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Emergency Management Program Based on Dijkstra's Shortest Path And GPS

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Abstract. *Emergency management plays a crucial role in maintaining public safety and reducing the loss of emergencies. Based on Dijkstra's shortest path algorithm and GPS technology, this study is dedicated to exploring an innovative emergency management program to enhance the efficiency and effectiveness of emergency response systems. The study deeply emphasizes the urgent importance of emergency management in protecting communities and critical infrastructures, especially as the need for advanced emergency response strategies becomes increasingly urgent with the frequent occurrence of disasters and accidents. To address this challenge, we propose a solution utilizing the Dijkstra shortest path algorithm. This algorithm is a well-validated method in graph theory that assists responders in determining the optimal paths for emergency vehicles, thus effectively reducing response time and fine-tuning resource allocation. At the same time, the introduction of GPS technology enhances the accuracy and real-time monitoring capabilities of the emergency management system, which can accurately track the location of emergency vehicles, simplify responder navigation, and provide up-to-the-minute information on road conditions and traffic congestion. This real-time data integration ensures rapid decision-making and flexibility to respond to changing emergency conditions. The study comprehensively summarizes a detailed framework for integrating Dijkstra's shortest path algorithm and GPS technology into existing emergency management systems, including system architecture, data flow, and communication protocols to ensure seamless integration and interoperability with current emergency response infrastructure. Evaluated through a series of simulations and case studies, the results clearly show that the solution delivers significant improvements in response time, resource utilization, and overall system performance compared to traditional emergency response strategies.*
Keywords: Dijkstra's shortest path algorithm; GPS technology; Emergency management; Resource allocation; Response time

1. **Introduction.** In today's society, emergency management plays a crucial role in maintaining public safety and reducing the impact of disasters and accidents. With the frequent occurrence of natural disasters and man-made accidents, an efficient emergency response system has become an indispensable component of social development [1]. However, traditional emergency response methods have revealed multiple shortcomings in the face of rapidly changing and complex situations, including long response times and inefficient resource utilization, which urgently requires an innovative and intelligent solution

to enhance the effectiveness and efficiency of emergency response [2]. The importance of emergency management lies in preventing, preparing for, responding to, and recovering from emergencies, with the aim of minimizing human casualties and property damage. However, traditional emergency management systems are often constrained by insufficient path planning and long response times, which result in rescue operations not being carried out quickly and efficiently, thus affecting the risk management and mitigation of the consequences of disasters and accidents [3].

By introducing Dijkstra's shortest path algorithm and GPS technology, this study aims to address the challenges faced by current emergency management systems, and to improve the system's intelligence and ability to respond to emergencies. Dijkstra's algorithm, as a well-established and reliable method in the field of graph theory, shows excellent performance in path planning, and is able to help the responders to quickly determine the optimal rescue path [4]. On the other hand, GPS technology provides precise location information and real-time monitoring functions, allowing emergency vehicles to reach their destinations quickly and know the road conditions instantly, thus significantly improving the overall efficiency of emergency response. In addition, with the increasing degree of social connectivity and technological advances, the results of this study will help promote the transformation of the emergency management system towards modernization and provide innovative ideas and technical support for future emergency response [5].

1.1. **Related work.** Emergency management is divided into urban road emergency management, emergency management of relief materials, emergency construction of rescue forces and emergency plan construction. Emergency management is a complete system; urban road emergency management is a branch of emergency management, divided into four stages: preparation, response, implementation, and recovery [6]. In recent years, both domestic and foreign countries have attached great importance to the study of emergency management of emergencies, and gradually formed a set of emergency management mechanisms and response programs to cope with emergencies in line with their own national conditions, and these experiences have a very important role to learn from in the emergency management of urban roads.

Deng et al. [7] are committed to ensuring road safety and designing signal light control systems to guide driver behavior during emergencies, thus realizing emergency management safety control. Pradhan and Mahinthakumar [8] conducted a study on the emergency management mechanism of roads under emergencies. They first delineate the emergency area and discuss how to dispatch vehicles to establish the emergency management control mechanism, and list the emergency management considerations in detail. By showing examples of typical lanes, they demonstrated the operation of the emergency management mechanism to prevent road blockages and reduce secondary accidents. Buzachis et al. [9] solved the problem of highway emergency management using a Decision Support System (DSS). They utilized spatial data already available in GIS to support emergency management needs, while generating new data in conjunction with other spatial functions to improve the transparency of emergency management on roads. The combination of GIS and emergency management modeling provides an effective spatial emergency management solution. The timeliness of emergency response is crucial for rapid response to emergencies and decision-making programs, and is also the focus of emergency management research by scholars at home and abroad [10]. Dudeja and Kumar [11] proposed a fast and effective method for calculating emergency response time, which is specifically designed to help managers measure emergency response time. By conducting a case study in San Patricio County, Bosse et al. [12] further optimize the experimental results to provide the local government with a more accurate basis for emergency response time.

Mitchell and Papadimitriou [13] propose an emergency response scheme based on the driver's perspective to deal with emergencies. Through the establishment of a simulation system, they concluded that drivers at different levels of emergency stimuli would adopt different response methods by instinctive reaction, which provides a more humanized basis for decision makers to respond to emergencies. Soltani et al. [14] proposed a concept of emergency response scheme for non-routine events in a dynamic road network model. They proposed an adaptive control theory and verified the reliability of the corresponding emergency response scheme through local traffic control experiments, which guided the rapid evacuation of vehicles. Qadir et al. [15] investigated the vehicle scheduling method during emergency implementation, which incorporates a visual sensing method to monitor the distance and count of vehicles during the emergency implementation, and to send out the alarm transmission in time for the Intelligent Transportation Management (ITM) to provide support for the theory of emergency management. Jorm et al. [16] developed three strategies for emergency recovery in response to emergencies from the perspective of road transportation: safety failure recovery, post-emergency facility recovery, and risk preparedness recovery, and continuously optimized the strategies through real-world cases in order to effectively protect the safety capabilities of people and property. Geiger et al. [17] focused on the optimization of existing emergency management systems for emergencies in the field of urban traffic management. They proposed a Particle Swarm Optimization (PSO)-based optimization method for decision-making in traffic management strategies, and made recommendations on road stability, which provide solutions for intelligent management in emergency response management for critical incidents.

1.2. **Motivation and contribution.** Road safety and emergency management have become critical in modern society, especially when responding to emergencies. In order to improve the efficiency and accuracy of emergency management, this study aims to explore an emergency management solution based on Dijkstra's shortest path algorithm and Global Positioning System (GPS). By combining these two technologies, the research aims to develop a smarter and faster road emergency management solution to respond to emergencies such as traffic accidents and natural disasters to further ensure road safety and reduce losses. Dijkstra's shortest path algorithm and GPS technology are integrated into the emergency management system, which can optimize the emergency rescue route planning and improve the scheduling and positioning of emergency supplies.

The contributions of the paper are mainly reflected in the following aspects:

(1) This paper innovatively integrates Dijkstra's shortest path algorithm and GPS technology into the existing emergency management system, and the successful integration of the two technologies injects the emergency management system with more efficient and smarter path planning capability.

(2) The Dijkstra's shortest path algorithm adds the road resistance function and fusion function, so that it can take into account the real-time traffic flow, road conditions and historical data in the path planning process, thus realizing a more accurate and smarter path planning scheme. Through the GPS will be all kinds of emergency materials positioning in the digital layer, summarize the current situation of materials, planning the optimal scheduling route, accelerate the input of emergency relief materials.

(3) Combine the real-time traffic flow prediction model with Dijkstra's shortest path algorithm to realize dynamic path planning. By monitoring real-time traffic flow and predicting future traffic conditions, the system can dynamically adjust the path planning to avoid congested road sections and select the optimal path.

2. Relevant theoretical analysis.

2.1. **Graph theory.** A data structure is said to be a graph, denoted by $G = (V, E)$, when its elements are divided into nodes and edges and any two nodes can be connected to each other by any edge [18], where G represents the graph, V represents the non-empty set of all nodes in G and denotes the number of nodes in the set by $|V|$, and E represents the set of all edges in G and denotes the number of edges in the set by $|E|$. It is common to use lowercase letters to represent nodes in a graph G. For example, u and v are two different nodes, and a form such as (u, v) is used to indicate that there is an edge connecting u and v in the graph G. When using graphs to represent Internet data, the real-life concrete things will be abstracted into nodes and edges. For example, when using graphs to represent transportation information networks, the site can be abstracted into nodes, the site whether there is a train between the abstraction of the existence of edges between the two nodes.

Suppose $p = \langle v_0, v_1, \ldots, v_k\rangle$ is a path from vertex v_0 to vertex v_k on graph G. p is a simple path if none of the vertices on p are the same except that v_0 and v_k can be the same. The weights of p are denoted:

$$w(p) = \sum_{i=1}^{k} w(v_{i-1}, v_i) \tag{1}$$

Suppose p is a simple path from s to t. If no simple path exists in the graph with weights smaller than those of p, then p is said to be a shortest path from s to t. The length of p is denoted $\mathrm{dist}(s, t)$ or $\delta(s, t)$.

2.2. **Dijkstra's algorithm.** Dijkstra's algorithm, conceptualized by Edsger Dijkstra in 1959, stands as a foundational method for determining the shortest path between nodes within a graph [19]. This algorithm serves as a strategic planning tool that initiates from a designated starting point and systematically explores the graph to identify the shortest paths to all other nodes, effectively solving the shortest path problem in directed graphs. Throughout its execution, Dijkstra's algorithm meticulously traverses all nodes in the graph, ensuring that a solution exists for finding the shortest path between any pair of points [20]. By exhaustively examining the graph's nodes, the algorithm guarantees that the shortest path between any two points can be determined with precision and efficiency. A crucial aspect to note is that Dijkstra's algorithm necessitates that all edges in the graph possess positive weights during the search process. This constraint is essential for maintaining the algorithm's accuracy and reliability. It is imperative that no negative-weight edges exist within the graph during the calculation of the shortest path, as the presence of negative weights could lead to computational inaccuracies and erroneous results during the search process. By adhering to these foundational principles and constraints, Dijkstra's algorithm emerges as a robust and dependable methodology for efficiently calculating shortest paths in graphs. Its systematic approach ensures that optimal routes can be identified in a wide array of applications, ranging from network routing and transportation logistics to project scheduling and resource allocation. The algorithm's reliance on positive edge weights underscores the importance of data integrity and consistency in optimizing pathfinding solutions across diverse domains.

Dijkstra's algorithm is characterized by searching around the starting node O as the center of the circle until it reaches the terminating node D. Its basic theoretical idea is to expand the path from the starting point to the target point, and to search for the shortest path for each passing point. In the process of searching the path, the distance value corresponding to each node is written down, and this value is the shortest path value from the starting node to the node [21]. For a weighted graph G, $d(v)$ denotes the length of the shortest path from the start node to the current node v, $k(v)$ denotes whether the current node v can be added to the set S, i.e., whether the shortest path is found or not; $p(v)$ denotes that the current node v is a pointer to the path trajectory of the terminating node, and $c(i, j)$ is the non-negative weight from node i to node j. The shortest path from the start node O to the terminating node j can be found by writing down the distance value corresponding to each node. For the start node O to the termination node D, the specific algorithm for solving the shortest path solution is described as follows:

Step 1: At the beginning of the algorithm, the relevant variables of the nodes are initialized according to Equation (2);

$$d(v) = \begin{cases} 0, & v = s, \\ \infty, & v \neq s \end{cases}; \quad k(v) = \text{false}; \quad p(v) = \{\} \tag{2}$$

Step 2: According to Equation (3), select a current node v with minimum weight from the nodes with $k(v) = \text{false}$ that have not yet found the shortest path; v is an endpoint of the first shortest path, and mark v as a node in the found shortest path solution;

$$d(v) = \min\{\, d(v_i) \mid k(v_i) = \text{false},\ v_i \in V\} \tag{3}$$

Step 3: According to Equation (4), for each node j with $k(j) = \text{false}$, compute and update $d(j)$ with the node pair formed by the node i with $k(i) = \text{true}$, and put j into $p(j)$ such that $k(j) = \text{true}$;

$$d(j) = \min\{\, d(j),\, d(i) + c(i, j)\} \tag{4}$$

Step 4: Repeat Step 3, when $k(D) = \text{true}$ for terminating node D, i.e., the terminating node is added to S, indicating that the algorithm finds the shortest path solution from the starting node O to the terminating node D. The specific flow of the algorithm is shown in Figure 1:

2.3. **GPS Positioning Principle.** The Global Positioning System (GPS) comprises a space satellite system, a ground monitoring system, and a user receiving system. GPS has made significant strides in various fields such as geographic surveying and mapping, engineering surveying, aerial photogrammetry, carrier navigation, and resource surveying. Particularly in radio navigation and positioning, GPS holds a prominent position [22]. The fundamental principle of the GPS navigation system revolves around measuring the distance from satellites with known positions to the user's receiver. This is achieved by calculating the time taken for the satellite signal to reach the user, multiplied by the speed of light [23,24]. In normal operation, GPS satellites continuously transmit pseudo-code navigation information. By analyzing and comparing this data, the system can swiftly calculate the distance between the satellite and the user, thereby determining the user's position within the geodetic coordinate system. This accurate positioning capability has revolutionized navigation and location-based services across a multitude of industries. The workflow of the GPS system involves a series of intricate processes that culminate in precise positioning. From the transmission of satellite signals to the reception and processing of these signals by user devices, the GPS system orchestrates a seamless exchange of information to pinpoint locations with remarkable accuracy. This intricate interplay between satellites, ground systems, and user devices ensures that GPS remains a cornerstone technology for navigation, mapping, and various other applications. The visual representation of the GPS workflow, depicted in Figure 2, illustrates the complex yet systematic steps involved in determining user positions through satellite-based navigation. This visualization serves as a valuable tool for understanding the interconnections and

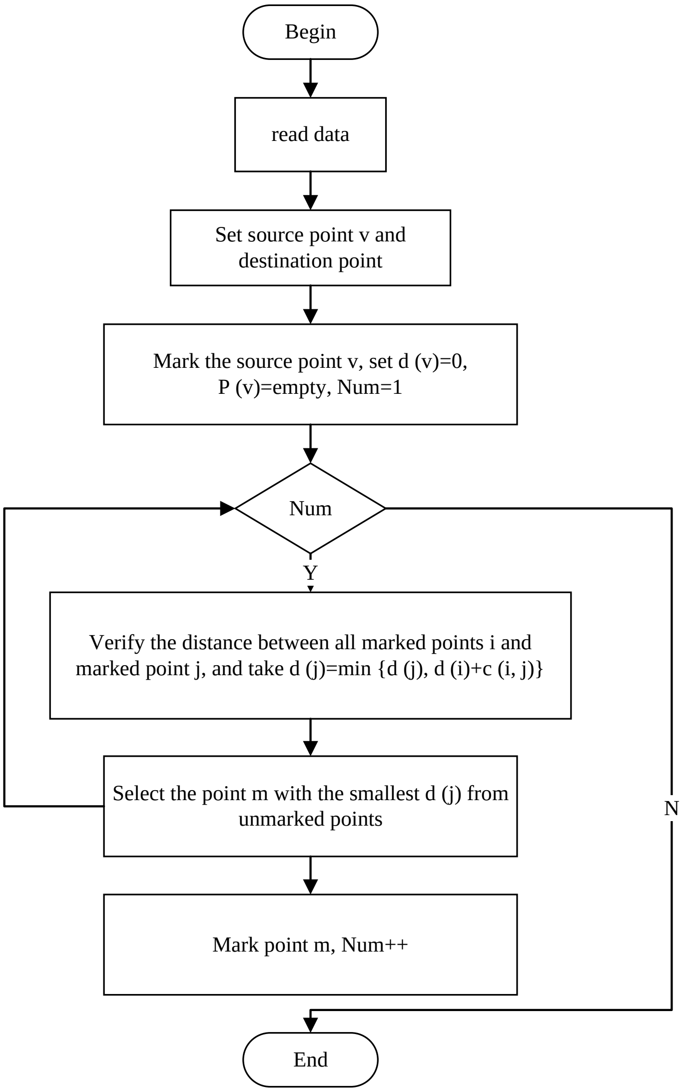

Figure 1. Dijkstra shortest path algorithm flowchart

dependencies within the GPS system, showcasing how satellite signals are leveraged to provide users with accurate and reliable location information.

3. **Research on emergency management programs based on Dijkstra's shortest path and GPS.**

3.1. **Shortest Path Planning Based on Improved Dijkstra's Algorithm.**

3.1.1. *Theory of road resistance function.* In urban road traffic planning and control, road resistance function is a crucial basic technology. The road resistance function reflects the distance, time and comfort between paths in the transportation network, or the combined effect of these factors [25]. Road resistance function solving method based on the relationship between the three parameters of traffic flow theory—traffic flow, traffic flow velocity, and traffic density—to determine the theoretical model of the road resistance function. Traffic flow refers to the number of participants in the unit of time through a path of traffic on the road; the value of the traffic flow vehicles for the traffic flow speed multiplied by the density of the traffic flow. The road resistance function model is calculated

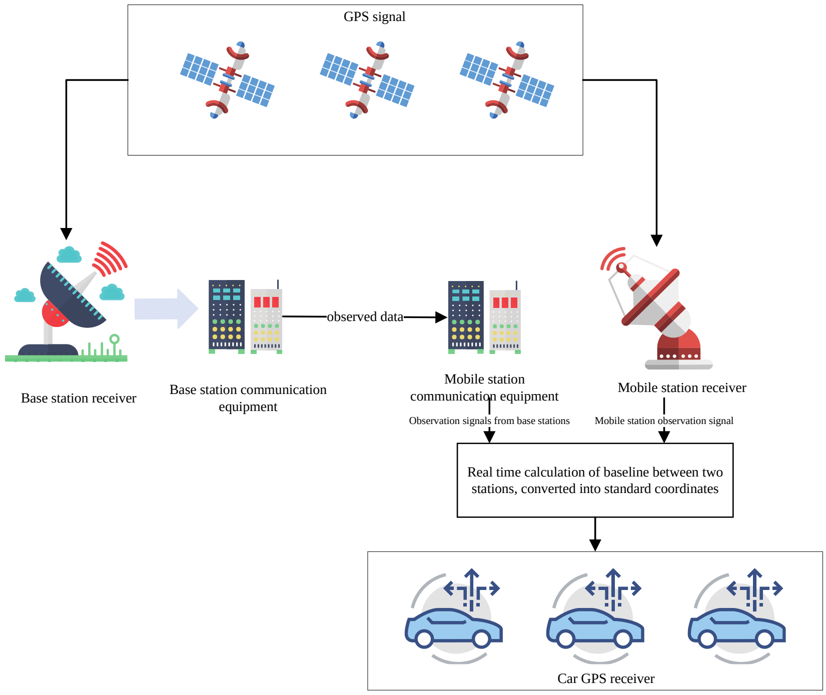

Figure 2. GPS workflow diagram

as follows:

$$T(p,q) = \frac{S(p,q)}{V(p,q)} \tag{5}$$

In the above equation $T(p,q)$ represents the time spent by motorized vehicles in passing through the path (p,q) and $V(p,q)$ represents the speed of the motorized vehicle when passing through the path (p,q). $S(p,q)$ represents the length of the path (p,q).

$$K = \frac{1}{D} \tag{6}$$

In the above equation K represents the path congestion density, D represents the spacing between two motorized vehicles in the path, and the value is the distance between the front of the current vehicle and the front of the next vehicle.

$$V(p,q) = \frac{V}{2} \pm \sqrt{\left(\frac{V}{2}\right)^2 - Q(p,q)} \times \frac{V}{K} \tag{7}$$

In the above equation $V(p,q)$ represents the speed of the motor vehicle when it passes through the path (p,q), and V represents the speed of the motor vehicle when the path is in a non-congested state. $Q(p,q)$ represents the traffic flow on the path (p,q). Calculating the speed of passing motor vehicles through the path (p,q): if $Q \leq VK/10$ (clear condition), take the positive sign; if $Q > VK/10$ (congested), take the negative sign; if $Q \geq VK/4$, the value under the square root is zero since no negative value can occur there.

3.1.2. *Fusion function.* In this paper, a fusion function is proposed to comprehensively consider the influence of path length and path elapsed time on the weights in Dijkstra's algorithm, and the degree of influence of the two on the path weights can be expressed using the fusion function.

$$W(p,q) = S(p,q) + \alpha T(p,q) \tag{8}$$

In the above equation $W(p,q)$ denotes the weight of path (p,q) when path length and path elapsed time are considered together.

$$\alpha = \frac{k_1}{k_2} \tag{9}$$

The value of α in the above equation is the ratio of the average path length to the average path elapsed time in the map, which can make the path elapsed time and the path length have the same effect on the path (p,q) weights.

$$k_1 = \frac{\sum_{p=1}^{N}\sum_{q=1}^{N} S(p,q)}{N^2} \tag{10}$$

The above equation denotes the average length of each path in path planning and N denotes the number of nodes in path planning.

$$k_2 = \frac{\sum_{p=1}^{N}\sum_{q=1}^{N} T(p,q)}{N^2} \tag{11}$$

The above equation denotes the average elapsed time of each section of path in path planning and N denotes the number of nodes in path planning.

3.2. **Traffic flow prediction model.** In 1960, Kalman and Bucy proposed the Kalman filter, which is essentially a state-space model of a linear stochastic system consisting of observation equations and state equations with linear stochastic coefficients [26, 27]. The filter is based on a linear least mean square unbiased estimation criterion, which utilizes the recursive nature of the state equation to best estimate the state variables of the filter in order to obtain the best estimate of the filtered signal.

The traffic flow prediction model incorporates a Conv-LSTM module and two Bi-LSTM modules. Figure 3 provides an overview of the model's architecture. The Conv-LSTM module combines a convolutional neural network with an LSTM network. The convolutional neural network extracts spatial features of traffic flow, which are then fed into the LSTM network to capture short-term temporal patterns. Recent research has introduced similar approaches that integrate CNN and LSTM for various applications, including traffic information analysis, network fault prediction, gesture recognition, and speech emotion analysis. Simultaneously, the Bi-LSTM module captures daily and weekly periodic features of traffic flow. These spatial-temporal and periodic features are merged into a feature vector by a feature fusion layer. Subsequently, the feature fusion layer is connected to two fully-connected regression layers for forecasting purposes. Additionally, an attention mechanism is incorporated into the Conv-LSTM module to dynamically assess the significance of flow sequences at different time points.

Kalman filter can be used for filtering and estimation of signals as well as for calculating the parameters of the model, and thus has important applications in the prediction of traffic conditions. The traffic flow prediction model equation can be written as:

$$\hat{x}(t+k) = h_0(t)\,V(k) \;+\; h_1(t)\,V(t-1) \;+\; h_2(t)\,x(t-2) \;+\; w(t) \tag{12}$$

where $\hat{x}(t+k)$ represents the predicted value of traffic flow at the moment of $t+k$; $x(t)$, $x(t-1)$, and $x(t-2)$ represent the real traffic flow at the moments of t, $t-1$, and $t-2$, respectively; h_0, h_1, h_2 represent the parameters of the model, which denote the observation noise.

In order to make the operation of the Kalman filter theory to predict the state variables simple, the following transformation is done for this purpose, such that

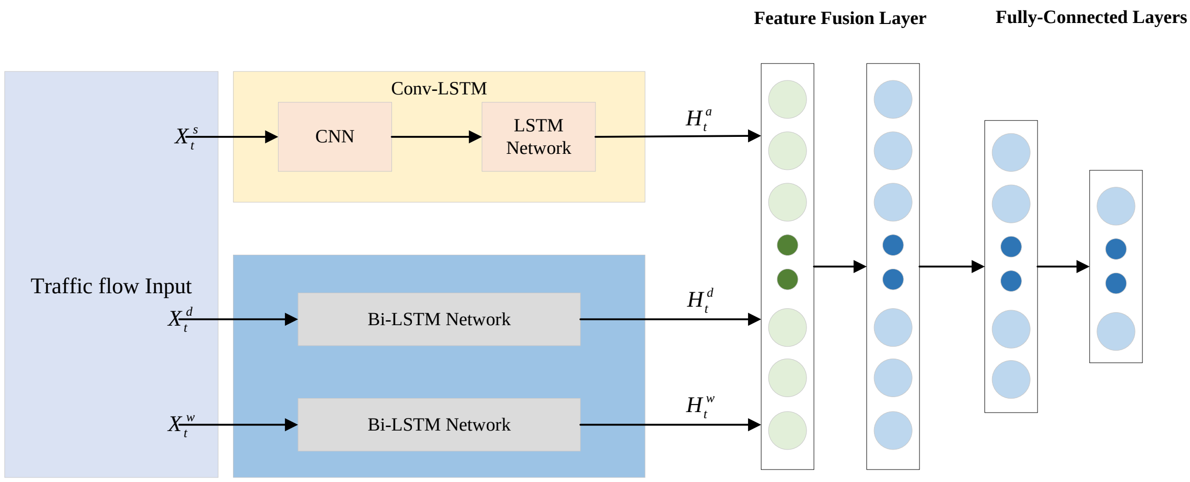

Figure 3. Schematic diagram of traffic flow prediction model

$$X(t) = [\, x(t),\, x(t-1),\, x(t-2)\,]^T \tag{13}$$
$$A(t) = [\, h_0,\, h_1,\, h_2\,] \tag{14}$$
$$Y(t) = x(t+k) \tag{15}$$

Then we have

$$X(t) = B(t)\, X(t-1) + u(t-1) \tag{16}$$
$$Y(t) = A(t)\, X(t) + w(t) \tag{17}$$

where $Y(t)$ denotes the observation, $X(t)$ denotes the state vector, $A(t)$ denotes the observation vector, $B(t)$ denotes the state transfer matrix, and the variance matrix of Gaussian white noise is $Q(t) = 1$.

3.3. **Realization of Emergency Management Program.** By harnessing the power of Dijkstra's algorithm for rapid determination of the shortest path, the emergency response team acquires the critical ability to meticulously plan optimal rescue routes, thereby vastly improving rescue efficiency and reducing time expenditures [28]. This strategic advantage not only expedites the rescue process but also enhances the overall effectiveness of emergency response efforts. Moreover, when coupled with a traffic flow prediction model, the integration enables proactive assessments of post-disaster road traffic conditions, including congestion and closures. This proactive foresight facilitates timely adaptations to rescue routes and resource allocation, empowering emergency management agencies to make well-informed decisions and optimize resource utilization, consequently minimizing wastage and enhancing rescue effectiveness. In the context of actual disaster response, the fusion of these two technologies plays a pivotal role in establishing an intelligent command center. By continuously monitoring real-time traffic statuses and disaster progressions, and by utilizing Dijkstra's algorithm for path planning, the command center is primed to swiftly respond to disasters. It can efficiently guide rescue teams to disaster sites via the most efficient routes and adjust operational strategies based on insights gleaned from the traffic flow prediction model [29]. Furthermore, the regular updating and refinement of these technologies are indispensable to maintain data accuracy and relevance.

Simultaneously, ongoing training sessions and drills are essential to enhance the proficiency of emergency responders in utilizing these technologies, thereby bolstering their disaster response capabilities. This concerted effort ensures that rescue operations can be executed promptly and effectively during times of crisis [30]. By continuously refining and optimizing the integration of Dijkstra's algorithm and traffic flow prediction models within emergency response strategies, organizations can heighten their readiness to navigate and mitigate the impacts of disasters, ultimately safeguarding lives and minimizing damages.

4. **Experiments and analysis of results.** In order to compare and analyze the effect of the proposed scheme, this paper will take the entrance to the stairs of the parking lot as the starting point, and a parking space in the parking lot as the target point, respectively, and take the matrix $S(p,q)$ representing the path distance as the weight matrix to carry out the path planning; take the matrix $T(p,q)$ representing the path time consuming as the weight matrix to carry out the path planning; and take the fusion function combining the path distance $S(p,q)$ and path time $T(p,q)$ as the weight matrix for path planning. According to the above three cases, the simulation results as shown in Table 1 can be obtained.

Table 1. Simulation results

Weighting Matrix	**Time/s**	**Distance/m**
Path distance matrix	31	108
Path Elapsed Time Matrix	19	111
Fusion Matrix	20	108

Following this, the paper proceeds to employ two distinct simulation environments to rigorously evaluate the proposed scheme. The first simulation environment involves a virtual setting, where the theoretical framework is put to the test under controlled conditions that mimic real-world scenarios. This virtual simulation allows for a detailed examination of the proposed approach's efficacy in a simulated but realistic context. In parallel, the study extends its analysis to a real electronic map environment, where the optimized scheme derived in the paper is put through its paces in a setting that closely mirrors actual operational conditions. By conducting tests in a real electronic map simulation environment, the research aims to validate the practical applicability and robustness of the proposed solution in a tangible, real-world context. By leveraging both virtual and real electronic map simulation environments, the paper endeavors to provide a comprehensive assessment of the proposed scheme's performance, shedding light on its effectiveness and feasibility across varying operational landscapes. This multi-faceted evaluation approach serves to bolster the credibility and applicability of the research findings, thereby contributing valuable insights to the field of emergency response optimization.

Table 2. Experimental results of virtual test road network

Experiment No.	**Number of nodes**	**Number of arc segments**	**Time spent by the classical A* algorithm to search the shortest path/s**	**Time spent by the optimization algorithm of this paper to search the shortest path/s**
1	100	500	0.010	0.011
2	500	20000	0.339	0.342
3	1000	10000	0.192	0.164
4	2000	200000	2.235	2.108
5	5000	80000	1.391	1.317

(1) In Windows XP operating system, Visual C++ environment, C++ language programming to realize a large-scale virtual test road network, can be artificially and arbitrarily controlled to generate the number of nodes, nodes belong to the road level and arc

section, and due to the randomness of the generation process, to ensure that the generated test environment for the algorithm of objectivity and fairness. C++ language is used to program the algorithm to be tested, the results show that: A * algorithm and the best path algorithm summarized in this paper, compared with the latter for the number of nodes, highway relatively more effective network computing; the former for the number of nodes, highway relatively less, arc density is relatively large network computing is more effective. Five of the results are selected and listed as shown in Table 2.

(2) Simulation test on the real navigation electronic map road network layer, test environment: Windows CE operating system, Mapinfo/MapX Mobile + Visual C++/EVC development platform, using ARM9 processor portable GPS navigation equipment. This simulation is completely in the embedded environment, so we used EVC to load MapX Mobile as the development environment. Based on our experience with Visual C++ loading MapX for research and testing, the program was modified accordingly and transplanted into the embedded environment for testing. Because of the limitations of the embedded hardware environment, the effect is not as ideal as the simulation on PC. Compared with the original algorithm, there has been a significant improvement, as shown in Table **??**.

Table 3. Real road simulation experiment

Experiment No.	Number of nodes	Number of arc segments	Time spent by the classical A* algorithm to search the shortest path/s	Time spent by the optimization algorithm of this paper to search the shortest path/s
1	245	612	0.03	0.02
2	556	1453	1.12	0.97
3	983	2875	2.52	1.33
4	2352	7432	3.21	1.57
5	3382	9231	4.01	1.97

5. **Conclusions.** This research delves into an innovative approach that harnesses the power of Dijkstra's algorithm and traffic flow prediction models within emergency response scenarios, with the overarching goal of enhancing emergency response efficacy and optimizing resource allocation. To begin with, the study delves into validating the efficacy of Dijkstra's algorithm in computing the shortest path, thereby empowering emergency responders to meticulously strategize the most efficient rescue routes. This strategic planning not only reduces time costs but also amplifies operational efficiency. Moreover, the integration of a traffic flow prediction model enables the anticipation of road traffic conditions, encompassing congestion levels and potential road closures. These predictive insights serve as decision-making aids for emergency management departments, aiding in the prevention of resource wastage and the enhancement of rescue effectiveness. Furthermore, the research delves into a comprehensive exploration of amalgamating sophisticated path planning algorithms with prediction models to further streamline the rescue process. By integrating machine learning and artificial intelligence technologies, the study aims to elevate the precision and timeliness of rescue decisions through extensive big data analysis and real-time monitoring, thus ushering in a new era of advanced emergency response strategies. Subsequent research will attempt to use the Monte Carlo tree search algorithm instead of the Dijkstra algorithm in order to further improve path planning.

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