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Applying Probabilistic Model Checking to Path Planning in an Intelligent Transportation System Using Mobility Trajectories and Their Statistical Data

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ABSTRACT
Path planning is an important topic of research in modern intelligent traffic systems (ITSs). Traditional path planning methods aim to identify the shortest path and recommend this path to the user. However, the shortest path is not always optimal, especially in emergency rescue scenarios. Thus, complex and changeable factors, such as traffic congestion, road construction and traffic accidents, should be considered when planning paths. To address this consideration, the maximum passing probability of a road is considered the optimal condition for path recommendation. In this paper, the traffic network is abstracted as a directed graph. Probabilistic data on traffic flow are obtained using a mobile trajectory-based statistical analysis method. Subsequently, a probabilistic model of the traffic network is proposed in the form of a discrete-time Markov chain (DTMC) for further computations. According to the path requirement expected by the user, a point probability pass formula and a multiple-target probability pass formula are obtained. Probabilistic computation tree logic (PCTL) is used to describe the verification property, which can be evaluated using the probabilistic symbolic model checker (PRISM). Next, based on the quantitative verification results, the maximum probability path is selected and confirmed from the set of K-shortest paths. Finally, a case study of an emergency system under real-time traffic conditions is shown, and the results of a series of experiments show that our proposed method can effectively improve the efficiency and quality of emergency rescue services.

KEY WORDS: path planning, intelligent traffic system, K-shortest paths, probabilistic model checking, path point planning.

1 INTRODUCTION

INTELLIGENT traffic systems (ITSs), which are believed to be crucial for relieving the pressures caused by urban traffic during the city development process(Porto, De Carvalho, & Porto, 2016), have been widely adopted in urban traffic networks. Path planning constitutes a core problem of ITSs; accordingly, researchers have proposed a variety of methods to obtain the shortest paths from traffic systems. Examples of these methods, which attempt to minimize the length of the path, include the Dijkstra algorithm (Dijkstra, 1959) and the A* algorithm (Goldberg, Kaplan, & Werneck, 2006). However, when considering traffic congestion, road construction and traffic accidents, vehicle guidance using shortest-path-based plans will lead to congestion because these methods cannot perform vehicle monitoring and traffic analysis in real time. To address this deficiency, shortest-path-based planning measures should be developed to further consider traffic conditions. This need is especially acute for emergency services, including ambulance, fire and rescue services. With regard to optimal path planning, the probabilistic shortest path should be considered to avoid traffic congestion.

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Figure 1 shows traffic congestion along a road segment (location B) due to a traffic accident. During a certain time interval, the number of vehicles passing through the congested segment (location B) at the intersection (location A) will quickly decrease. In contrast, the number of vehicles passing through other road segments will increase significantly; this change is attributed to the occurrence of traffic congestion on the road segment at location B. However, given an effective method of recording and analyzing traffic data, the traffic system can become more intelligent, and as a result, daily travel will become more convenient. The existing traffic infrastructure (Poongodi Chinnasamy, Premalatha J, Lalitha K & Vijay Anand D, 2017) is equipped to record the mobile trajectory data of vehicles; these data, which reflect real-time traffic information (Liu W, Pan R, Guo X, & Xu Feng, 2012), are collected by sensors, vehicle detectors, mobile GPS services (Deng et al., 2016) and intelligent video surveillance, among other techniques. Thus, mobile trajectory data on the flow of traffic can be collected to calculate the passing probability associated with each road segment, and these data can be used to monitor and forecast the flow of traffic to make suitable plans (Huang, Chun, Song, Jun, & Chen, 2017). Vehicles can then be properly and efficiently directed to their destinations (Bo Mi & Dongyan Liu, 2017), thereby easing traffic congestion.

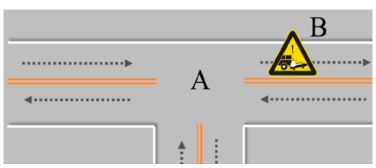

Figure 1. Traffic Congestion on a Road Segment.

As mentioned above, the existing traffic infrastructure is used to monitor and collect these streamed data in real time to perform vehicle route and path planning. Accordingly, when a traffic accident has occurred, it is necessary to utilize these data to provide reasonable driving directions. In particular, transit time and survival probability should be considered during emergency rescue services. For example, planning the path between a hospital and first aid station is very important for rescue services. In general, the shortest-path method may lead to slower travel, the result of which may be the loss of time or even lives. To address this issue, we would like to consider the probability factors and then calculate the probability of road traffic based on statistical data extracted from the mobile trajectories of vehicles. Ultimately, the maximum probability path derived from the K-shortest path (KSP) can be selected and provided to the driver.

From a technical perspective, ITS-based traffic network models should be constructed for formal analysis. Thus, probabilistic model checking is applied to verify the passing probabilities of vehicles within traffic networks. Specifically, traffic network directed graphs (TNDGs) are proposed to describe the traffic system features, and a probabilistic traffic flow relationship (PTFR) is used with statistical traffic probability data to generate the probabilistic characteristics. Based on TNDGs and the probabilities of road segments, a vehicle behavior model (VBM) is proposed for use in traffic systems. A probabilistic label transition system (PLTS; Gao, Miao, & Zeng, 2013)-based probabilistic behavioral model is used to formalize the VBM for further verification. The verification property is then described using probabilistic computation tree logic (PCTL; Svoreňová, & Kwiatkowska, 2016), where a point probability pass formula (P3F) and a multiple-target probability pass formula (MTP2F) are proposed to design the path point planning scheme. The key concept involves calculating the probability from the starting point to the ending point; the target point with the greatest probability is taken as the final point in the planned path. Next, the probabilistic symbolic model checker (PRISM) is integrated to apply the verification property to the TNDG model. By analyzing the verification results, the optimal planned path is determined from the KSP. Finally, a case study involving hospital first aid (HFA), which requires ambulances to travel through a certain blood station before reaching a first aid station, is discussed to demonstrate the feasibility of our method. In addition, a series of experiments are conducted to show that our method is effective in generating optimal planned paths.

The remainder of this paper is organized as follows. Section 2 presents the method of constructing the formal model in the traffic network. Section 3 describes a path point planning method based on a traffic network model. Section 4 uses a case study to demonstrate the effectiveness of the proposed path point planning method, following which Section 5 reviews related work. Finally, Section 6 presents the conclusions and provides future research directions.

2 FORMAL DEFINITIONS

THE geographic features of traffic networks are first extracted. These features include two main elements, namely, nodes and edges. TNDGs are then proposed based on these elements and the probabilistic data.

2.1 Description of Features in Traffic Networks

A traffic network is abstracted as a directed graph that consists of directional edges and nodes. Each road intersection is abstracted as a node, and each road is abstracted as a directed edge. However, due to the complexity of traffic networks, such networks cannot be formalized as a simple collection of nodes and edges. Descriptions of their features are as follows.

Definition 1 (descriptions of the features of traffic networks). The features of traffic networks are divided into the following four categories, which depend on the actual road features.

1) One-Way Roads. As shown in Figure 2, this type of road can be simply abstracted as a directed edge that is consistent with its direction of travel.

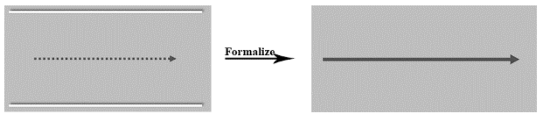

Figure 2. **Traffic on a One-Way Road.**

2) Two-Way Roads. Figure 3 shows two types of roads: single-lane roads and multilane roads.

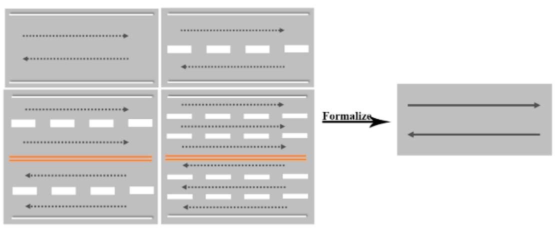

Figure 3. **Traffic on a Two-Way Road.**

3) Crossroads. Each road has a starting point and an ending point, and an intersection can be regarded as the starting point or the ending point of a road. As shown in Figure 4, different roads are joined at intersections, which are connected to form a traffic network.

An intersection, which represents the transportation hub of a traffic network, is a complex structure. As a result, intersections are represented by nodes, and the lanes that converge at intersections are formalized by four sets of directed edges that point in different directions.

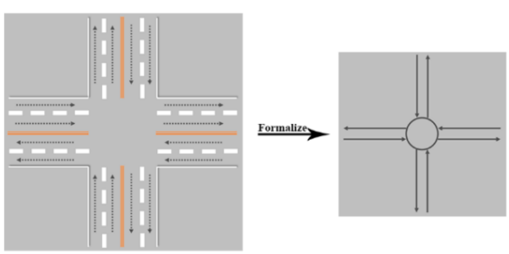

Figure 4. **Traffic at a Crossroads.**

4) T-junctions. A T-junction is similar to a crossroads. Figure 5 shows the formalization of a T-junction.

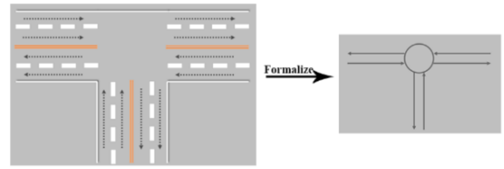

Figure 5. **Traffic at a T-junction.**

Based on the formalizations presented above, the processes by which vehicles traverse a traffic network can be regarded as a process of moving from one node to another node via a specific edge. Therefore, according to Definition 1, a traffic network can be formalized as a traffic network directed graph (TNDG). Note that special statuses, such as U-turns and anchoring, should be handled carefully. A U-turn can be regarded as the process by which a vehicle begins moving in the opposite direction at a junction point. Anchoring can be regarded as the process in which the present location does not change over time.

2.2 *Analysis and Processing of Traffic Flow Data*

The probability of the flow of traffic is obtained from the mobility trajectories derived from the statistical data, which show the number and the transfer probability of vehicles at each intersection in different directions for a given traffic network. Thus, based on the descriptions of the features of traffic networks provided in Definition 1, the formal model of a traffic network is defined below.

Definition 2 (probabilistic traffic flow relationship, PTFR). The PTFR is defined as PTFR=(S, T, N, P), where

1) S is a set of nodes in the TNDG.

2) T is a variable that represents the value of a time interval.

3) $N(S,S)\rightarrow\mathbb{N}$ represents the traffic data relationship, where $\mathbb{N}$ represents the number of vehicles that pass from the initial node to the destination node during the time interval T.

4) $P(S,S)\rightarrow[0,1]$ is the traffic probability relationship, which represents the probability of vehicles passing from the initial node to the destination node.

The probability value can be computed using the statistical formula $P(S_i,S_j)=\dfrac{N(S_i,S_j)}{\sum_{k\in M} N(S_i,S_k)}$, where M is the set of nodes that can be reached directly from node S_i. The probability relationship of the traffic flow reflects the probabilities that vehicles travel along different sections over a period of time.

2.3 *Traffic System Vehicle Behavior Model*

Next, probabilistic relationships and traffic networks are considered for integration. Based on the probabilities of roads, a VBM is proposed for use in traffic systems. Each node is abstracted as a state, and each edge is abstracted as a series of transitions.

Definition 3 (vehicle behavior model, VBM) The traffic system VBM is defined as VBM=(S, $Init$, $\sum$, AP, L), where

1) S is a set of states.

2) $Init \subseteq S$ is an initial state.

3) $\sum \subseteq S \times Distr(S)$ denotes a state transition relationship that represents the transitions of vehicles between different states, where $Distr(S) \rightarrow [0,1]$.

4) AP is a set of atomic propositions.

5) $L: S \rightarrow 2^{AP}$ represents the label function, which maps each state to a set of atomic propositions.

The VBM includes an automata model and a performance model to describe the states of vehicles driving between different intersections. When using a graphical description of a VBM, a state is represented by a circle, and a transition relationship is indicated by a directional arrow. Each state maps to a single intersection, and each transition represents the behavior of a vehicle driving from the initial intersection to the destination intersection. To address this model, the mobile trajectory data are used as the source of the PTFR. The VBM is then generated by combining the TNDGs and the PTFR. If the probability value of an edge is greater than 0, a probability transition occurs.

To better illustrate the VBM, a case is given here. Figure 6 illustrates a road map of the HFA process. As shown in the diagram, there are both two-way roads and one-way roads. In the traffic network, hospital H is located at the upper-left corner, blood station A is located at the upper-right corner, and blood station B is located at the lower-left corner. The instrument M embedded in the road represents a vehicle detector, and the instrument N represents a surveillance camera. All instruments are used to record mobile trajectories to support the statistical analysis of the data.

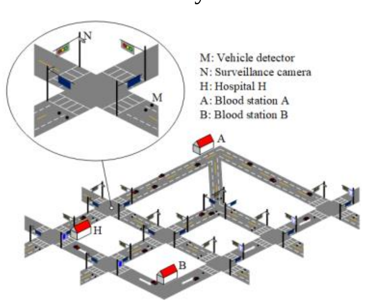

Figure 6. Road Map Used in the Sample HFA Process.

The diagram of the traffic network is abstracted as a TNDG according to Definition 1. The probabilities of each path in the traffic network are computed using Definition 2, after which the road map is transferred to the VBM, as shown in Figure 7. Node 1 corresponds to hospital H in Figure 6, while nodes 3 and 7 correspond to blood stations A and B, respectively. Suppose that the weight of each path is 1 and that there is a medical emergency request at node 10 due to a traffic accident. To address this emergency process, an ambulance needs to reach one of the blood stations to replenish its blood bags before it can proceed to the rescue point to address the emergency.

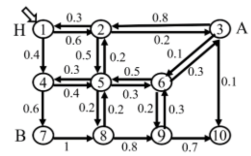

Figure 7. Example of a Vehicle Behavior Model.

The KSP problem is a type of variation of the shortest-path problem. The difference is that the KSP problem involves finding multiple alternative optimization paths between the starting and ending points.

Table 1. Top 3 Paths and the Corresponding Weights.

ID	Path	Station	Weight
Route 1	$1 \rightarrow 2 \rightarrow 3 \rightarrow 10$	A	3
Route 2	$1 \rightarrow 2 \rightarrow 3 \rightarrow 6 \rightarrow 9 \rightarrow 10$	A	5
Route 3	$1 \rightarrow 4 \rightarrow 7 \rightarrow 8 \rightarrow 9 \rightarrow 10$	B	5

As shown in Table 1, the Eppstein KSP algorithm (Eppstein, 1998) returns the top 3 paths (https://github.com/bsmock/k-shortest-paths), which addresses the needs of the emergency rescue process in our example. However, the passing probability in a traffic network is neglected. In practice, according to the features of Markov chains, the ambulance departs from hospital H, and the probability of reaching the help point via blood station A within 20 time steps is 0.277149. However, if blood station B is selected, the probability of reaching the help point is 0.40938. Obviously, we would prefer to select route 3 as the optimal planned path because the probability of reaching blood station B is much higher than that of reaching blood station A. Thus, the shortest-path method does not return the optimal planned path.

3 PATH POINT PLANNING

TO find the probabilistic shortest path, the quantitative properties of the VBM are checked to compute the probabilities used in the path selection process. Thus, the expected demand is formalized as a PCTL formula.

Definition 4 (probabilistic computation tree logic, PCTL). The verification property is given in the form of PCTL, and the syntax is defined as follows:

$$\varphi ::= true \mid false \mid a \mid \varphi \wedge \varphi \mid \varphi \vee \varphi \mid \varphi \rightarrow \varphi \mid \neg \varphi$$

$$P_{\sim p}[X_{\varphi}] \mid P_{\sim p}[\varphi U \varphi] \mid P_{\sim p}[\varphi U^{\leq k} \varphi] \mid P_{\sim p}[F_{\varphi}] \mid P_{\sim p}[G_{\varphi}]$$

where $\sim\in\{<,\leq,>,\geq\}$, 0<p<1 is a probability bound or threshold, a is an atomic proposition, φ and φ are formulae, and $k\in\mathbb{N}$ is a natural number that denotes a time step. The symbol P represents the probability operator, and the symbols ***X***, ***F***, ***G*** and ***U*** are temporal operators that indicate the "ne***X***t state", the "***F***uture state", the "***G***lobal state" and "***U***ntil", respectively. For example,

1) $P_{<0.1}[F<=100\&errors>5]$: with a probability of 0.1 or less, more than 5 errors will occur within 100 time steps.

2) $P_{=?}[!proc2\ U\ proc1]$: What is the probability that process 1 terminates before process 2?

The VBM attributes are described using the PCTL formula to express the complex target tasks of the model. Based on PCTL, we propose the following two types of definitions for generating formula templates.

In real road systems, we should consider that some special points should be visited when the starting point and the ending point are set. The P3F returns the value of the probability starting from the initial state to the destination state, and the special points are included in the path planning.

Definition 5 (point probability pass formula (P3F) template). The P3F is designed to find the maximum probability from a set of candidate points in the traffic network. It is defined as

$$P\ bound\ [pathprop]$$

where *bound* denotes the probability bound, and *P* is an expression that evaluates to a double in the range of [0, 1]. In addition, *pathprop* is the assertion.

The P3F template guides the generation of the verification property formula for the VBM. This formula can be used to detect behavioral requirements and to return the passing probability in the model. For example, we use "*P=? [s=1 & ten=true]*" to represent the probability in the VBM of passing through a specific point (i.e., node 10) and reaching node 1.

Next, we consider that most drivers will change their planned paths in the case of traffic congestion. Given more than one candidate point, the MTP2F calculates the probability of starting from each candidate point. For example, if there are multiple hospitals that can serve as starting points in the case of HFA, it is necessary to select one hospital as the starting point. Thus, we use the MTP2F to evaluate the planned paths to confirm which are substantially better.

The probability is used as an evaluation indicator, and the candidate point with the maximum probability is selected as the starting point in the planned path. Thus, we extend the P3F template and add the filter to consider multiple states as starting points.

Definition 6 (multiple-target probability pass formula (MTP2F) template). The MTP2F template is defined using the following form:

$$filter(op, prop, states)$$

where *op* is the filter operator, *prop* is any property, and *states* is a Boolean-valued expression that identifies a set of states that will be filtered. The argument *states* is optional; if it is omitted, the filter is applied over all states. For example,

1) *filter(max,P=?[F"error"],x=0)* gives the maximum value of the probability of reaching an "*error*" state when starting from any state satisfying $x=0$.

2) *filter(forall,P>=1[F"done"],"ready")* checks whether we will eventually reach a "*done*" state with a probability of 1 from any state that satisfies the label "*ready*".

The MTP2F takes *filter* as a keyword and requires the use of a nested formula to also satisfy the formula syntax of PRISM. The MTP2F can compute results for all specified states at the same time, whereas the operator can be used to filter the template results to produce a single value. Note that the filter operators include *min*, *max*, and *count*, among others.

Considering an HFA process such as that shown in Figure 6, if there are multiple hospitals, we should find the hospital with the best location to optimize the rescue efficiency. If the P3F template is used, it is necessary to reconstruct the VBM and use different hospital nodes as the starting point. Significantly, if the MTP2F template is used, we simply need to change the property formula instead of reconstructing the VBM. Different nodes can then easily be set as the initial node based on the VBM. This process increases the efficiency of the model checking and expedites the process of emergency rescue.

In our paper, the formal method that uses the P3F and the MTP2F to quantitatively verify the properties of the VBM to compute the probability of the shortest path is called path point planning. The definition of path point planning and the corresponding algorithm are as follows.

Definition 7 (path point planning). Path point planning is defined as follows:

$P_{set}::=\{path_i\ |\forall i \bullet P_{pathi} > V_{user},\ path_i \in \{path_1, path_2, path_3, \ldots, path_k\}\}$

In the VBM, the KSP algorithm is used to generate the set of shortest paths $\{path_1, path_2, path_3, \ldots, path_k\}$. The paths with relatively low probabilities are removed to ensure $\forall i \bullet P_{path_i} > V_{user}$, where V_{user} is a value predefined by the user. Subsequently, each path in the refined set $\forall i$, and $path_i$ represents the point planning path. This process of finding $path_i$ is called path point planning.

Note that the probability of each shortest path can be obtained to evaluate the planned path because PRISM can help us quantitatively verify the properties of the P3F and the MTP2F against the VBM. Table 2 shows the algorithm used in path point planning.

Table 2. Path Point Planning Algorithm.

ALGORITHM: Path Point Planning Algorithm (P3A)

INPUT: Traffic Network Diagram G; Node end; Traffic data D={S_i, S_j, d}; Node Array assign;

OUTPUT: Probabilistic Shortest Paths;

$N \leftarrow S \times S \times N$;
For each element in data D do;
  $N(S_i, S_j) \leftarrow$ *data;*
End;
  Directed Array Dire $\leftarrow \{S_i, S_j, N(S_i, S_j)\}$;
  Dire $\leftarrow$ *directed in G;*
  $P \leftarrow S \times S \times \Re$;
For each dire in Dire do
  $P(S_i, S_j) \leftarrow \frac{N(S_i, S_j)}{\sum_{k \in M} N(S_i, S_j)}$;
End
  Convert G to VBM according to P;
For node in assign do
  $P[i] \leftarrow P$=?[F end=true & node=true];
  $i++$;
End
P_{max}={$path_1$, $path_2$, $path_3$, …, $path_i$}$\leftarrow P$[] order by probability;
Max={$path_1$, $path_2$, $path_3$, …, $path_i$}$\leftarrow$K_Shortest(G);
Return paths set based on P_{max} and Max;

In the path point planning algorithm, M is a set of nodes that can be reached directly from node S. In addition, the input variables are the TNDG, the mobile trajectory data triplet, the target point set and the destination node. The output is the set of probabilistic shortest paths. Specifically, the target point set represents the points that must be passed through along the planned path, such as a blood site in the case study of providing medical aid. Furthermore, each path in the KSP set must also pass through a point in the target point set. The algorithm first constructs the VBM, which is an abstraction of the traffic network; it includes the transition relationships of vehicles to different sections at intersections and the passing probability of each section calculated using the PTFR model. Second, to obtain the passing probability, the VBM is verified using the properties of the P3F and the MTP2F. The paths in the KSP set with lower probabilities based on the verification property results will be excluded. Finally, the probabilistic shortest path is determined by combining the KSPs.

4 CASE STUDY AND SIMULATION EXPERIMENTS

TO illustrate the effectiveness of our proposed method, a case study and simulation experiments involving a traffic network are discussed. In the first part, a sample city traffic network is introduced, and the mobility trajectories derived from the statistical data are collected and displayed. In the second part, the validity of our method is assessed using probabilistic model checking from the perspective of selecting the optimal planned path.

4.1 Case Study and Data Simulation

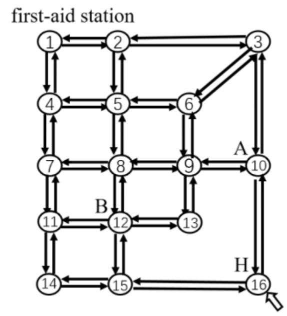

Figure 8. Sample City Traffic Network.

Figure 8 shows a feature description of a city traffic network. Suppose an emergency rescue is requested at node 1 due to a traffic accident. Node 16 is hospital H, while nodes 10 and 12 are blood stations A and B, respectively, which provide blood supplies to injured people. An ambulance from hospital H must reach a blood station to obtain blood packs before proceeding to the emergency point to perform the emergency rescue.

To illustrate the complexity of the transportation system and the traffic network, Table 3 shows the traffic conditions collected from the statistical data of the traffic network. Each road segment is uniquely identified by its segment ID, which is determined by the starting point and the ending point. The weight of each directed edge is assumed to be 1. The current flow field $vel/\Delta t$ represents the number of vehicles that pass along the road segment during the specified unit of time. For example, the starting point of the road segment with segment ID 8 is node 3, and the ending point is node 10. The weight of this road segment is 1. Two vehicles drive along this section during time unit Δt. Route planning based on traffic conditions is crucial in this case.

The traditional path planning method primarily calculates the shortest path from the initial node to the destination node. Table 4 shows the top 5 shortest paths that satisfy the medical assistance process. These paths were identified using Eppstein's algorithm. These five paths all start from node 16 and end at node 1, and they pass through nodes 10 or 12. However, we cannot guarantee that these routes represent acceptable plans because the shortest-path approach ignores the probability of road access in traffic networks. As a result, the planned paths may not be optimal if congestion occurs along the planned paths.

4.2 Assessment of the Validity of Our Method

We implement the proposed algorithms in Table 2, design an HFA process for simulating traffic systems, and integrate PRISM into this system to verify the P3F and MTP2F properties to compute the probability of each shortest path.

Table 3. **Traffic Conditions of the Traffic Network.**

Segment ID	Weight	Start node	End node	Current flow ($vel/\Delta t$)
1	1	1	2	3
2	1	1	4	3
3	1	2	1	2
4	1	2	3	4
5	1	2	5	6
6	1	3	2	8
7	1	3	6	8
8	1	3	10	2
9	1	4	1	8
10	1	4	5	6
11	1	4	7	5
12	1	5	2	2
13	1	5	4	6
14	1	5	6	5
15	1	5	8	10
16	1	6	3	2
17	1	6	5	10
18	1	6	9	3
19	1	7	4	5
20	1	7	8	9
21	1	7	11	4
22	1	8	5	7
23	1	8	7	6
24	1	8	9	4
25	1	8	12	8
26	1	9	6	4
27	1	9	8	5
28	1	9	10	1
29	1	9	13	3
30	1	10	3	1
31	1	10	9	1
32	1	10	16	1
33	1	11	7	8
34	1	11	12	8
35	1	11	14	5
36	1	12	8	11
37	1	12	11	10
38	1	12	13	4
39	1	12	15	4
40	1	13	9	5
41	1	13	12	7
42	1	14	11	3
43	1	14	15	8
44	1	15	12	4
45	1	15	14	5
46	1	15	16	1
47	1	16	10	3
48	1	16	15	1

Table 4. **Top 5 Paths and Their Corresponding Weights.**

ID	Path	Weight
Route 1	16→10→3→2→1	4
Route 2	16→10→9→6→5→2→1	6
Route 3	16→10→9→8→5→2→1	6
Route 4	16→15→12→8→5→2→1	6
Route 5	16→15→12→8→5→4→1	6

Next, a series of experiments are conducted to evaluate the effectiveness of different methods. All experiments are conducted on a B250 M-D3H GIGABYTE PC with a 4.20-GHz Intel Core i3-7350k CPU and 16 GB of memory running Windows 10. The first experiment involves the use of the P3F to evaluate the planned paths. The second experiment involves the use of the MTP2F to evaluate the planned paths.

4.2.1 Data preparation

We first consider the case shown in Figure 8 to construct the VBM. The resulting probability matrix of the flow of traffic is shown in Table 5 according to the traffic conditions shown in Table 3.

After the probability matrix is combined into the VBM, Figure 9 shows the transition relationships. Here, s=0 through s=16 map onto node 1 through node 16 in the TNDG. The initial node, namely, s=16, is marked by a hollow arrow.

The discrete-time Markov chain (DTMC; Kwiatkowska, Norman, & Parker, 2010; Kwiatkowska, Norman, & Parker, 2011) is used to formalize the VBM. The formal VBM=(S, $Init$, Σ, AP, L) is as follows:

S={1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16};

$Init$={16};

Σ={ $1 \xrightarrow{0.5} 2$, $1 \xrightarrow{0.5} 4$, $2 \xrightarrow{0.167} 1$, $2 \xrightarrow{0.5} 5$, $2 \xrightarrow{0.333} 3$, $3 \xrightarrow{0.444} 2$, $3 \xrightarrow{0.444} 6$, $3 \xrightarrow{0.112} 10$, $4 \xrightarrow{0.421} 1$, $4 \xrightarrow{0.316} 5$, $4 \xrightarrow{0.263} 7$, $5 \xrightarrow{0.087} 2$, $5 \xrightarrow{0.261} 4$, $5 \xrightarrow{0.435} 8$, $5 \xrightarrow{0.217} 6$, $6 \xrightarrow{0.667} 5$, $6 \xrightarrow{0.133} 3$, $6 \xrightarrow{0.2} 9$, $7 \xrightarrow{0.278} 4$, $7 \xrightarrow{0.5} 8$, $7 \xrightarrow{0.222} 11$, $8 \xrightarrow{0.28} 5$, $8 \xrightarrow{0.24} 7$, $8 \xrightarrow{0.16} 9$, $8 \xrightarrow{0.32} 12$, $9 \xrightarrow{0.308} 6$, $9 \xrightarrow{0.385} 8$, $9 \xrightarrow{0.077} 10$, $9 \xrightarrow{0.23} 13$, $10 \xrightarrow{0.333} 3$, $10 \xrightarrow{0.334} 9$, $10 \xrightarrow{0.333} 16$, $11 \xrightarrow{0.381} 7$, $11 \xrightarrow{0.381} 12$, $11 \xrightarrow{0238} 14$, $12 \xrightarrow{0.379} 8$, $12 \xrightarrow{0.345} 11$, $12 \xrightarrow{0.138} 13$, $12 \xrightarrow{0.138} 15$, $13 \xrightarrow{0.417} 9$, $13 \xrightarrow{0.593} 12$, $14 \xrightarrow{0.3} 11$, $14 \xrightarrow{0.15} 15$, $15 \xrightarrow{0.4} 12$, $15 \xrightarrow{0.15} 14$, $15 \xrightarrow{0.45} 16$, $16 \xrightarrow{0.833} 15$, $16 \xrightarrow{0.167} 10$, $16 \xrightarrow{0.833} 15$}

AP={one, two, three, four, five, six, seven, eight, nine, ten, eleven, twelve, thirteen, fourteen, fifteen, sixteen}

L(s=1)={one=true}, L(s=2)={two=true}, L(s=3)={three=true}, L(s=4)={four=true}, L(s=5)={five=true}, L(s=6)={six=true}, L(s=7)={seven=true}, L(s=8)={eight=true}, L(s=9)={nine=true}, L(s=10)={ten=true}, L(s=11)={eleven=true}, L(s=12)={twelve=true}, L(s=13)={thirteen=true}, L(s=14)={fourteen=true}, L(s=15)={fifteen=true}, L(s=16)={sixteen=true}.

Table 5. **Probability Matrix of Traffic Flow.**

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
1		0.5		0.5												
2	0.167		0.333		0.5											
3		0.444				0.444				0.112						
4	0.421				0.316		0.263									
5		0.087		0.261		0.217		0.435								
6			0.133		0.667				0.2							
7				0.278				0.5			0.222					
8					0.28		0.24		0.16			0.32				
9						0.308		0.385		0.077			0.23			
10			0.333						0.334							0.333
11							0.381					0.381		0.238		
12								0.379			0.345		0.138		0.138	
13									0.417			0.593				
14											0.3				0.7	
15												0.4		0.15		0.45
16										0.167					0.833	

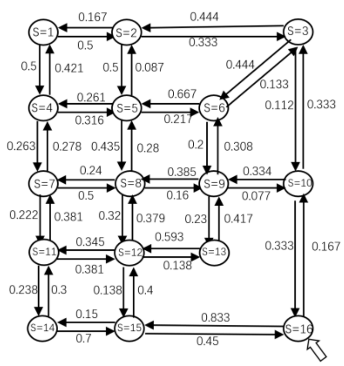

Figure 9. **Visualization of the Vehicle Behavior Model.**

4.2.2 Experiments using the P3F

There are various unreachable factors given the complexity and variability of real-time traffic conditions. The shortest path is probably not the optimal path. A higher probability indicates a greater reachability of the destination point for a route beginning at the starting point and passing through a final point as well as a smaller probability of encountering congestion. Therefore, we should analyze the verification results of the set of points that a given path must pass through and remove the points with relatively low probabilities. Considering the formal verification, we would like to use the P3F to evaluate the planned path.

According to the P3F template given in Definition 5, the formula set of reachability properties generated based on the state coverage criterion (Chen, Miao, & Qian, 2008) is listed in Table 6, which is supported by PRISM.

Table 6. **Formula Set of Reachability Properties Obtained Using the P3F.**

ID	Property formula
P1	$P=?[F<100s=1\&one=true]$
P2	$P=?[F<100s=1\&two=true]$
P3	$P=?[F<100s=1\&three=true]$
P4	$P=?[F<100s=1\&four=true]$
P5	$P=?[F<100s=1\&five=true]$
P6	$P=?[F<100s=1\&six=true]$
P7	$P=?[F<100s=1\&seven=true]$
P8	$P=?[F<100s=1\&eight=true]$
P9	$P=?[F<100s=1\&nine=true]$
P10	$P=?[F<100s=1\&ten=true]$
P11	$P=?[F<100s=1\&eleven=true]$
P12	$P=?[F<100s=1\&twelve=true]$
P13	$P=?[F<100s=1\&thirteen=true]$
P14	$P=?[F<100s=1\&fourteen=true]$
P15	$P=?[F<100s=1\&fifteen=true]$
P16	$P=?[F<100s=1\&sixteen=true]$

Each property formula shown in Table 6 returns a specific probability value. For example, formula P7 indicates the probability of reaching node 1 within 100 time steps by following a path beginning at the initial node 16 and passing through node 7. These formulae are then verified by PRISM. If the probability value is lower than the expected probability value of the system, the traffic behavior is unreachable. Attempting to follow such paths will affect the efficiency of HFA and endanger the lives and safety of people. When the probability value is small, the planned path should be adjusted dynamically to improve the reliability of the path planning process.

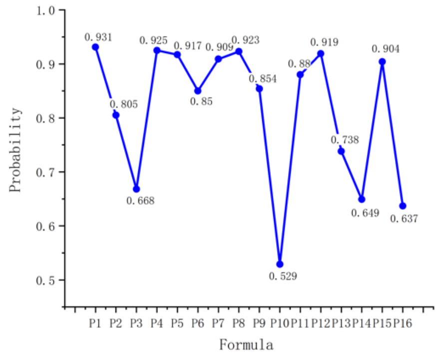

Figure 10. Verification Results Obtained Using the P3F.

Figure 10 shows the verification results obtained for each formula shown in Table 6. The probability value of the path that passes through node 10 (0.529) is the smallest. However, the probability values of the plans that pass through nodes 3, 13, 14 and 16 are less than 0.8. To address this issue, we recognize that a risk of traffic congestion exists when these nodes are included in the routes. When a planned route is requested, these nodes should be excluded. The probability value of the path that passes through node 1 (0.931) is the greatest, and the probability values of the paths that pass through nodes 4, 5, 7, 8, 12 15 exceed 0.9; thus, these paths are considered candidates. In this way, we can effectively avoid traffic congestion.

Table 7. Replanned Paths Obtained Using Path Point Planning.

ID	Path	Weight
Route 4	16 → 15 → 12 → 8 → 5 → 2 → 1	6
Route 5	16 → 15 → 12 → 8 → 5 → 4 → 1	6

In this case, the ambulance must pass through either node 10 or node 12 to supplement its blood supply before reaching the first aid station. Figure 10 shows that the probability of P10, which reaches node 1 from node 10 to node 16, is 0.529; additionally, the probability of P12, which reaches node 1 from node 12 to node 16, is 0.919. Therefore, the probability of passing through node 12 is much higher than the probability of passing through node 10. For the purposes of HFA, paths that pass though node 12 should be preferentially selected. In contrast, combined with the KSPs shown in Table 4, the probability values of routes 1-3, which pass through node 10, are smaller. The probability values of routes 4 and 5, which pass through node 12, indicate that they should be selected. Finally, considering the KSPs and the verification result analysis, the replanned paths obtained by path point planning are shown in Table 7. This path plan returns the shortest paths with the highest probabilities.

4.2.3 Experiments using the MTP2F

Due to the changing probabilities of road segments, navigation systems must constantly adjust the planned paths provided to the driver. Therefore, it is necessary to consider some special points that the driver must visit.

In the case of HFA, it is assumed that there are multiple hospitals that can serve as starting points for HFA. Thus, we use the MTP2F to evaluate the planned paths and confirm which paths are substantially better.

Thus, we change the requirements for the number of hospitals, while the other conditions remain unchanged. As shown in Figure 9, we specify that there are hospitals at nodes 3, 15 and 16. Each of these nodes could be selected as the starting point depending on the actual situation. In addition, we still consider nodes 10 and 12 to represent blood stations A and B, respectively, which provide blood supplies to injured people.

Based on the MTP2F template given in Definition 6, the formula set of reachability properties generated using the state coverage criterion and supported by PRISM is given in Table 8.

Table 8. Formula Set of Reachability Properties Obtained Using the MTP2F.

ID	Property formula
F1	$filter(min, P=?[F<100\ s=1\&twelve=true], s=3)$
F2	$filter(min, P=?[F<100\ s=1\&twelve=true], s=15)$
F3	$filter(min, P=?[F<100\ s=1\&twelve=true], s=16)$
F4	$filter(min, P=?[F<100\ s=1\&ten=true], s=3)$
F5	$filter(min, P=?[F<100\ s=1\&ten=true], s=15)$
F6	$filter(min, P=?[F<100\ s=1\&ten=true], s=16)$

The formulae shown in Table 8 can choose different initial nodes in the VBM and select the minimum probability scheme via computations. For example, formula F1 indicates the minimum probability of a route starting from node 3 and passing through node 12 to node 1 within 100 time steps.

Figure 11 shows the verification results obtained using the MTP2F. The probabilities of F4, F5 and F6, which reach the target point (node 10) from each initial node, are much lower than the probabilities of F1, F2 and F3, which pass through a different ending point (node 12). This result is consistent with the P3F experiment, which suggests that we should select node 12 as a necessary point in the traffic network. Moreover, choosing a different hospital as the starting point in the HFA process results in substantial changes in the path. In property formulae F1, F2, and F3, the probability value of F1 (0.839), which starts at node 3 and passes through a target point (node 12) to reach node 1, is the smallest, while the probability value of

F2 (0.925), which starts from node 15 and passes through a target point (node 12) to reach node 1, is the greatest. In summary, node 15 is recommended as the starting point for HFA. This planned path produces the shortest planned routes and the maximum probabilities and can arrive at a final point during emergency rescue operations.

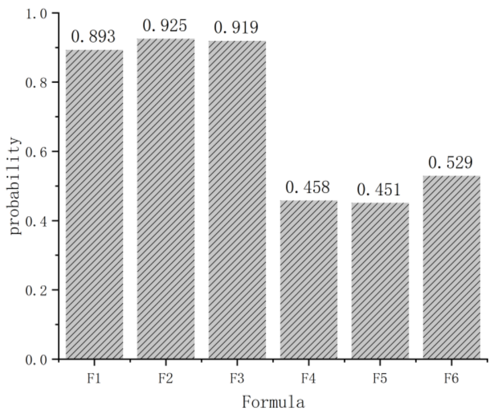

Figure 11. **Verification Results Obtained Using the MTP2F.**

5 RELATED WORK

ITSs play indispensable roles in urban transportation throughout the world. The goals of an ITS are to establish communications between users, vehicles and urban infrastructures and to provide more sustainable and efficient transport conditions.

The development of ITSs over decades has resulted in a systematic information chain (Jarašūniene, 2007). Digital maps, global information systems, mobile phone positioning, and satellite navigation systems are used for positioning; traffic detectors, weather monitoring and vehicle detectors are used to obtain data; data dictionaries, data fusion, data exchange, map data matching and other technologies are used for data processing; and traffic congestion detection, path planning, auxiliary driving systems and other technologies are used to apply the acquired information. Given the emergence of new technologies (Cao, Chen, & Li, 2006; Chaturvedi, & Srivastava, 2017; Munjal, & Verma, 2016), ITSs present new technical characteristics and development directions. Moreover, the development and construction of ITSs has made the traffic planning process more scientific and has allowed ITS facilities to be more effective. In addition, with the wide application of ITS technology, vehicle navigation systems, which constitute an important component of ITSs, has become a basic element of daily life; in turn, path planning is an indispensable function of vehicle navigation systems. Based on an ITS, this paper focuses on path planning during the process of driving a vehicle. Presently, traffic congestion is becoming increasingly serious, but improved path planning can effectively alleviate this problem in urban traffic. However, it is still challenging to develop optimal vehicle navigation systems given the inability to handle unexpected events. In this section, we give a review of the major techniques that are most closely related to our work.

Traditional path planning approaches, such as the Dijkstra and A* algorithms, focus on static programming, which assumes that the traffic network is stable. Chang, Jheng, Chang, and Lo (2015) and Deng, Chen, Zhang, and Mahadevan (2012) introduced fuzzy theory, which effectively reduces the path calculation time, into the path search algorithm. Furthermore, Na (2013) and Zhu, Liu, Gao and Wang (2014) focused on improving the traditional Dijkstra algorithm, while Wang, Zhou, Zheng, and Liang, Y (2014) proposed a hierarchical A* algorithm to accommodate large-scale path planning problems. In addition, Ding (2013), Sun, and Li (2016) and Zhao and Liu (2015) aimed to optimize the A* algorithm from different aspects, such as performing weighted optimizations and improving the heuristic functions involved. These algorithms improve the search speed and effectively reduce the risk of an exponential increase in the path planning cost. However, static path planning methods use historical data to predict road traffic flow conditions and congested sections, and the traffic network is assumed to be stable.

To address this problem, dynamic path planning algorithms that depend on ITSs are used. Several studies of dynamic path planning have been conducted. For example, He, Cao and Li (2012) presented a density-velocity traffic flow model to predict traffic conditions and proposed a dynamic candidate path selection algorithm to reduce the overhead of collecting redundant data. Guo, Li, Zhang and Zhai (2018) also employed a density estimation scheme to obtain the global density information of a traffic system. Wang, Pan, Xu, Jia and Meng (2015) and Wu, Li, Zhang, Guo, and Qi (2016) developed a method that identifies paths with the smallest time costs that can be used by vehicles to reach a destination. Kim, and Kim (2015) used environmental data in a vehicle-to-vehicle (V2V) communication environment to create a collision risk index, which considers the time to collision (TTC) as a criterion in conducting path planning; the application of this collision risk index could result in more effective planning of routes in practical applications. More recently, Hu, Xia and Kuang (2017) proposed a path planning scheme based on dynamic traffic information for use in vehicle navigation systems; this system can automatically avoid traffic jams and can reduce costs to the user. In addition, Zhang (2014) applied ant colony optimization to Internet-based vehicle path planning applications in vehicle environments. However, the approaches presented above do not consider a very common problem in path planning; specifically, they are likely to lead to another congested region after bypassing a congested route.

Wang, Shan, Lu, Zhang, Shen and Bai (2015) established a hybrid ITS that uses both vehicular ad hoc networks (VANETs) and cellular systems within public transportation systems to enable efficient real-time communication among vehicles, roadside units (RSUs), and a vehicle-traffic server; a stochastic Lyapunov optimization technique is exploited to address the globally optimal path planning problem. Furthermore, Rajabi-Bahaabadi, Shariat-Mohaymany, Babaei and Ahn (2015) proposed a new multiobjective path-finding model; to this end, they used the nondominated sorting genetic algorithm, the parameters of which were tuned using the Taguchi method. Faigl and Hollinger (2014) used a self-organizing map (SOM) architecture to provide a unified solution to multigoal path planning problems. Bopardikar, Englot and Speranzon (2015) presented a novel path planning algorithm that begins from a probabilistic roadmap and efficiently constructs a product graph that is used to search for near-optimal solutions to multiobjective optimization problems. All of these approaches make predictions of the overall situation, thereby ensuring the balance of traffic networks as a whole. However, in most cases, path planning occurs in the context of frequent updates to the traffic network given the dynamic nature of traffic networks, and such updates always greatly affect the performance of route planning. Consequently, these approaches cannot guarantee the timeliness and efficiency of path planning.

To address this problem, Xu, Guo, Ding, Sun and Liu (2012) applied a set of effective techniques to avoid both unnecessary calculations on very large graphs and excessive recalculations caused by traffic condition updates. More recently, Zhang, Hsueh, Lee and Jhang (2016, 2017) presented the path planning by caching (PPC) method to address new path planning queries in real time by efficiently caching and reusing historically queried paths. However, the identification of the optimal planning path cannot be ensured while improving the performance because of the lack of a reasonable path planning model. In sum, the above approaches cannot process real-time information in a timely manner; thus, they are unable to cope with emergencies.

Unlike the works discussed above, this paper adopts the DTMC approach for use in formal modeling and analysis. The probabilistic shortest path within a traffic network is chosen and recommended to the user. As an innovation, probabilistic data on the flow of traffic are calculated using mobile trajectories. This approach can respond to emergencies in traffic systems, thereby avoiding traffic jams. The experimental results show that the method proposed in this paper can effectively improve the efficiency and service quality of emergency rescue services.

6 CONCLUSION

GIVEN the rapid increases in urban traffic congestion worldwide, existing path planning methods cannot address emergencies in a timely manner. In this paper, mobile trajectory data are collected and analyzed to generate probability values, and a PTFR model is proposed. Subsequently, a VBM is constructed, and a method for generating verification properties is discussed. The proposed path point planning scheme, which improves the reliability of path planning and ensures that medical assistance and other services are more efficiently delivered, is then described.

Uncertainties associated with traffic networks, such as data losses and GPS signal instability, seriously affect the accuracy of path point planning. Furthermore, due to the wide variety of traffic conditions and data, mismatches between the speed of data acquisition and processing may arise. Therefore, in future work, data platforms that can conduct the analysis and processing of massive data acquired from heavy traffic will be studied. We will also consider applying Storm or Spark to the streamed data to guarantee the real-time reliability of path point planning.

7 DISCLOSURE STATEMENT

NO potential conflict of interest was reported by the authors.

8 ACKNOWLEDGMENTS

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10 NOTES ON CONTRIBUTOR

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