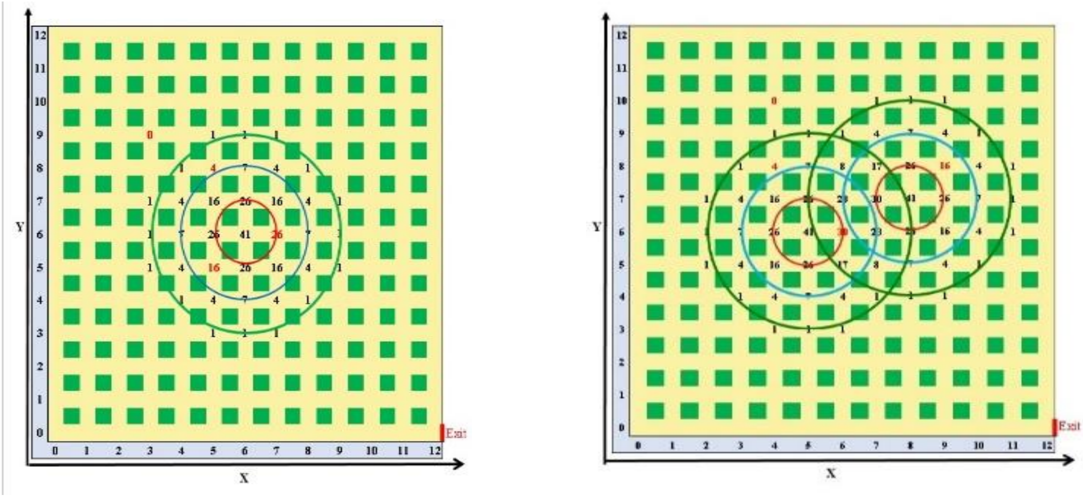
3.2. Joint Probability

In a real case scenario, it is possible for several fire events to happen simultaneously. We use joint probability to represent the danger values of points within the interacting area for several fire events. For all fire events, they are mutually independent to each other. Thus, when two fires sources interact, the probability of the danger values change. F_1 and F_2 stand for fire source 1 and fire source 2. And the P(F_1) represents the probability of the danger value for F_1. After interacting, the final probability of the danger value is calculated using Equation (10).

$$\begin{aligned} P(F_1 \cup F_2) &= P(F_1) + P(F_2) - P(F_1 \cap F_2) \\ &= P(F_1) + P(F_2) - P(F_1) \cdot P(F_2) \end{aligned} \tag{10}$$

Figure 4 shows the distribution of the nonzero danger values for each point in the platform while others stand for zero if it does not show anything. All the probability values shown in Figure 4 should be divided by 273. From Figure 4 (b), the center of fire source one and two are points (5, 6) and (8, 7) respectively. Totally, there are 8 points within the interaction area, and the coordinates are (7, 7), (6, 6), (6, 7), (7, 6), (6, 5), (7, 8), (7, 5), and (6, 8). After interacting, the new danger values of the points listed above are updated using Equation 4. The points (7, 7) and (6, 6) are on level_2 in Table 3 which means the new danger value is 30/273. The (6, 7) and (7, 6) points are on level_4 which means the new danger value is 23/273. Also, (6, 5) and (7, 8) are on Level_5 which means the new danger value is 17/273. The last pair is (7, 5) and (6, 8), which are on Level_7, meaning the new danger value is 8/273. For example, the new value of (7, 7) is P(F1)+P(F2)-P(F1)·P(F2)= (26+4-26*4/273)/273=30/273.

The platform is drawn in three different radium circles, i.e., r, 2r and 3r, which stand for different danger levels. The most dangerous node is the center of the red circle and it is safe if the distance of the point is beyond the 3r circle from the center where the danger value is zero.



(a) Single fire source (b) Double fire source

Figure 4. Distribution Example of Danger Values with μ=0 and σ=

3.3. Weighted Estimation Value t(n)

The values listed in Table 1 are all the danger values of coordinates. In order to emphasize the difference between danger and safety, we use the weighted value t(n) of danger values divided by level_5 or level_9 for single source fire events or two source fire events.

For single source fire event, the weighted value t(n) is obtained using Equation (11). And the listing of weighted values is shown in Table 2. For two source fire events, the weighted value t(n) is calculated using Equation (12). Further, the new danger value after interacting are listed in Table.3.

$$\text{Weighted Value } t(n) = \frac{danger\,value}{Level_5\ danger\,value} \tag{11}$$

$$\text{Weighted Value } t(n) = \frac{danger\,value}{Level_9\ danger\,value} \tag{12}$$

3.4. A* Searching Algorithm

In this security system, the algorithm we use is an A* searching algorithm to find the shortest escaping path. And the f(n) value of the node (i, j) is calculated using Equation (13).

$$f(n)=g(n)+h(n)+t(n) \tag{13}$$

where : f: the total estimated value of the current node
g: the displacement from the start node to the current node
h: the predicted displacement from the current node to the target node
t: the relative weighted value of danger value.

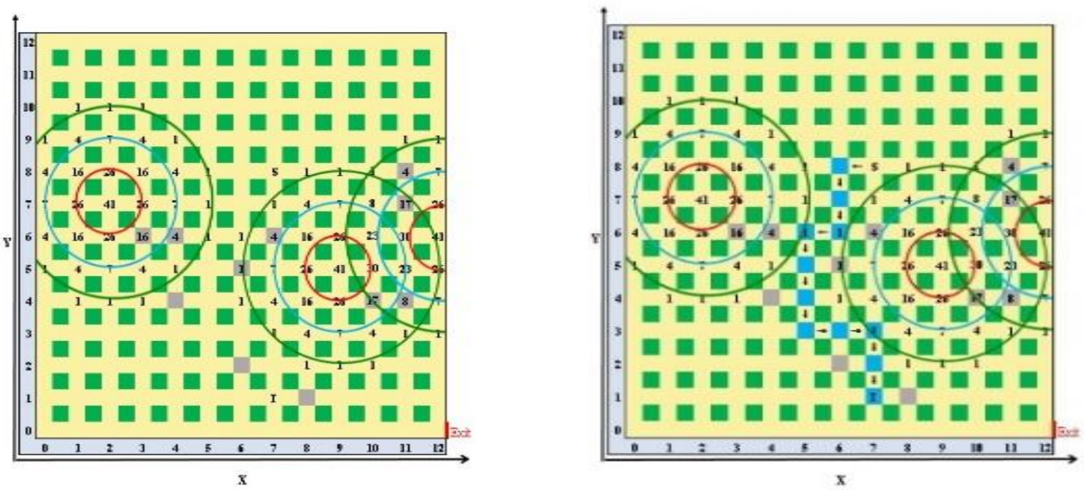
We give an example to illustrate the planning of the escaping path after searching for fires, as shown in Figure 5. We get the 3 fire sources which are located at (2, 7), (9, 5), and (12, 10). The starting point is S (7, 8) and the target point is T (7, 1). The obstacles exist in the following positions: (3, 6), (4, 4), (4, 6), (6, 2), (6, 5), (7, 6), (8, 1), (10, 4), (11, 4), (11, 7), (11, 8). For all the obstacles plotted with gray color in the platform, we set the weighted value t as 200 meaning it is much more difficult to pass through.

Table 2. Weighted Value t(n) for Single Fire Source

Level #	Danger Values	Weighted Value t(n)
Level_1	L1	L1/L5=L11
Level_2	L2	L2/L5=L12
Level_3	L3	L3/L5=L13
Level_4	L4	L4/L5=L14
Level_5	L5	L15
Level_6	L6	L6/L5=L16

Table 3. Two Fire Sources Interaction with Weighted Value

Level #	Danger Values	Weighted Value t(n)
Level_1	L1	L1/L9=L21
Level_2	L2	L2/L9=L22
Level_3	L3	L3/L9=L23
Level_4	L4	L4/L9=L24
Level_5	L5	L5/L9=L25
Level_6	L6	L6/L9=L26
Level_7	L7	L7/L9=L27
Level_8	L8	L8/L9=L28
Level_9	L9	L29
Level_10	L10	L10/L9=L210

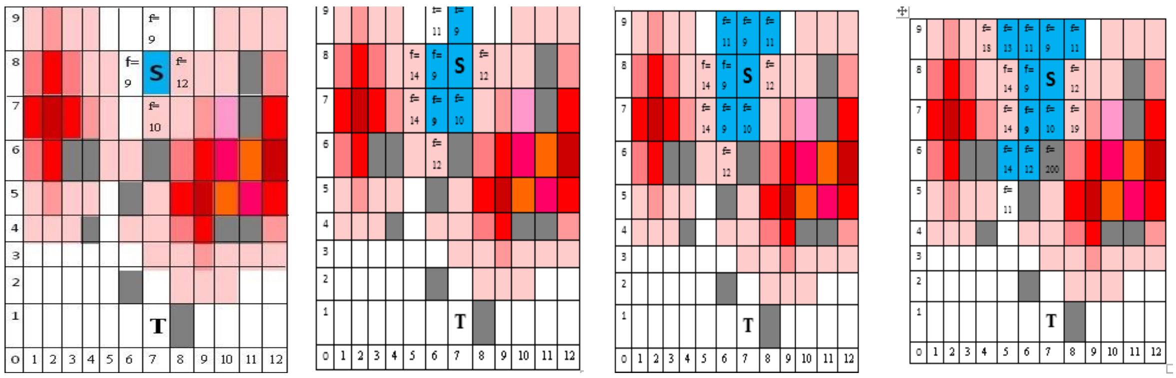


(a) Initial diagram (b) Diagram with shortest path

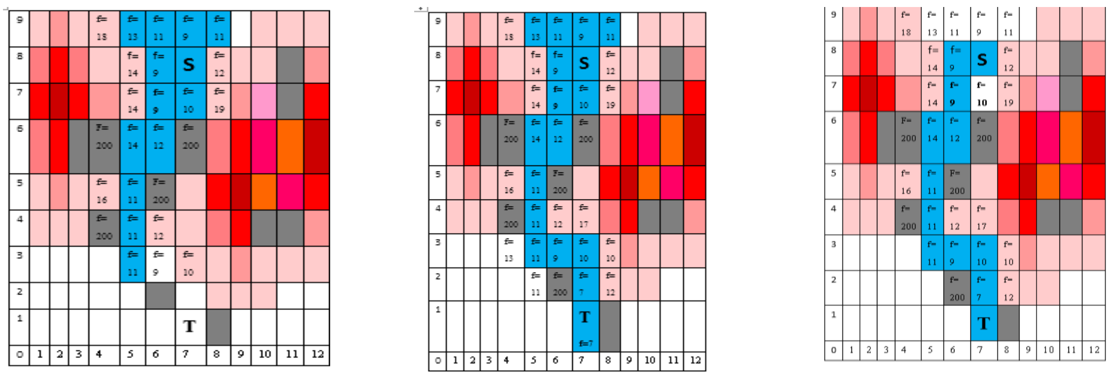
Figure 5. Distribution of danger values with joint probability

4. RESULT AND DISCUSSION

Whenever detecting the fire source, the robot sends the related information to the supervised computer and other robots. After it is confirmed, the three fire sources in our example were located at the positions (2, 7), (9, 5), and (12, 10) with a danger value L1. There are 3 circles in 3 colors for each fire center shown in Figure 5. The centralized computer calculates the danger values for the adjacent nodes of 3 fire centers. Especially, it calculates the danger values of the interacting area by joint probability. All the danger values are shown in Figure 5. Then, the supervised computer initiates the planning of the shortest path from S. Using the A* algorithm, the supervised computer calculates the g(n), h(n), and weighted value t(n) individually. Then, we calculate the danger value and weighted value of the danger cost of each node. Finally, these values are summed up using the heuristic function f(n) of the implemented node (i, j). The centralized computer select the minimum cost f as shown in Figure 6(b) from all adjacent nodes to be the extension node of the shortest path from the starting node to the target node.



(a) Start node S (7, 8) (b) Add in (6, 8), (6, 7), (7, 9), (7, 7) (c) Add in (6, 9), (8, 9) (d) Add in (6, 6), (5, 6), (5, 9)



(e) Add in (5, 5), (5, 4), (5, 3) (f) Add in (6, 3), (7, 3), (7, 2), T (g) Discard (5, 9), (6, 9), (7, 9), (8, 9), (7, 7)

Figure 6. Construct processing from (a) Initial to (g) the final shortest escaping path

From the starting point S, we calculate all the f values of adjacent nodes of S using the A* searching algorithm shown in Figure 6(a), and we select the smallest f value to be the extension node. The sequence of extension nodes from S (7, 8), (6, 8), (6, 7), (7, 9) to (7, 7) is the previous processing for final shortest escaping path, as shown in Figure 6(b). From node (6, 6) in Figure 6(c), there are two nodes with an f value of 1l, lower than that of node (6, 6). Then, we need to go back to survey (6, 9) and (8, 9) with an f value of 11. Thus, (6, 9) and (8, 9) are inserted into the Closed list as extension nodes as shown in Figure 6(c). In Figure 6(d), after node (6, 6) with f=12, we need to visit node (5, 9) with f=13.

Then, there are 3 nodes adjacent to the previous extension nodes with the same f value of 14, i.e., (5, 8), (5, 7), (5, 6). In order to find the shortest path, we select the node closest to T which is node (5, 6) in Figure 6(d). So, (6, 6), (5, 9), and (5, 6) are the sequence of extension nodes as shown in Figure 6(d). The nodes (5, 6), (5, 5), (5, 4), and (5, 3) are the sequence of extension nodes with the lowest f values as shown in Figure 6(e). From node (5, 3), the extension node is (6, 3) with the lowest f value, 9. Then, nodes (7, 3) and (7, 2) are the extension nodes seen in Figure 6(f). The last node is the destination note T (7, 1) with the lowest f value of 7 as seen in Figure 6(f). Finally, we need to check the sequence of extension nodes. Although we choose the nodes with the lowest f values, but some of them should be discarded from the escaping path for they are neither continuous nor do they exist in the escaping path. So, all the nodes marked blue from S to T is the shortest escaping path as shown in Figure 6(g).

There are two kinds of graphic searching algorithms, blind search and heuristic search. The most famous searching is Dijkstra algorithm in blind search which is not so efficient and computing complexity. Oppositely, heuristic information is used in heuristic method to choose the best node from current set to extend the path. It improves the intelligence and efficiency during the searching. The pathfinding algorithm we use is A* algorithm. A* searching algorithm is one of widely used heuristic function to find the shortest path. A* is similar to Dijkstra's algorithm which is A* algorithm without heuristic function to find a shortest path. A* is like Greedy Best-First-Search in using a heuristic to guide itself. The A* searching not only inherit to have the advantage of Best-First-Search (BFS) algorithm with low time-space and excellent efficiency, but also have the merits of Dijkstra algorithm with admissibility and completeness.

During planning the escaping path, we emphasize the system spent much time on compassing from obstacles. Especially, the robot controller to avoid obstacles is the robust technique for improving efficiency to path plan [7]. Further, the location determination [of mobile robots is the critical point of efficiency to find the shortest escaping path in fire scene. RFID [12] is the good solution for location determination of indoor robot. Finally, experimental results show up the high reliability and efficiency of the proposed system.

5. CONCLUSION

We have designed the security system for detecting fire sources and planning a safe escaping path. We used the Gaussian 2D discrete mass function to calculate the danger values for all points on the platform. The temperature of the fire source is uniformly descended from the center of the fire to its outside surroundings. Joint probability is used to calculate the new danger values of interacting nodes for double fire events. In order to save people, we find the shortest path as soon as possible by using an A* searching algorithm. Also, since danger values are directly proportional to the air-fuel ratio and the increasing temperature rate with distance, which means that the safest escaping path is to find the path with most oxygen and lowest temperatures. Our treatment reflected an affordable solution to the potential quantities of efficiency without complex computing. From experimental results, it is verified the system having sufficient efficiency and excellent reliability.

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