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2D Patrol Path Planning Based on Ant Colony Algorithm

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Abstract. Police patrol is an essential and important means to maintain the public security and social stability. However, the role of the experience-based patrol in the development of the social security prevention and control system is also declining. To address the problems of a fuzzy patrol path and irrational path planning in the conventional patrol mode, practical alert data from 2019-2021 was pre-processed and used. On the basis of the Maklink graph theory, optimized patrol paths were improved using the ant colony algorithm. Specifically, 2D path planning in presence of buildings was analyzed. In the study, we take two sites with high incidence of cases as key patrol points and finally calculates the shortest 2D walking patrol path to avoid obstacles between the two points. This study facilitates daily patrol by policemen in terms of enhanced accuracy and practical effectiveness.

Keywords: prevention and control by patrol, path planning, ant colony algorithm, Maklink graph theory

1 Introduction

The goals of patrol include crime prevention and deterrence, apprehension of offenders, creation of a sense of public security and satisfaction, provision of non-crime-related services, traffic control, and identifying and solving community problems with respect to crime and disorder. Efficient patrol to reduce criminal alerts has been a long-standing issue for the police therefore rational patrol path planning using big data technology is of great significance to patrol. On one hand, the grass-root units are typically facing the issue of a limited police force, while conventional patrol modes achieve full coverage of patrol by increasing the number of policemen participating in the patrol. This has been a severe wastage of grass-root police forces. Therefore, patrol path optimization can reduce the burden of grass-root police units by facilitating optimization of the allocation of police forces. On the other hand, the conventional experience-based patrol which have been repeating the previous patrol route, is readily exposed to 'blind patrol' and 'blind inspection' and can only handle instead of preventing the cases. If the public security dynamics of the area is not mastered, the high incidence of cases are not clear, then street patrol is just 'blind patrol' and 'blind inspection'. Patrol path optimization can help to improve patrol accuracy and precisely determine the possible location and other related information of the cases, so as to achieve early prevention and deterring. Overall, in public security patrol, the precise design of the key patrol points that need attention and the establishment of the optimized path can ensure the reasonable deployment of the police force and the scientific and effective surveillance by public security police thus, reap high benefits with low patrol costs.

Despite tremendous changes in technology, society, work, political scenes, economies, and work forces themselves, the purpose of patrol today still remains traditional, as it has always been. To address the problems of a fuzzy patrol path and irrational path planning in the conventional patrol mode, multi-dimensional data was integrated and sites with a high incidence of crime alerts in the city were obtained by data processing. The efficient patrol paths were then generated, by using Maklink graph theory and the Dijkstra algorithm under the framework of the ant colony algorithm, so that the two-dimensional prevention and control structure of modern society is more rational and accurate. This study aims to improve patrol routes by 2D patrol path planning based on ant colony algorithm (ACO), so as to enhance police patrol efficiency. The contributions of this study are as follows:

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- The analysis of public security high incidence cases and selection of sites with high incidence of cases is conducted by data processing;
- Development of a visualized patrol route by applying the ant colony shortest path algorithm;
- In the general framework of ACO, a 2D walking patrol path which avoiding all the obstacles such as buildings and public facilities is finded by means of Maklink graph theory and Dijkstra algorithm.

The structure of this paper is as follows. Section 2 presents an extensive literature review related to the patrol path planning. Section 3 elaborates the public security high incidence cases analysis done by using the ant colony algorithm to generate and draw the shortest patrol path for systemic planning of a two-dimensional patrol path with the help of Dijkstra algorithm and MAKLINK graph theory. The results are discussed and summarized in Section 4.

2 Literature Review

For a long time, patrol has been playing a significant role in the public security. In 1829, Robert Bill established modern professional police in UK and defined police patrol as walking patrol along the designated path to improve the inspection rate. In 1973, George Kelly tried to improve the working efficiency of the patrolmen. Specifically, the location and the time of previous cases were analyzed by computers and the results facilitated the patrol. Within one year, the working efficiency of patrolmen was improved by 20% while the crime rate in this region decreased by 18%. Therefore, it is deduced that patrol can reduce the crime rate by improving the police visibility on the streets and deterring potential suspects [1].

Owing to the continuous expansion and development of New York City, Bill Bratton, the then Director of the New York Police Department, proposed a police reform by establishing and implementing a novel data-driven performance assessment system (CompStat). CompStat collects and integrates a wide range of police data and uses big data statistics and analysis to identify crime patterns and hotspots. As a result, the police patrol mode is transformed from passively approaching the sites of cases to actively planning the patrol path [2]. In Germany, patrol is mainly executed by the public security police who patrol key areas such as subway stations, which reflects the characteristics of strengthening patrol path planning in key areas at sensitive times [3]. Wang *et al.* proposed six modes of patrol, that is, straight line patrol, circular and square patrol, fixed line patrol, broken line patrol, along-line patrol, and cross-line patrol in terms of patrol modes. The results showed that although the patrol paths of police in all countries didn't show any common pattern, and all the police aimed at informing people that the police were on patrol without letting criminals know their patrol paths, so as to maximize the patrolling effects [4]. To address the problem of undulating terrain for patrols in hilly areas, Wang *et al.* proposed a 3D map construction method so that the patrol path based on the ant colony algorithm could be optimized [5]. Vania *et al.* analyzed the police patrol teams specifically to respond to family violence in Brazil. The results indicated that the victims who participated in the MdP patrol programs were much less likely to suffer repeated assaults or femicide than those who did not participate in these programs. Also, this study further explored the patrol effects of combining police patrols with characteristic elements of local protection [6]. Michael *et al.* studied the stochastic vehicle routing problem (SS-VRP-R). Based on probabilistic knowledge about the appearance of requests, the SS-VRP-R seeks a priori sequences of vehicle relocations and optimizes the expected responsiveness to the requests [7]. Samanta *et al.* summarized the problems related to police patrols, like decision-making problems arising in path design, resource allocation, and jurisdictional planning, from an operations research (OR) perspective [8]. Wu *et al.* used two game theory models for assigning police patrol shifts and used a mixed-strategy Nash equilibrium approach to derive the risk value of patrolling each area [9]. Whereas, a study was conducted on the influence of gender-based factors on the perception of barriers to a police patrol career [10]. Additionally, police patrol instruments, including license plate readers and GPS data of radio, have also been investigated [11-12]. Yang *et al.* focuses on developing models to estimate the expected length of the shortest path of traveling salesman problem in three-dimensional space. A total of 500 experiments are performed for each scenario, and the average length of the shortest path is calculated [13]. Gao *et al.* improves the hybrid algorithm between the improved artificial fish swarm algorithm (AFSA) and the dynamic window algorithm (DWA) for global path planning of coal mine patrol robot and introduces the improved genetic algorithm (GA) to enhance the path planning accuracy [14].

Although studies on the patrol path have been conducted from a variety of perspectives, these studies are based on different application scenarios, which combine different application functions and scenario requirements while planning the patrol path. Some studies have following limitations:

- Most are from the algorithmic enhancement perspectives, while the actually visual walking patrol line taken by the basic units especially, police stations have rarely been discussed.
- Lack of analyzing the two-dimensional path planning for public security in the presence of the buildings in the framework of ant colony algorithm.

In summary, previous police patrol systems focused on analyzing the operating characteristics and summarizing the current problems and providing corresponding suggestions and countermeasures from various perspectives whereas, all the existing studies based on the algorithm modeling have certain operability [15-16]. There are some researches focus on improving ACO by optimizing the shortest path problem through various algorithms. In this study, we pay more attention on the walking patrol path which avoiding all the obstacles such as buildings and public facilities. Therefore, by making full use of the advantages of public security big data and integrating the internal public security data and the external social data, this study used selected algorithms to identify the patrol alerts and the sites with a high incidence of crime cases in a specific areas to improve the optimized patrol path based on MAKLINK graph theory, and analyze the two-dimensional path planning in the presence of the buildings in the framework of ant colony algorithm, to carry out further exploration at the theoretical level.

3 Smart Patrol Path Planning

3.1 Data Pre-Processing

The city of larceny cases (2330 cases) pertaining to the key targets of street patrol from June 2019 to May 2021which were selected and analyzed, so that the sample involved all kinds of holidays, weather, climate, as well as scenarios before and after the Covid-19 outbreak. Sensitive data related to the personal information of personnel involved in the cases were desensitized to prevent privacy breaches.

In this study, data were pre-processed using the following steps: 1. Data screening: Data with deficient information were manually excluded, such as the cases with missing geographic codes, incomplete addresses, and data beyond a rational range or with inconsistent coordinates of the case address; 2. Data duplication: Duplicate alerts raised by repeated calling and/or registration, were combined into one alert; 3. Numerical codes correspondence: Larceny city alerts were divided into different categories according to the locations of the cases [17-19]. In the police alert database, these specific categories were displayed in the form of special numerical codes with certain criteria as shown in Table 1 of few illustrative cases.

Table 1. Case information (After desensitization)

No.	Creation time	Closing time	Category	Geographic code	Detailed address
1	2021052908	2021053017	Burglary	118.793, 32.004	No. 108, A Road
2	2021052920	2021053007	e-bike theft	118.791, 32.029	No. 336, B Road
3	2021052614	2021052915	Car break-in	118.813, 32.016	No. 165, C Road

3.2 Selection of Sites with High Incidence of Cases

By analyzing the case information on the basis of the pivot tables, we get a clear understanding of the frequency of the occurrence of larceny cases with their specific geographical locations to determine the patrol sites that need to be focused during the patrolling. In this process, the coordinates of the locations where the cases occurred were counted in the pivot tables. Let $A = \{A_1, A_2, \ldots, A_n\}$ represent each patrol point of Police Station A, and rank them based on the number of cases. The probability of A_1 patrol point is defined as follows:

$$P_A^1 = \frac{A_1}{\sum_1^n A_i}. \tag{1}$$

Hence, this study ranks the number of cases at each location and obtains the patrol points for each area using the comparative probability. The locations with cases of low frequency (<4) occurrences were excluded being of less priority, and the locations with high frequency of occurrences are presented in the form of longitude and latitude to facilitate the execution of the subsequent steps. The frequency of crime in the location determines the path of patrol, and the lowest value of 4 in this study is the experience value obtained after communicating with experienced patrol personnel. Table 2 illustrates the sample information of the sites with a high incidence of cases after the pivot tables are processed, and the final table contains 42 locations which reflect the high frequency of crime.

Table 2. Information of sites with high incidence of cases (Partial information)

No.	Horizontal coordinate (longitude)	Vertical coordinate (latitude)	Detailed address	Frequency of case occurrence
1	132.792	12.906	No. 99, D Road	10
2	118.791	92.234	No. 28, E Lane	6
3	211.803	91.009	No. 325, F Road	4

3.3 Primary Path Planning

Primary planning of patrol path is done after the sites with a high incidence of cases in certain areas are determined. Path planning algorithms are the prerequisite in planning the optimized patrol path. Currently, common path planning algorithms used include the Dijkstra algorithm, Floyd algorithm, ant colony algorithm, simulated annealing algorithm, and greedy algorithm. Among these, the ant colony algorithm has the advantages of fewer iterations, better solutions, and slower convergence speed [20-21]. Hence, in this study, the primary planning of the patrol path was done by using the ant colony algorithm.

Principles of Ant Colony Algorithm. Inspired by the behavior of the ants in finding the best way to locate food, a probabilistic bio-mimetic ant colony algorithm was proposed by Marco Dorigo in 1992 to identify the optimized path. With negligible sight, ants search food in darkness and identify the shortest path from colony to food. This is attributed to the pheromone released by the ants during crawling to identify their paths, and can change their crawling direction according to the concentration of pheromone while searching food, until they reach the food source [22]. Since pheromone evaporates over the time, ants can find the shortest path between the colony and the food source by crawling multiple times. Some of the literatures have introduced the improved algorithms such as enlarged roulette method, functional dependencies, genetic algorithm and fuzzy-based ant colony optimization [23-25]. In this study we first introduce the basic principle of the ant colony algorithm.

Fig. 1 depicts the fundamental principles of the ant colony algorithm. Herein, Point A refers to the colony, Point B refers to the location of the food that the ant needs to carry, and Point C refers to a random point outside Path AB. Points A, B, and C form an equilateral triangle. At moment t_0, Ants 1 and 2 simultaneously start from Point A in the lookout to carry food back to the colony. Assuming that they crawl at the same speed and deposit the pheromone of the same amount and concentration, the Ant 1selects Path AC while, the Ant 2 selects Path AB; at moment t_1, Ant 1 reaches Point C along Path AC and tends to crawl toward Point B along Path CB, and Ant 2 reaches Point B. Since pheromone exists on Path BA and no pheromone exists on Path BC, Ant 2 tends to select Path BA to return to Point A; at moment t_2, Ant 1 reaches Point B and obtains food. Since the amount of pheromone on Path BA is twice that on Path BC, Ant 1 tends to return to Point A along Path BA, while Ant 2 tends to restart from Point A. Similarly, since the amount of pheromone on Path AB is twice of that on Path AC, Ant 2 will reach Point B along Path AB to obtain food for the second time.

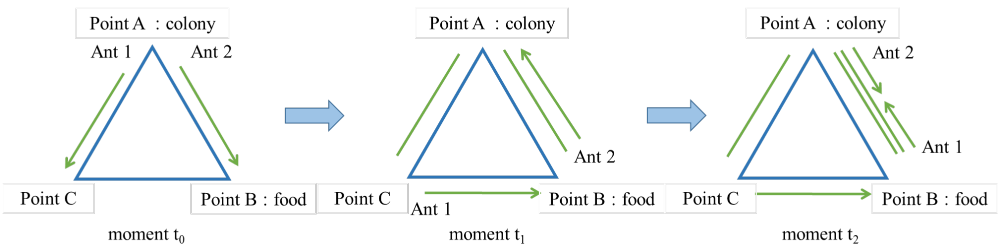

Fig. 1. Principles of ant colony algorithm

Over the past years, numerous studies and applications based on the ant colony algorithm have been developed by the researchers in China and abroad and widely applied in data analysis, robot-based problem solving, power, telecommunication, hydraulic engineering, mining, chemical industry, construction, transportation, and other fields [23-25].

Basic Mathematical Principles of Ant Colony Algorithm. In order to further understand the basic idea of ant colony algorithm (ACO), it is necessary to use a mathematical model to describe the whole implementation process. The Ant colony algorithm is originally used to solve the traveling salesman problem (TSP). The mathematical description of TSP can be formulated as follows: Let, $C = \{c_1, c_2, \ldots, c_n\}$, represents the undirected n points coordinate set. The collection of any two points connected components in C namely, $L = \{c_i, c_j \in C\}$ and $d_{ij}\,(i, j = 1, 2, \ldots, n)$ are Euclidean distances between $c_i\,(x_i, x_i)$, and $c_j\,(x_j, x_j)$ of l_{ij} arbitrary points, which is defined as:

$$d_{ij} = \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2}. \tag{2}$$

Let, $G = (C, L)$ represent the directed graph. The optimal solution condition of TSP problem is to find the combination with the shortest Hamiltonian circle length in the directed graph G, that is, to find the closed curve in $C = \{c_1, c_2, \ldots, c_n\}$ that makes n points visit once again and the sum of the access distances to get the least path [26].

Let, b_i (t) represent the number of ants at point i at time t , $\tau_{ij}(t)$ represents the pheromone content on path (i, j) at time t, m represent the number of ants, and n represents the space of TSP problem, so $m = \Sigma_{i=1}^{n} b_i$ (t); $\Gamma = \{\tau_{ij}(t)|c_i, c_j \in C\}$ represents the set of pheromone contents on the l_{ij} connection path between any two points at time t.

State Transition Probability Function. In the process of solving the problem, ant k ($k = 1, 2, \ldots, m$) goes to the current point c_i based on the content of τ on l_{ij}. The records visited by ant k in the process of searching for optimization are in $tabu_k$ ($k = 1, 2, \ldots, m$), and the $tabu_k$ is updated in real time during the system iterative search [27]. In the ant colony algorithm at time t, ant k selects the next point c_j at the current point c_i, according to the state transition probability $p_{ij}^k(t)$. The state transition probability function is defined as follows:

$$p_{ij}^k = \begin{cases} \dfrac{[\tau_{ij}(t)]^\alpha [\eta_{ij}(t)]^\beta}{\Sigma_{S \subset allowed_k} [\tau_{is}(t)]^\alpha [\eta_{ij}(t)]^\beta}, \; j \subset allowed_k \\ 0, \; else \end{cases}, \tag{3}$$

where, $allowed_k = \{c - tabu_k\}$ represents the alternative point where ant k has not arrived; α is the pheromone heuristic factor representing the importance parameter of the track, and the importance degree of pheromone action on the path in the iterative search process, β represents the significance of revelatory information of the path itself [28]. The heuristic function $\eta_{ij}(t)$, is defined as follows:

$$\eta_{ij}(t) = \frac{1}{d_{ij}}, \tag{4}$$

where, d_{ij} represents the distance between the two adjacent points i and j. The smaller is d_{ij} of ant k, when both $\eta_{ij}(t)$ and $p_{ij}^k(t)$ are high [29]. Therefore, this function represents the expected size of the individual ant transition from c_i to c_j.

Pheromone Updates Strategy. In the process of optimization, ants selectively release pheromones according to the length of the route they have traveled, after moving one point or traversing all the points. In order to avoid excessive interference of heuristic information with residual pheromones, pheromone updating process should be carried out when pheromone is released in the optimization process, that is, pheromone updating strategy [30]. The pheromone content on the path is updated in real time according to the situation of the ant. The pheromone content on the path l_{ij} is updated and adjusted at $t + n$ according to the following strategy.

$$\tau_{ij}(t+n) = (1-\rho)\tau_{ij}(t) + \Delta\tau_{ij}(t), \tag{5}$$

$$\Delta\tau_{ij}(t) = \Sigma_{k=1}^{m}\Delta\tau_{ij}^{k}(t), \tag{6}$$

where, ρ represents the pheromone volatilization coefficient on the path, $1-\rho$ represents the pheromone residual coefficient, $\rho \in [0,1]$; $\Delta\tau_{ij}^{k}(t)$ represents the pheromone increment at path l_{ij} at time of ant k in the current cycle, initially and $\Delta\tau_{ij}(0)$. $\Delta\tau_{ij}(t)$ represent the pheromone increment at path l_{ij}.

$$\Delta\tau_{ij}^{k}(t) = \begin{cases} \dfrac{Q}{L_k}, & \text{If the k}th\text{ ant passes through } (i,j) \text{ in the cycle} \\ 0, & else. \end{cases} \tag{7}$$

Where Q represents pheromone intensity which affects the solving speed of the algorithm and L_k represents the length of ant k's travel path in the current search [31].

The Implementation Steps of Ant Colony Algorithm.

Parameter Initialization. For all algorithms, parameter settings are of great significance since they can be continuously tuned to obtain the desired optimized solutions. Table 3 lists rational values of different parameters in the ant colony algorithm [15].

Table 3. Parameters of ant colony algorithm

Parameters	When the value is too large	When the value is too small	Rational value
Ants amount (m)	The amount of pheromone on different paths shows a small difference, weakening the positive feedback effect, resulting in slower convergence speed and longer computation time.	The pheromone concentration of some paths that have never been searched for may decrease to zero, leading to premature convergence and reduced global optimality of the solution.	Typically, 1.5 times the target value
Maximum number of iterations (t)	The computation time is longer	Fewer paths are available for selection, resulting in the population falling into local optimum.	[100, 500]
Pheromone evaporation factor (ρ)	Pheromone evaporates fast, which may lead to a better path being excluded.	The amount of pheromone on different paths shows a small difference, and the convergence speed is reduced.	[0.2, 0.5]
Pheromone factor (α)	The possibility of the ant choosing a path that it has already crawled over may be increased, resulting in lower search randomness.	The ant population is prone to fall into purely random search, resulting in the population falling into local optimum.	[1, 4]
Heuristic function factor (β)	Its convergence speed is faster, but it is prone to fall into local optimum.	The ant population tends to fall into a purely random search, making it hard to find the optimal solution.	[3, 5]

Path Establishment. Each ant randomly selects a location as its starting point and maintains a path memory vector to store the food that the ant passes through in turn. The key in this step is to compute the probability of the ant crawling from the current location to the next location and then use the roulette wheel selection method to select the further location. The roulette wheel selection method is the easiest and most commonly used selection method. In this method, the selection probability of each individual is proportional to its fitness value, that is, the higher the fitness, the higher is the selection probability. In this study, instead of only selecting the path with maximum pheromone concentration, paths with different concentrations of pheromone are also considered, which can avoid the problem of falling into local optimum.

Pheromone Update. Pheromone is a volatile chemical substance and the ants deposit new pheromone while crawling over the path hence, pheromone gets constantly updated. In this study, the ant-cycle model was used to simulate pheromone updates and the pheromone increment denoted as Q/L_k is related to the searching path instead of the specific path; the pheromone is updated at the moment when Ant k completes the search of the path, and pheromone on all the paths are updated. Fig. 2 shows the simulated path graph. Assuming that Ant k, passes over the path is 1->2->5->6->3->4->1, then the total path length L_k is 19. For the convenience of computation and to meet the normal value range, pheromone constant Q is set as 38, pheromone evaporation factor ρ is 0.5, then pheromone increment Q/L_k is 2. The path pheromone matrix of Ant k is shown in Fig. 3.

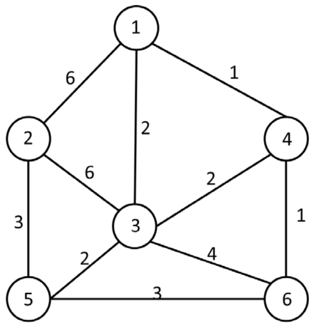

Fig. 2. Simulated path

	1	2	3	4	5	6
1	0	3	3	3	3	3
2	3	0	3	3	3	3
3	3	3	0	3	3	3
4	3	3	3	0	3	3
5	3	3	3	3	0	3
6	3	3	3	3	3	0

⇨

	1	2	3	4	5	6
1	0	3.5	1.5	3.5	1.5	1.5
2	3.5	0	1.5	1.5	3.5	1.5
3	1.5	1.5	0	3.5	1.5	3.5
4	3.5	1.5	3.5	0	1.5	1.5
5	1.5	3.5	1.5	1.5	0	3.5
6	1.5	1.5	3.5	1.5	3.5	0

Fig. 3. Pheromone update matrix of ant-cycle model

Iteration Results. In this step, the algorithm determines whether the maximum number of iterations is reached after multiple iterations, if yes, then the optimal output solution is obtained.

Algorithm Realization. In algorithm realization, 42 points with a high incidence of cases obtained were labeled in MATLAB according to their respective latitude and longitude coordinates. For example, the point numbered 1 is "No. 108, C Road" with the geo-coded location "118.793, 32.004". According to the previous steps, the initial parameter settings will have a greater influence on the experimental results. Therefore, in this study, the maximum number of iterations NC_max is set as 200, the ant amount m is 63, the pheromone factor α is 2, the heuristic function factor β is 4, the pheromone evaporation factor ρ is 0.2, and the pheromone constant Q of each ant is 20.

Fig. 4 shows the optimized path obtained after computation using MATLAB. The locations of sites with a high incidence of cases and the shortest path between the two locations are shown in the figure and labeled in the PGIS system to obtain an optimized patrol path, as a recommended patrol path for the grass-root patrolmen.

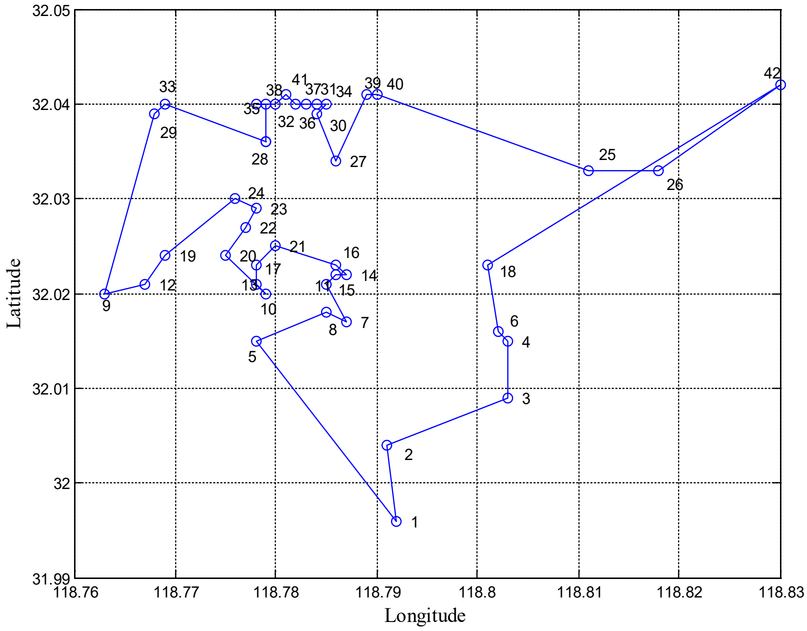

Fig. 4. Schematic of optimized path obtained by using ant colony algorithm

2D Path Planning. The impact of the obstacles such as buildings and public facilities on path planning cannot be ignored, and some areas, such as pedestrian streets, business clusters, and tourist attractions which are too crowded for the police cars to enter in the destined site. Therefore, in the general framework of the ant colony algorithm, this section tries to find a walking patrol path avoiding all the obstacles from the starting point to the endpoint in a real patrol environment with the presence of obstacles such as buildings and public facilities, by means of Maklink graph theory and Dijkstra algorithm.

Technical Principle of Maklink Graph Theory and Dijkstra Algorithm. Maklink graph theory is a method of constructing free spaces. In this method, a convex polygon is pre-defined, and the space is divided into two parts namely, the free space and the obstacle space. Free space is constructed by using defined basic shapes, and the obstacle space constructed is presented as a global connectivity graph and thus, path planning is performed on the graph.

Dijkstra algorithm is an algorithm that is used to find the shortest path by starting from one point to traverse all the other points in a weighted graph. Fig. 5 shows a simple weighted graph, and the numbers on the lines indicate the distance between the two endpoints of the lines. Assuming Point A is the starting point, Point D is the end point, and only another point can be reached from one point at any moment, then the basic process of the Dijkstra algorithm is as follows: at moment t_0, Point B or Point C can be reached by starting from Point A. The distance from Point A to Point B is set as 2, and the distance from Point A to Point C is 7. At this moment, Point A cannot reach Point D, so the distance from Point A to Point D is set as ∞; at moment t_1, it can be observed that any point can be reached regardless of starting from Point B or Point C. Based on the principle that the path with the shortest distance is retained when there are different paths to reach any point, the distance from Point A to Point C is updated to 5, and the distance from Point A to Point D is updated to 14; at moment t_2, the computation process is similar to moment t_1.At this moment, the distance from Point A to Point D is updated to 10 through the above computations and the shortest path from Point A to Point D becomes A->B->C->D with distance 10.

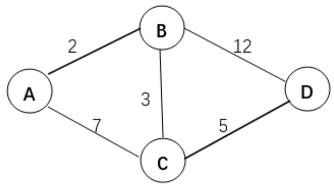

Fig. 5. A Simple weighted graph

The Implementation Steps of 2D Path Planning. Since the data of the obstacles such as buildings and public facilities are hard to obtain, and given that 2D planning of patrol paths in the whole areas require huge hardware, Point 13, "No. 302, Z Road" and Point 10, "No. 68, C Road" are shown in Fig. 6 were taken as examples in this section. The tool MATLAB R2020a was used in following steps.

(1) Labeling of the obstacles and starting points: Fig. 6, a 2D depicts the map model drawn in MATLAB.

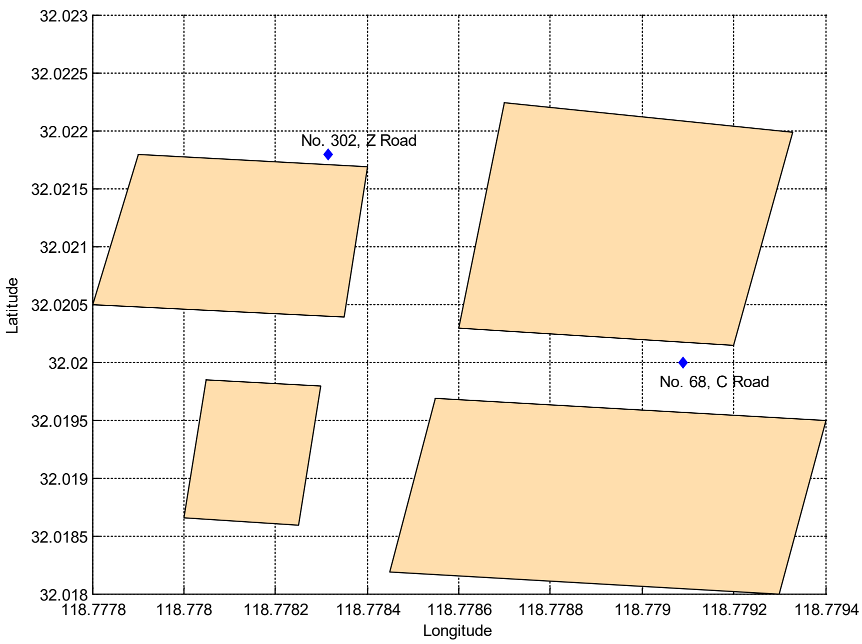

Fig. 6. 2D Map model

(2) Construction of an undirected network graph: The Maklink line is a line connecting the vertices of any two obstacles that do not intersect with other obstacles, as shown by the dotted lines in Fig. 7. The midpoints on the lines were then labeled as V1, V2, V3, ……, Vn, and the starting points, end points, and labeled midpoints were connected to get an undirected network graph to facilitate the initialization of path planning in the next step.

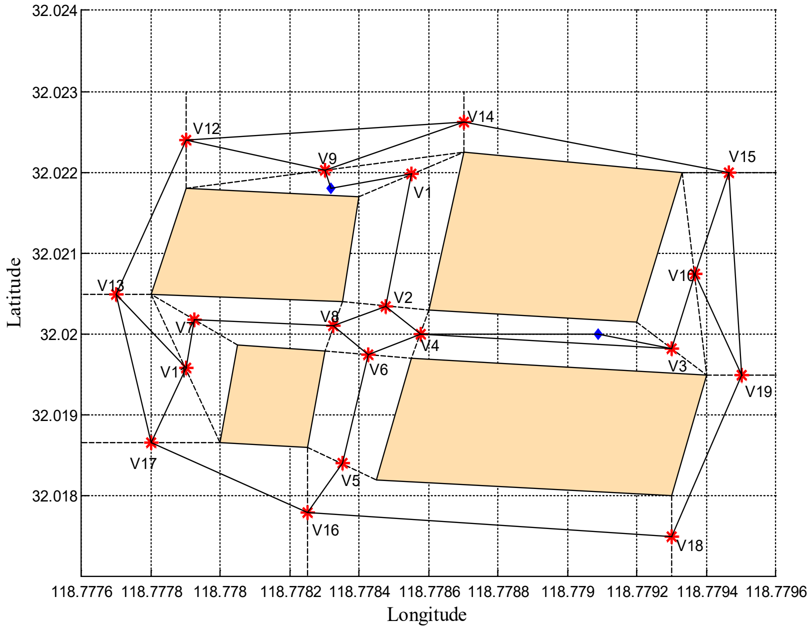

Fig. 7. Undirected network graph

(3) Initial path planning by the Dijkstra algorithm: On the basis of the undirected network graph and the Dijkstra algorithm, an initial shortest path in a two-dimensional environment was obtained, as shown by the solid lines in Fig. 8. It is noticed that starting from the point "No. 302, Z Road" to the end point "No. 68, C Road" pass three green colored Maklink lines and three midpoints V1, V2, and V4.

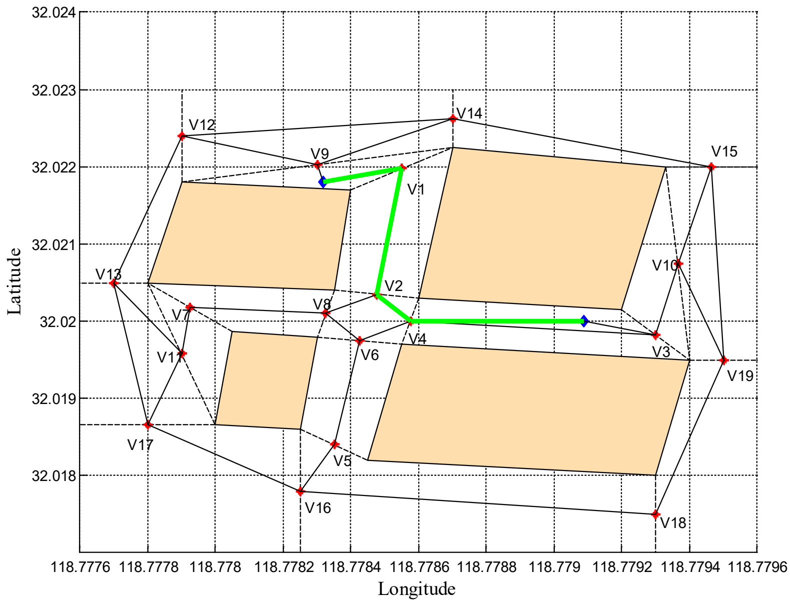

Fig. 8. Initial path in the Dijkstra algorithm

(4) 2D path optimization: The initial path obtained by the Dijkstra algorithm in the previous step has good scope for improvement. Assuming the endpoints of the Maklink line as P1 and P2, any point on the Maklink Line can be expressed as

$$p\,(h) = p1 + (p2 - p1) * h, \tag{8}$$

where, $h \in [0,1]$. Then we just need to find a path which passes through three proper points on the Maklink line. This step was implemented by means of the ant colony algorithm used in the previous steps to obtain the red dotted line 2D optimized patrol path as shown in Fig. 9.

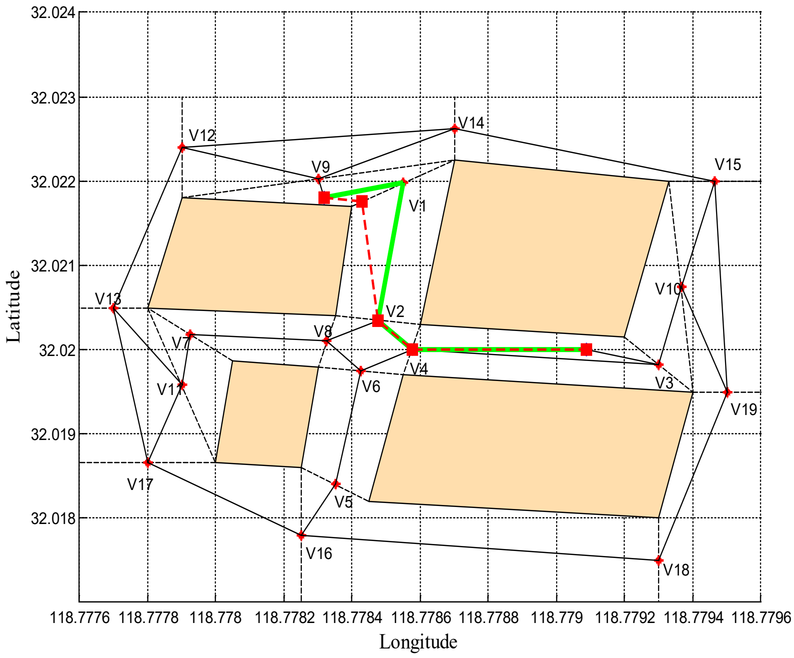

Fig. 9. 2D Optimized patrol path

3.4 Limitations of the Study

Difficulty in Data Acquisition. The data used in this study are relatively homogeneous and insufficient. The acquisition of the buildings data needs the collaboration from many parties hence, if such study is conducted directly in Public Security Geographic Information System (PGIS), more systematic and comprehensive results can be obtained.

Practical Constraint in Application. The social security prevention and control system involves metros, buses, street patrol, community management, special industry, and unit internal security. The construction of the patrol system is only one of the fields, which makes the breadth of the study and the connection with the rest of the fields inadequate. Besides, this study mainly focused only on the hypothetical case locations and without actual labeled suspects involved and the two elements “people” and “location” can also be linked organically.

High Hardware Requirements. The content of this paper needs to be fed back to the mobile terminals of the police task force, who are conducting the relevant work in real time, requiring high investment in both the 5G network and the mobile terminals of the police force.

4 Conclusions

In this paper, multidimensional data were integrated and processed to obtain the sites with a high incidence of crime cases in specific area. Based on the MAKLINK graph theory, the optimized patrol path was improved in the framework of the ant colony algorithm, and two-dimensional path planning in the presence of obstacle buildings was analyzed. The proposed smart patrol path planning has certain advantages in terms of improved patrol accuracy, using novel technology and scientific algorithms, and enhanced social service effectiveness, which is of great help in the patrolling of the public security police and has good research prospects. However, this study is theoretical and lacks practical application and feedback.

In future it is envisaged that the influencing factors such as “people” and “thing” with “location” can be incorporated to adjust and optimize the experimental results, and other parts of the social security prevention and control system can be discussed in an integrated manner, so that the public security work can truly enter the fast lane to “smart” planning, accelerating the operation of the command department and improving the efficiency of the investigation department.

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