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AUTOMATIC DETECTION OF URBAN TRAFFIC INCIDENTS AND SUPPORTING DECISION MODEL FOR POLICE DISPATCHING BASED ON TRAVEL TIME

Guangyu Zhu, Jingxuan Zhang, Haotian Lin and Peng Zhang

It is very important to get the complete and timely information of urban road traffic incidents and then to make a reasonable strategy for police dispatching. By improving the efficiency of sending police, the loss of traffic incidents and the pressure of traffic police will be reduced greatly. An assistant decision model of police dispatching based on the information of automatic traffic incident detection is proposed in this paper. Firstly, an automatic traffic incident detection algorithm is put forward based on travel time of urban road section. Two severity dimensions of traffic incidents could be detected, and the average detection time could be reduced significantly. Then, an assistant decision model of police dispatching is established based on Bayesian decision theory by utilizing the results of automatic incident detection algorithm as well as the experience of police officer who in charge of police duty scheduling. Even though the police officer doesn't get the clear and complete information of incidents; he can also qualify the probability of actual states of different traffic incidents with the aided model. Case studies indicate that the model can help police officer to make the strategies of police dispatching and then reduce the risks of decision-making at a certain extent.

Keywords: travel time, automatic traffic incident detection (ATID), supporting decision model for police dispatching, police duty scheduling

Classification: 03F45

1. INTRODUCTION

The traffic incidents on urban roads refer to incidents that cause traffic congestion and affect the operation efficiency of the urban road transportation system. In recent years, with the dramatic increase of the number of automobiles and trips in cities, the number of traffic incidents on roads has also kept growing. According to an investigation conducted by Federal Highway Administration, among the delayed trips on urban roads, 50% to 60% are caused by various kinds of traffic incidents. As the happening of a traffic incident is random in nature, it is one of the core functions of traffic police departments in the implementation of traffic organization and protection of the traffic safety of cities to detect and effectively handle these random traffic incidents in time.

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1.1. Traditional process for traffic incident handling

At present, most traffic incidents are handled manually. After receiving the report for the incident, the traffic police department shall determine the nature and state of the incident in the first place, and then develop the police dispatching plan, including whether to dispatch the police, how many policemen to be dispatched, etc. See Figure 1.

According to Figure 1, there are two key steps to develop a reasonable police dispatching plan:

(1) Get the report and relevant information about the traffic incident timely and accurately;

(2) Develop the best police dispatching plan with limited information about the incident.

As a matter of fact, during the process of making a decision on police dispatching based on information about a traffic incident, there may be some uncertain factors. For instance, when the incident happens, if the type, the severity and other information of the incident cannot be obtained with information devices, in most cases, the incident will be reported by travelers passing by or the party involved. Manual reporting has two defects: First, the report is often not timely enough. For example, if the reporter is not familiar with the reporting system, the report will be delayed. Second, some report information is not complete, as most reporters are not professionals so that they are unable to describe the state of the traffic incident, the demand for onsite rescue and other important information clearly. These problems will make it more difficult to making police dispatching decision. Thus, this paper studies how to use limited information about traffic incidents to support the police dispatching decision so as to enhance the efficiency and quality of report management. The following solutions are hereby proposed: catch traffic incidents and identify relevant information rapidly by the automatic detection method for traffic incidents based on traffic flow parameters; combine the information about traffic incident acquired by the automatic traffic incidents detection method and experience of report management policemen to develop police dispatching plans, so as to enhance the efficiency and accuracy of the management of traffic incidents.

1.2. Automatic incident detection

The automatic traffic incidents detection refers to the technical method to identify and analyze traffic incidents with traffic flow parameters by the Automatic Incident Detection (AID) method. Generally, the spot where traffic incident happens will become a flow bottleneck spot on the road. Hence, it will cause the following two phenomena:

1) In the upstream section of the spot where the traffic incident happens, there will be more and more vehicles and traffic will become slower and slower. In terms of traffic flow parameters, the speed of vehicles slows down, the density of vehicles increases, and the occupation rate of the road increases.

2) In the downstream section of the spot where the traffic incident happens, the number of vehicles drops, and the travel time for a vehicle to go through the whole road section increases.

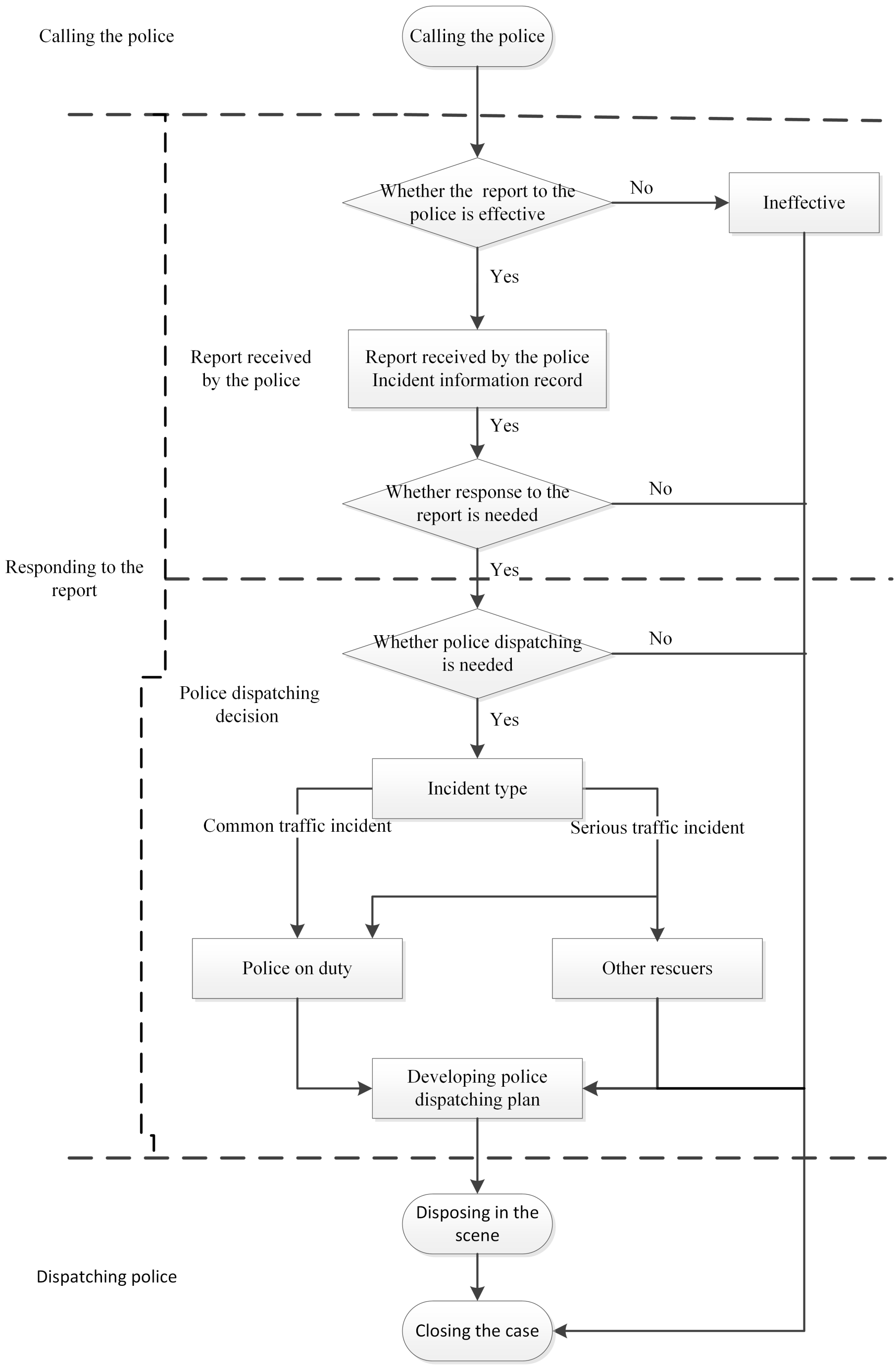

Fig. 1. Flowchart of traditional traffic incident handling process.

According to the foregoing phenomena, scholars developed different AID algorithms based on two types of parameters including the occupation rate and the travel time. The foundation of all these methods is to find out abnormal modes lying in data of road traffic flow parameters by means of statistics and analysis and then speculate traffic incidents hidden in the traffic flow. The earliest AID algorithms are the California algorithm and the improved AID algorithm developed by California Department of Transportation [13]. After that, a large number of traffic incident detection methods have been developed, such as the Standard Normal Deviate (SND), double exponential smoothing method, Bayesian algorithm, auto regressive integrated moving average (ARIMA), McMaster algorithm, low pass filtering method [1, 6, 9, 19], traffic incident detection method based on random forests [10], etc. These methods are well applied not only to freeways but also to fast ways in cities [3]. Among various automatic incident detection AID algorithms, the standard normal deviate algorithm [9] is widely applied with its simple model structure and excellent detection performance [11]. Its principle is: Assume a traffic parameter is subject to normal distribution, the parameter in normal distribution can be determined according to historical data of the traffic flow parameter; according to the standard normal distribution deviation target, the confidence coefficient of the traffic parameter's compliance with normal distribution can be verified, so as to determine the abnormality of the traffic parameter. These abnormal values may correspond to a certain type of traffic incident. As the value of the occupation rate parameter is sometimes ambiguous, this paper chooses the travel time as the traffic flow parameter for the traffic incidents detection. The travel time can be acquired with flow, speed and other traffic flow parameters, which, however, are usually not quite accurate. In recent years, the floating vehicle detection technique has been widely applied in the process of the detection of traffic flow on urban roads [11, 25].Floating vehicles are equipped with GPS devices to acquire the real-time position, speed, driving direction and other traffic incident about vehicles with the GPS positioning, and acquire the driving path of vehicles by means of map matching. The traffic flow information detected by a floating vehicle can reflect the traffic state of the road in a timely and accurate manner and can also detect sub-trunk roads, by-passes and other road sections where fixed detectors cannot be installed. This method can perform the detection in a wider scope compared to the plate identification method, vehicle length matching method, etc. [21]. Meanwhile, a floating car does not cost much. Thus, in recent years, floating cars are used to detect road traffic flow parameters and acquire the travel time and other parameters in a lot of large cities. Great progress has been made for the research on AID algorithm for the automatic traffic incident detection based on the time taken by floating cars [4, 12, 16, 17, 22].

1.3. Police dispatching decision based on traffic incident detection

At present, some scholars make aided decision of police dispatching based on historical case information, knowledge of experts, preset rules, etc. what's more they developed a aided decision system of police dispatching based on a knowledge database [8, 15, 23, 24]. There are not many theoretical researches on the modeling of police dispatching decision and the optimization of police dispatching effect. Currently, similar theoretical researches and relevant models related to supporting detection for emergency treatment in other fields (such as medical, nuclear management, biological, chemical and other fields) [5, 7, 14, 20, 18] provide enlightenment and reference for this paper.

2. AUTOMATIC TRAFFIC INCIDENT DETECTION ALGORITHM BASED ON TRAVEL TIME IN THE ROAD SECTION

This section is based on the standard normal deviate algorithm. It provides the Automatic traffic incident detection algorithm based on travel time in the road section according to the parameter for travel time provided by floating vehicles.

2.1. Standard normal deviate algorithm based on travel time in the road section

(1) Traffic incident detection principle based on the standard normal deviate algorithm The general standard normal deviate algorithm can conduct detection for a certain traffic flow parameter. Set the traffic parameter to be detected as x, and set the detection value of x at time t as x_t. Let $x_i, (i = 1, 2, \ldots, n)$ be n sample values. Then, the average value $\bar{x}$ and the standard deviation S_x of x are respectively:

$$\bar{x} = \sum_{i=1}^{n} x_i, \; s_x = \sqrt{\frac{1}{n-1}\sum_{i=1}^{n}(x_i - \bar{x})^2}. \tag{1}$$

The deviation detection is conducted for the detection value x_t with $\bar{x}$ and S_x. The standard deviation of the detection value x_t is:

$$SND_t = \frac{x_t - \bar{x}}{s_x}. \tag{2}$$

Compare the standard deviation of the detection value x_t and the quantile of the standard normal distribution. If the standard deviation increases significantly and is larger than a certain contribution value of the standard normal distribution function, it means x_t is a abnormal value and a traffic incident may have happened.

(2) The standard normal deviation detection algorithm based on travel time

Step 1: Determine the sampling period of the parameter for the travel time in the road section, and set this period as T (normally 30 minutes).

Step 2: Set the time when vehicle No. i (v_i) drives into the road section as t_i, and the time when v_i drives out of the road section as $\tilde{t_i}$, and set the driving time of v_i as TT_i.

Step 3: For a certain vehicle v_j, record the number of vehicles driven into the road section before v_j during a period of T (time), that is, v_i meets the formula $t_j - T < t_i \leq t_j$.

Step 4: There are n vehicles driven into the road section during the statistical period in the previous step. Calculate the average value and standard deviation of the travel

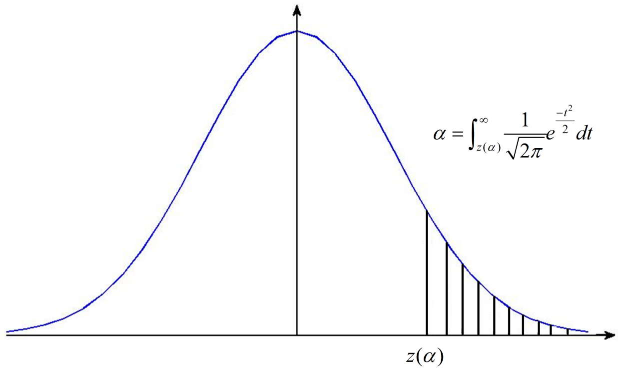

Fig. 2. Flowchart of traditional traffic incident handling process.

time of the n vehicles, and set them as $\bar{x}$ and S_x respectively.

$$\bar{x}_j = \frac{1}{n} \sum_i TT_i, \; s_j = \sqrt{\frac{1}{n-1} \sum_i (TT_i - \bar{x}_j)^2}. \tag{3}$$

Suppose the travel time for these vehicles complies with a certain normal distribution $N(\mu, \sigma^2)$, where both the average value and the variance are unknown. Then $\bar{x}$ and S_x are unbiased estimator of μ and σ respectively.

Step 5: Set the threshold value α, and calculate SND_j, the standard normal deviation of v_j according to (2) and (3). If, then there may be some traffic incidents. Wherein, is the right-quantile threshold value of standard normal distribution (see Figure 2).

Step 6: Return to Step 2 and continue detecting the next vehicle.

2.2. Case 1

Figure 3 shows that, on November 5, 2013, a group of travel time data detected in a road section of Beijing. The detection period is from 13:55 to 15:21. According to the actual police reporting record, slight traffic congestion happened in this road section from 14:21 to 14:27 and an accident (crash between two vehicles) happened at 15:10, which caused serious traffic congestion in subsequent vehicles. In this case, the foregoing standard normal deviation algorithm is adopted to verify the detection effect of traffic incidents with this algorithm.

According to Figure 3, it is obvious that, during the traffic congestion period and after the occurrence of traffic accidents, the travel time taken by vehicles will increase significantly.

The standard normal deviation of each sample point is calculated. Figure 4 Shows the result.

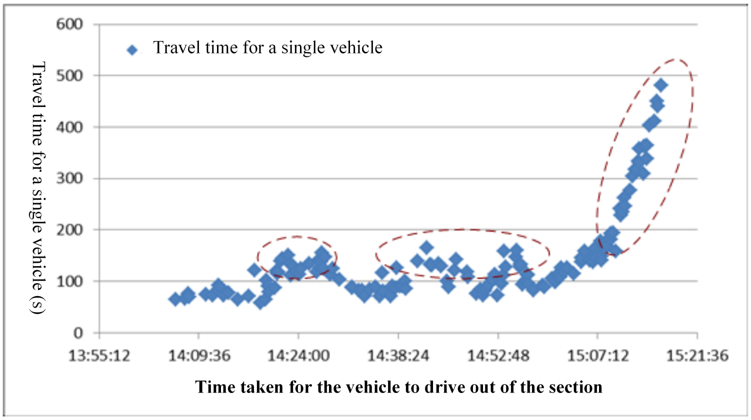

Fig. 3. Vehicle travel time data related to traffic incident.

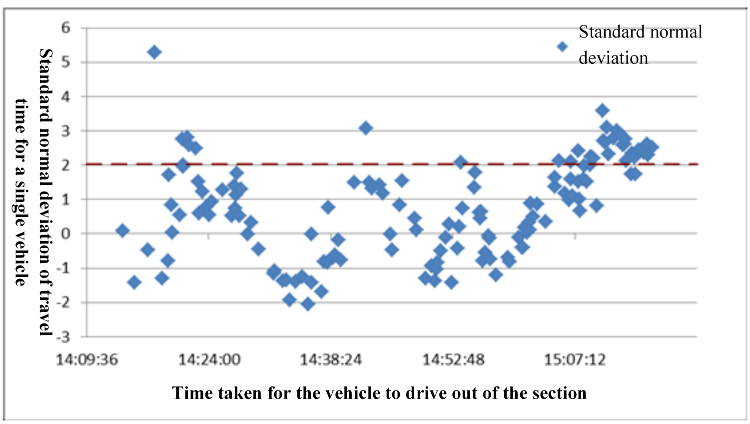

Fig. 4. SND data of single vehicle travel time which related to common traffic incidents.

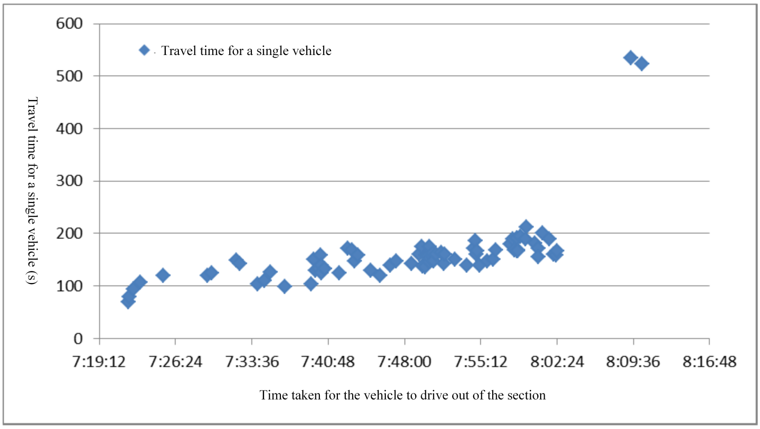

Fig. 5. Vehicle travel time data related to a serious traffic accident.

According to Figure 4, the absolute value of the standard normal deviation of most data of travel time data for most vehicles does not exceed 2. However, as a result of the three traffic incidents, the travel time increases, and the standard normal deviation exceeds 2. The Z quantile closer to 2 is: $Z(0.01) = 2.3263$. In other words, under normal circumstances, the standard normal deviation of 99% of the travel time for vehicles will not exceed $Z(0.01)$. Suppose $\alpha_1 = 0.01$, and set $Z(0.01) = 2.3263$ as the threshold value. If the travel time for vehicles exceeds the threshold value, some traffic incidents may happen. Of course, this travel time may be noise points, as floating vehicles may stop to take passengers during the process.

2.3. Calculation case 2

Figure 5 shows the travel time data for vehicles before and after the occurrence of a serious traffic accident (rear-end) in Beijing at around 7:59, December 20, 2013. The statistical period is from 7:58:01 to 8:10:24.

According to Figure 5, the travel time sample data for vehicles before the accident happens are stable. However, from 8:02 to 8:09, no floating vehicles were detected to driven out of the road section, but a large number of floating vehicles were detected to stick in the road section. the statistical result of the data samples up to 8:11is shown in Table 1.

According to the foregoing table, among the vehicles that entered at 8:00:31, four vehicles were stuck for a long time. If the residence time of a floating vehicle exceeds a certain threshold value, the travel time will increase significantly and the standard normal deviation will be significantly higher than $Z(\alpha_1)$. It means that, there may be a serious traffic accident that has happened in the road section so that the vehicles cannot be driven out of the road section in a short time. For this kind of sample vehicles, a smaller threshold value α_2 can be set. Set the current moment as t, and the time when

Time when the vehicle drove into the road section	Time when the vehicle drove out of the road section	Travel time (s)	Duration of detention (s)(Up to8:11)
7:58:01	8:00:37	156	
7:58:14	Driven into other road sections		
7:58:30	Driven into other road sections		
7:58:31	8:01:41	190	
7:59:24	8:02:04	160	
7:59:40	8:02:19	159	
7:59:40	8:02:26	166	
8:00:31	8:09:25	534	
8:01:40	8:10:24	524	
8:01:40	Stuck		548
8:02:23	Stuck		517

Tab. 1. Vehicle travel time in an accident period.

a vehicle driven into the road section as t_α. If $t - t_a > Z(\alpha_2)$, a serious traffic accident may have happened in the road section. $\alpha_2 = 0.001$, that is, $Z(\alpha_2) = 3.0902$, can be set as the threshold value. Calculate the standard normal deviation by comparing the travel time of the former two vehicles and the residence time of the latter two vehicles behind to check whether the travel time is too long. See Figure 6.

Please note: Considering the randomness of the travel time the driving of floating vehicles in this amount of samples, even if the travel time is normal as detected by the standard normal deviate algorithm, there is not necessarily that there is a traffic incident. However, a traffic incident may cause the continuous happening of abnormal travel time. Thus, in the actual application of the algorithm, we can set $N = 3$, that is, 3 floating vehicles or among 4 successive floating vehicles, thre are 3 vehicles abnormal, it can be determined that a traffic incident has happened.

2.4. Evaluation of the automatic incident detection algorithm

The effectiveness of the traffic AID algorithm can be evaluated according to the detection rate (DR), the false alarm ratio (FAR), mean time to detect (MTTD) and other targets [2]. Suppose there are AN traffic incidents, and the number of incidents detected correctly is DN_r. Then the detection rate could be defined as:

$$DR = \frac{DN_r}{AN} \times 100\,\%. \tag{4}$$

Suppose that the calculation methods have been applied for DN times in total. Among others, the number of errors in the detection result is DN_f, among the detection results and then the FAR could be got from formula (5):

$$FAR = \frac{DN_f}{DN} \times 100\,\%. \tag{5}$$

Suppose the number of incidents correctly detected by the algorithm is $n = DN_r$, and for each incident i, set the happening time as $AT(i)$ and the time when it is detected

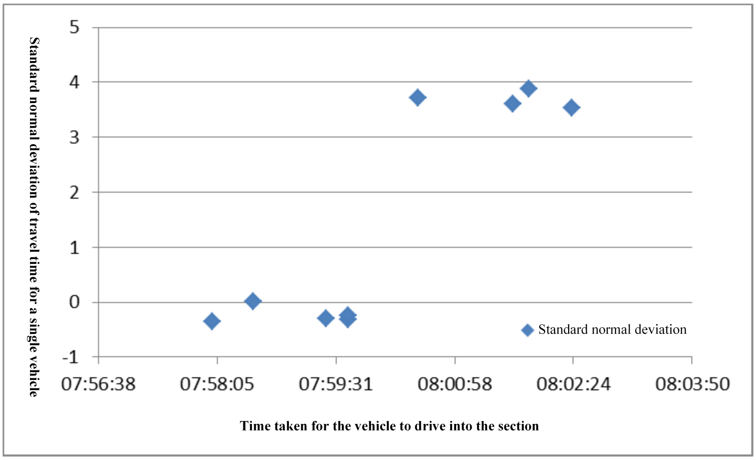

Fig. 6. SND data of single vehicle travel time which related to a serious traffic incident.

by the algorithm as $TI(i)$. Then the average detection time could be obtained from formula (6):

$$MTTD = \frac{1}{n}\sum_{i=1}^{n}[TI(i) - AT(i)]. \tag{6}$$

DR can evaluate the achievement rate of the detection of accidents that actually happen. The higher the DR is, the higher the probability of the identification of traffic incidents that have actually happened is. The FAR evaluates the correctness of the detection result obtained by the algorithm. In other words, for the overall correct determination of common incidents and traffic incidents, the lower the FAR is, the lower the probability of the failure to detect traffic incidents or wrong alarms of normal situations is. The MTTD can evaluate the operation efficiency of the automatic incident detection method. The less the MTTD is, the faster the incidents can be detected and handled, so as to reduce the losses caused by accidents.

3. BASED ON AUTOMATIC INCIDENT DETECTION

Assistant decision model for police dispatching based on the automatic traffic incidents detection refers to a process a police dispatching plan is developed through the interactive decision between the supporting detection system and report handlers based on information about the traffic incident provided by the automatic detection algorithm. As the decision can be made only based on part of the information about the traffic incident, the assistant decision model for police dispatching based on the automatic traffic incidents detection is a typical decision method based on uncertain information.

3.1. Modeling analysis of assistant decision model for police dispatching

The key goal for the establishment of a decision model is to reduce the decision risks. The automatic detection algorithm may result in the wrong determination of information about a traffic incident and thus arouse decision risks. For example, serious incidents may be deemed as common incidents, as a result of which, the policemen dispatched may be not enough or without enough rescue capability. The insufficient police dispatching effect may even cause the second incident; if a common incident is deemed as a serious incident, the policemen dispatched may be excessive, which is a waste of police resources. The wrong determination in information about traffic incidents may directly affect the effect of the police dispatching decision system. Thus, the goal in this section is to study how to detect the uncertainty of the detection result obtained from the automatic detection algorithm so as to reduce the risk in the supporting decision model. According to the case analysis in Section 2, two types of traffic incident information can be provided to the supporting decision system through the automatic detection algorithm:

(1) Type of traffic incidents (such as common incidents and serious incidents);

(2) the happening probability a certain type of incidents (verify the prior probability, which is defined as the probability obtained from the information of the past experience and analysis).

In order to reduce the supporting decision risk, the prior probability shall be corrected according to the experience of the report handlers to obtain the posterior probability (The posterior probability is an estimated probability after modification of the original prior probability based on new information) of the incident, so as to select the best decision as the police dispatching plan.

3.2. Assistant decision model of police dispatching traffic incidents based on the Bayesian decision theory

This paper establishes the supporting police dispatching decision models for traffic incidents based on the Bayesian Decision Theory

3.2.1. Data definition

The result of the automatic detection is analyzed by the report handler. First, the state of traffic incidents shall be classified, and then some corresponding measures to be taken shall be determined. Without the loss of generality, detection results for traffic incidents are marked as "normal", "common traffic incidents" and "serious traffic incidents". Measures that could be taken are marked as "no police dispatching is needed", "police dispatching" and "police dispatching and more measures". Results obtained from the automatic detection are set as $\{X_1, X_2, X_3\}$ according to the severity and the corresponding measures as$\{D_1, D_2, D_3\}$. When measure D_i is applied to the incident X_j that is at state i, the resulting loss is set as u_{ij}. Then the payoff matrix is obtained:

$$U = \begin{bmatrix} u_{11} & u_{12} & u_{13} \\ u_{21} & u_{22} & u_{23} \\ u_{31} & u_{32} & u_{33}. \end{bmatrix} \tag{7}$$

Set the probability that traffic incident X is at a certain state as:

$$p_i = P(X = X_i), \quad i = 1, 2, 3. \tag{8}$$

Then the sampling space for the traffic incident in the road section is:

$$\{(Z_i, P_i)\}, \quad i = 1, 2, 3. \tag{9}$$

Set the detection result provided by the automatic detection algorithm as the observed value $Y \in \{X_1, X_2, X_3\}$. When the actual state of the traffic incident is X_i, then X_j, the probability of observation result for the automatic detection can be expressed as:

$$p_{ij} = P(Y = X_j | X = X_i). \tag{10}$$

During the process of actual detection, the state of the traffic incident can also be determined by means of TV monitoring, data observation and other methods according to the experience of the observer. Set the result provided by the report handler as the observed value $Z \in \{X_1, X_2, X_3\}$. Then when the actual state of the incident is X_i, the probability that the report handler determines the state of the incident as X_j is:

$$q_{ij} = P(Z = X_j | X = X_i). \tag{11}$$

Thus, when the actual state of the incident is X_i, the detection result obtained from AID algorithm is X_j, and the probability that the result obtained from the judgment of the report handler is X_k is as follows:

$$q_{ijk} = P(Y = X_j, Z = X_k | X = X_i). \tag{12}$$

For the same traffic incident, the result obtained from the automatic detection may be consistent with the judgment of the report handler. Thus, the incident $Y = X_j$ is not independent from the incident $Z = X_k$.

3.2.2. Judgement of traffic incident occurrence probability

It is a posterior probability issue to analyze the actual incident probability based on the result obtained from the AID algorithm and the manual judgment of the report handler. It equals to revising prior probability P_i based on the automatic detection algorithm and the experience of the report handler. As the decision made in the supporting decision system is prior to that made by the report handler. Thus, the process of correction can include the following two steps:

(1) Correction based on the supporting decision system

$$\begin{aligned} y_{ij} =& P(X = X_i | Y = X_j) \\ =& \frac{P(Y = X_j | X = X_i) P(X = X_i)}{\sum\limits_{k=1}^{3} P(Y = X_j | X = X_k) P(X = X_k)} \\ =& \frac{p_{ij} p_i}{\sum\limits_{k=1}^{3} p_{kj} p_k} \end{aligned} \tag{13}$$

(2) Correction based on the result obtained from the police judgement

$$\begin{aligned} z_{ijk} =& P(X = X_i | Y = X_j, Z = X_k) \\ =& \frac{P(Y = X_j, Z = X_k | X = X_i) P(X = X_i)}{\sum_{l=1}^{3} P(Y = X_j, Z = X_k | X = X_l) P(X = X_l)} \\ =& \frac{q_{ijk} p_i}{\sum_{l=1}^{3} q_{ljk} p_l}. \end{aligned} \tag{14}$$

3.2.3. Police dispatching decision and evaluation

When different decisions on police dispatching ("no police dispatching", "police dispatching" and "police dispatching and more measures") work on different types of traffic incidents, three kinds of effects will be generated, that is, "appropriate police force", "insufficient police force" and "excessive police force". Under the circumstance of appropriate police force, the police force dispatched is not excessive and is able to handle the incident in a timely and proper manner; under the circumstance of insufficient police force, the police force dispatched is unable to handle the incident in a timely and effective manner; under the circumstance of excessive police force, though the incident can be handled effectively, some part of the police force will be idle during the process of the incident management, or according to the experience in the management of incidents, the police force dispatched exceeds the size of dispatched under the circumstance of "appropriate police force". Thus, in the first place, the definition and evaluation method for police dispatching decision loss is provided in this section, and the decision losses for several types of police dispatching measures are studied.

(1) Definition of police dispatching decision loss

Normally, a traffic incident may cause traffic congestion and delay. Thus, the loss caused by the traffic incident can be described with the "total delay time" (unit: number of car per hour). Accordingly, the payoff from the effect of the police dispatching decision on a certain type of traffic incidents can be expressed by the reduced loss value of the total delay time caused by the traffic incident. Create a "vehicle number – time" function as shown in Figure 7. Wherein, the horizontal axis stands for time, and the vertical axis stands for the total number of vehicles at the place where the incident happens. Normally, suppose the vehicle flow matches conditions for free flow:

$$Q' = \frac{\mathrm{d}Q(t)}{\mathrm{d}t} = q_0 \tag{15}$$

The derivative of the function $Q(t)$ is the number of vehicles that pass a certain spot, that is, the real-time flow. In Figure 7, OB stands for the function curve of "number of vehicles – time" under normal circumstances, and its gradient stands for the flow under normal circumstances. OA stands for the situation in a time between the happening of the incident and the police handle it; during this period of time, the flow decreases

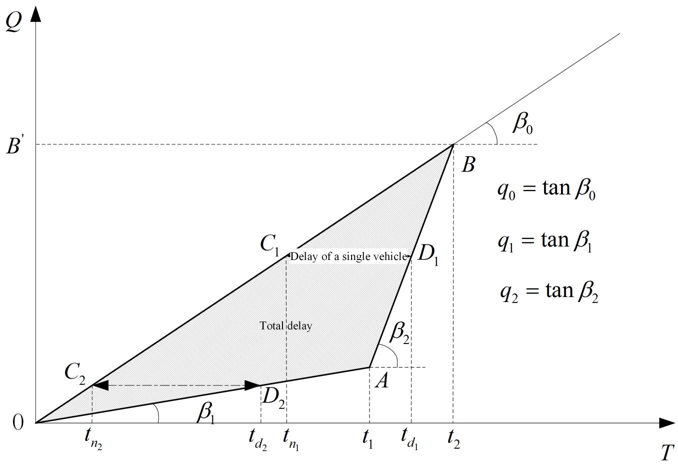

Fig. 7. Calculation of total delay time.

under the effect of the traffic incident. AB stands for the situation in a time from the start of the incident management to the end of the incident management; as the road is clear, the flow is higher than that under normal circumstances. Set the time when the incident happens as 0, and then the straight line OB is the function of "vehicle number – time" under normal circumstances, and the gradient is $OB = q_0$. Set the time when the police arrive at the site for management as t_1; after t_1, the traffic starts to be in order again. During the period $(0, t_1)$, $\forall t \in (0, t_1), q(t) < q_0$, and the mean pass flow is $\frac{\int_0^{t_1} q(t)\,\mathrm{d}t}{t_1}(< q_0)$. In this case, the curve of the function of "vehicle number - time" during the period is approximate to a straight line whose gradient is smaller than q_0. Set the straight line as OA, set the point of intersection between the straight line OA and the vertical line t_1 as A. It supposed that at the time t_2, after the management of the incident, the flow restore to q_0. Then during the period (t_1, t_2), the mean pass flow is $\frac{\int_{t_1}^{t_2} q(t)}{t_2 - t_1}$. Considering the detention of vehicles, it can be assumed that the vehicles in the queue pass the spot where the incident happens. Set the flow as q_2 and $q_2 > q_0$; at the time t_2, all vehicles in the queue are cleared, and the flow is restored to q_0. During this process, under the ideal circumstance, the curve of passing vehicles is the straight line OB in the figure. The happening of the incident changes the shape of the curve into OAAB. The inferior fovea of the curve stands for the delay of the horizontal distance between each vehicle on the vertical coordinate and OB due to the time taken for the vehicle to pass the road section where the incident happens. Thus, the total delay time can be expressed with the area of OAB (unit: number of vehicles/s).

$$\begin{aligned} S_{\Delta OAB} &= S_{\Delta OBB\perp} - S_{\Delta OAA\perp} - S_{ABB\perp A\perp} \\ &= \frac{1}{2} q_0 t_2^2 - \frac{1}{2} q_1 t_1^2 - \frac{1}{2}(q_0 t_2 + q_1 t_1)(t_2 - t_1) \\ &= \frac{1}{2}(q_0 - q_1) t_1 t_2 \end{aligned} \tag{16}$$

Besides, t_2 can be obtained from other variants:

$$q_1 t_1 + q_2(t_2 - t_1) = q_0 t_2 \tag{17}$$

$$t_2 = \frac{q_2 - q_1}{q_2 - q_0} t_1. \tag{18}$$

There is a total delay time:

$$\begin{aligned} u &= S_{\Delta OAB} \\ &= \frac{(q_2 - q_1)(q_0 - q_1)}{2(q_2 - q_0)} t_1^2. \end{aligned} \tag{19}$$

Wherein, q_0 can be obtained from the upstream and downstream detector, q_1 can be obtained from the upstream detector, q_2 is related to the specifications of the road design, and t_1 stands for the time when the police arrive at the site.

(2) Evaluation method for police dispatching decision based on the total delay time

The effect of the police dispatching decision can be evaluated based on the total delay time. In general, under the circumstance of appropriate police force, the total delay time is the sum of the delay time of all vehicles passing the road section from the happening of the incident to the complete restoration of the incident; under the circumstance of insufficient police force, the total delay time is the sum of the delay time of all vehicles passing the road section from the occurrence of the incident, the management of the incident of the police involved and the gradual alleviation of the traffic congestion; under the circumstance of excessive police force, the total delay time can be divided into two parts: The first part equals the total delay time under the circumstance of appropriate police force, which means the effect of the management of the incident equals that under the circumstance of appropriate police force. The second part equals additional delay time caused by any potential incidents; in other words, when a incident happens at a certain probability in a nearby road section, the second incident cannot be handled in time as the police force is occupied by the first incident, resulting in delay time. To be specific, for the actual state X_i of the incident and D_j, the decision that may be made:

• When $i = j$, appropriate police dispatching measures are adopted for different incidents. In other words, there is no delay if there is no incident and no police force is dispatched, $u_{11} = 0$; otherwise, $u_{ii} (i = 2, 3)$ can be obtained from formula (19) according to t_1 and the data of the road section flow.

• When $i > j$, the police force is insufficient and the incident is not handled in time. When no police force is dispatched, t_0 is the mean time taken by the management of an incident. Under the circumstance of police dispatching with insufficient police force, it can be deemed as that the traffic police has evaluated the state of the incident again after arriving at the site and then dispatch reasonable police force, that is, $t_1 = t_0 + t$, where t stands for the time taken for the police dispatching each time.

• When $i < j$, the police force dispatched is excessive, which cause potential incidents cannot be handled in time. Set the time taken for the police to arrive at the incident spot after receiving the order as t', the frequency of incidents that happen in surrounding areas is p (number of times/day), t'' corresponds to t_1 as. Then the standard normal deviation of the happening of incidents in other spots during this period of time is $\sum 2pt'$, and the expected time of happening is t'. In this case, due to the excessive police force dispatched, the police are unable to respond to emergencies, and the expected time taken for them to handle the second incident after returning to the deployment spot is $\sum 2pt'^2$.

Set the total delay time as a function related to time. Then the excessive police force dispatched results in the increase of the response time and the total delay time for the potential second incident. The increment of delay time generated from potential incidents in each area includes:

$$\Delta u = u(t'' + 2pt'^2) - u(t'') = \frac{(q_2 - q_1)(q_0 - q_1)}{2(q_2 - q_0)}(4p^2t'^4 + 4pt'^2t'') \tag{20}$$

wherein, q_1 is a historical estimated value instead of a detection value for the current incidents. Then the expected increment of delay time caused by excessive police force is $\sum \Delta u$. That is, the total delay time is $u_{ii} + \sum \Delta u$.

3.2.4. Calculation of the optimal decision

In the condition that the posterior probability where the incident is at a certain state and the effect of different police dispatching plans are known, the payoff matrix can be adopted to calculate the payoff expectation for each kind of decision in the expectation of obtain the optimal decision.

(1) Optimal supporting decision based on automatic detection algorithm

Suppose the result obtained from the automatic detection algorithm is $Y = X_j$. Then the probability of X_k for incidents obtained is the posterior probability under the circumstance of $Y = X_j$. The correction of the probability makes the expected payoff of the decision D_i more accurate. Set u'_{ij} as the expected payoff of D_i under the circumstance of $Y = X_j$:

$$\begin{aligned} u'_{ij} &= \sum_{k=1}^{3} u_{ik} P(X = X_k | Y = X_j) \\ &= \sum_{k=1}^{3} u_{ik} y_{kj} \end{aligned} \tag{21}$$

Thus, the optimal supporting decision based on the automatic detection algorithm is:

$$D_j^* = \max\{u'_{ij}\}, \quad i = 1, 2, 3 \ldots. \tag{22}$$

(2) Optimal decision combining automatic detection algorithm and judgment of the report handler

In the process of actual decision, apart from the judgment result obtained from the automatic detection algorithm, that is, the observed value Y, the result obtained from the judgment of the report handler for the traffic incident shall also be taken into consideration. As a matter of fact, after the report handler makes a judgment for the state of the incident, if the optimal decision obtained from the calculation of the posterior probability according to the updated objective state is different from the original optimal decision, it means the original decision is not always the optimal decision. Set the result obtained from the automatic detection algorithm as $Y = X_j$ and the result obtained from the judgment of the report handler as $Z = X_k$. The report handler provides more information for the process of police dispatching decision, so that the probability where the incident is at a certain state is further corrected. Express the payoff expectation of decision D_i under this circumstance with u''_{ijk}:

$$\begin{aligned} u''_{ijk} &= \sum_{l=1}^{3} u_{il} P(X = X_l | Y = X_j, Z = X_k) \\ &= \sum_{l=1}^{3} u_{il} z_{ljk} \end{aligned} \tag{23}$$

For each existing observed value $Y = X_j$, a payoff matrix E_j is finally formed according to formula (23) for the different $Z = X_k (k = 1, 2, 3)$ and the decision $D_i (i = 1, 2, 3)$, and:

$$E_j = \begin{bmatrix} u''_{1j1} & u''_{1j2} & u''_{1j3} \\ u''_{2j1} & u''_{2j2} & u''_{2j3} \\ u''_{3j1} & u''_{3j2} & u''_{3j3}. \end{bmatrix} \tag{24}$$

The row $k(k = 1, 2, 3)$ in the matrix E_j is the payoff expectation of the decision D_i $(i = 1, 2, 3)$ based on the judgment of the report handler $(Z = X_k)$. Each row of E_j has the maximum expected payoff value:

$$u''_{f(k)jk} = \max\{u''_{ijk}\}, \quad i = 1, 2, 3. \tag{25}$$

Under the ideal circumstance:

$$u''_{j1} = u''_{j2} = u''_{j3}. \tag{26}$$

In other words, $D^*_{j1} = D^*_{j2} = D^*_{j3} = D_l$. Obviously, $D^*_j = D_l$. That is to say, the optimal detection under each assumption equals the optimal decision when only information obtained from the automatic detection algorithm. In this case, no matter what judgment is made by the report handler, the optimal decision obtained from the Bayesian Decision Theory and the supporting decision can be applied directly. If optimal decisions D^*_{jk} in each row are different from each other, it means each judgment of the report handler ($Z = X_k$) corresponds to an optimal decision. In this case, it is impossible to decide which one is the real optimal decision. Thus, the supporting decision model must require the report handler to conduct observation and judgment again to find out the optimal decision D^*_{jk} under this circumstance.

4. CASE ANALYSIS

Take the travel time data obtained from the detection of floating vehicles in 10 (bidirectional) road sections in a ring road of a major city from 16:00, December 18, 2013 to

16:00, December 19, 2013. According to the actual reporting, 62 incidents happened in these road sections.

4.1. Automatic incident detection based on standard normal deviation algorithm

The travel time data can be detected with the standard normal deviation algorithm. By this algorithm, common incidents and serious traffic accidents can be detected. Run the automatic detection algorithm with the fixed parameters including $\alpha_1 = 0.01$, $\alpha_1 = 0.001$, $\alpha_1 = 0.05$ and, and the result of the detection is shown in Table 2.

	Actually normal	Actually a common incident	Actually a serious accident
Not detected		6	0
Determined as a common incident according to the detection	2	40	1
Determined as a serious accident according to the detection	0	1	14
Total		47	15

Tab. 2. AID results under $\alpha_1 = 0.01$ and $\alpha_1 = 0.001$.

Run the automatic detection algorithm with the fixed parameters including $a_1 = 0.05$ and $a_2 = 0.005$, and the result of the detection is shown in Table 3.

	Actually normal	Actually a common incident	Actually a serious accident
Not detected		2	0
Determined as a common incident according to the detection	6	42	0
Determined as a serious accident according to the detection	0	3	15
Total		47	15

Tab. 3. AID results under $\alpha_1 = 0.05$ and $\alpha_1 = 0.005$.

Compare the two groups detection results with the actual situation, and provide the algorithm performance under the two groups of thresholds according to formulas (4) to (6). See Table 4.

Threshold value	DR	FAR	MTTD
$\alpha_1 = 0.01, \alpha_1 = 0.001$	96.8%	9.09%	134s
$\alpha_1 = 0.05, \alpha_1 = 0.005$	90.3%	5.17%	201s

Tab. 4. Contrast of AID performance between two sets of threshold.

By comparison, in the condition $\alpha_1 = 0.01$ and $\alpha_1 = 0.001$, though the FAR is higher, the detection rate is more satisfactory (96.8%). It means that the rate of the accidents detected correctly is higher. And the MTTD is only 134s. That is to say the time spent by detecting accidents is shorter. The detection algorithm performance under the circumstance of $\alpha_1 = 0.01$ and $\alpha_1 = 0.001$ is better according to the actual situation. Traffic incidents that actually happen and those that are detected are classified by the detection result obtained from the automatic detection algorithm according to the police dispatching decision and case conclusion record, and then the statistics about different traffic incident records are obtained. See Table 5. Wherein, the number of actually normal states is obtained from the conversion in periods of 15-minute.

Not detected	Actually normal	Actually a common incident	Actually a serious accident
Determined as normal according to the manual judgment	1841	0	0
Determined as a common incident according to the manual judgment	11	2	0
Determined as a serious accident according to the manual judgment	0	0	0
Not detected	Actually normal	Actually a common incident	Actually a serious accident
Determined as normal according to the manual judgment	5	0	0
Determined as a common incident according to the manual judgment	1	40	0
Determined as a serious accident according to the manual judgment	0	2	0
Not detected	Actually normal	Actually a common incident	Actually a serious accident
Determined as normal according to the manual judgment	0	0	0
Determined as a common incident according to the manual judgment	0	1	2
Determined as a serious accident according to the manual judgment	0	2	13

Tab. 5. History record statistics of AID and police dispatching decision.

Based on the statistics in Table 5, the prior probability and the posterior probability and of the incident state can be obtained from the Bayes formula. See Tables 6 − 8.

	Actually normal	Actually a common incident	Actually a serious accident
p_i	0.9677	0.0245	0.0078

Tab. 6. Prior probability p_i.

p_{ij}	Actually normal	Actually a common incident	Actually a serious accident
Not detected	0.9968	0.0032	0
Determined as a common incident according to the detection	0.0426	0.8936	0.0638
Determined as a serious accident according to the detection	0	0	1

Tab. 7. Posterior probability p_{ij}.

q_{1jk}	Not detected	Determined as a common incident according to the detection	Determined as a serious accident according to the detection
Determined as normal according to the manual judgment	1	1	0.3333
Determined as a common incident according to the manual judgment	0.8462	0.0244	0
Determined as a serious accident according to the manual judgment	0.3333	0	0
q_{2jk}	Not detected	Determined as a common incident according to the detection	Determined as a serious accident according to the detection
Determined as normal according to the manual judgment	0	0	0.3333
Determined as a common incident according to the manual judgment	0.1538	0.9756	0.3333
Determined as a serious accident according to the manual judgment	0.3333	0	0.1333
q_{1jk}	Not detected	Determined as a common incident according to the detection	Determined as a serious accident according to the detection
Determined as normal according to the manual judgment	0	0	0.3333
Determined as a common incident according to the manual judgment	0	0	0.6667
Determined as a serious accident according to the manual judgment	0.3333	0	0.8667

Tab. 8. Posterior probability p_{ijk}.

Run the automatic detection algorithm ($\alpha_1 = 0.01$ and $\alpha_1 = 0.001$) during the period of time between 7:00 and 19:00 on December 20, 2013, which is used to support the report handler for decision. 3 traffic incidents are detected through the algorithm. Table 9 shows for detailed information about the incident. Wherein, flow parameters are defined in Chapter 3, the unit is "number of vehicles/s", and the designed flow of 1,800 vehicles per hour on each lane is considered as the maximum flow of the road section.

Serial No.	Time	Direction	Detection result	Actual state	q_0	q_1	q_2
1	7:25	East-west	Common traffic incident	Common traffic incident	1.439	0.723	2
2	7:59	East-west	Serious accident	Serious accident	0.906	0.251	1.5
3	17:57	West-east	Common traffic incident	Normal state	1.217	1.138	2

Tab. 9. 3 examples of AID alarm.

The length of this typical road section is 1.13km, and 1 patrol policeman is allocated to this road section. According to the police calling record the frequency of the happening of traffic incidents in neighboring areas is 0.235 times per hour, and the mean time t_1 taken by the police to arrive at the site after receiving the report is 10 minutes, wherein, the time t' taken by dispatching is 7 minutes. If the incident is handled by drivers on their own through negotiation, it usually takes 15 to 20 minutes. According to the decision analysis on three traffic incidents, the expected loss matrix for each incident is obtained from the formulas 23 – 24. See Table 10.

In Incident 1, if it only depends on the result obtained from the automatic detection algorithm, the optimal decision is police dispatching. According to the judgment of the report handler, the corrected optimal decisions are respectively "no police dispatching is needed", "police dispatching" and "police dispatching". In this case, the report handler makes the correct decision of police dispatching upon the verification of onsite monitoring information and detection data. In Incident 2, the result obtained from the automatic detection algorithm is "a serious traffic incident happened", and the corresponding optimal decision is to "dispatch more policemen". No matter what the judgment of the report handler about the state of the incident is, the optimal supporting decision is to dispatch more policemen. Thus, after verified by the report handlers, this optimal decision is approved directly. In Incident 3, the optimal decision is police dispatching. The corrected optimal decisions are respectively "no police dispatching is needed", "police dispatching" and "police dispatching". However, as a matter of fact, no traffic incident has happened, and the traffic flow detected before and that after the incident do not differ from each other a lot. Thus, the loss value of the decision of "police dispatching" and "no police dispatching is neededV is smaller. In this case, the report handler corrected the supporting decision upon the verification of onsite monitoring information and detection data and made the correct decision of "no police dispatching is needed".

Supporting decision(Incident1)	Loss value	Loss value(normal according to the manual judgment)	Loss value (a common incident according to the detection)	Loss value (a serious accident according to the detection)
No police dispatching is needed	218.37	0.02	243.48	249.58
Police dispatching	35.27	3.27	39.11	39.94
More policemen to be dispatched	41.2	6.26	45.22	46.19
Supporting decision(Incident2)	Loss value	Loss value(normal according to the manual judgment)	Loss value (a common incident according to the detection)	Loss value (a serious accident according to the detection)
No police dispatching is needed	551.61	276.89	483.46	565.25
Police dispatching	118.1	57.8	101.23	121.47
More policemen to be dispatched	34.53	25.63	35.31	34.37
Supporting decision(Incident3)	Loss value	Loss value(normal according to the manual judgment)	Loss value (a common incident according to the detection)	Loss value (a serious accident according to the detection)
No police dispatching is needed	11.65	0.001	12.99	13.32
Police dispatching	2.65	6.26	2.23	2.13
More policemen to be dispatched	8.13	6.26	8.34	8.39

Tab. 10. Expected losses under different incidents and decisions.

5. CONCLUSION AND PROSPECT

First, this paper proposed an AID algorithm based on travel time, which could detect two types of traffic incidents with different levels of severity and significantly reduce the MTTD; second, this paper established a assistant decision model of police dispatching for traffic incidents based on the Bayesian Decision Theory. Before the report handler acquired information about the state of traffic incidents clearly, this model could correct the probability of the happening of traffic incidents. According to the analysis of the cases, the models hereunder had good supporting police dispatching decision effect, where decisions made by the supporting decision system could be corrected through the judgment of the report handler even if they deviated from the actual situation to some extent. Meanwhile, the models hereunder could reduce the time taken by making a police dispatching decision, which could reduce the risks and losses arising from wrong decision to some extent. For the time being, the supporting decision model could only make decisions according to the specific results determined according to the classification of threshold values by the automatic detection algorithm. During the process of classification, part of the information might be lost, as a result of which the decision quality was reduced. In recent years, with the development of rough sets and other mathematic tools, methods are provided for making the decision based on discrete data some tools, which can also be considered as a direction for the subdivision of models hereunder. Moreover, the incident sample space for the research of police dispatching decision was limited, where only three types of state were considered. As a matter of fact, in future researches, the incident state can be classified to some extent, so that the result of the research can match the actual situation of road traffic incidents better.

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