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RESEARCH PAPER

Traffic Incident Prediction on Intersections Based on HMM

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Abstract: The intersection is an area where many accidents occur. Reasons for accidents are due to complicated intersection designs and the congested travel conditions. For these reasons, traffic incident detection is more complicated. This paper uses the intersections of Huaihai South Road and Jiefang Road as an example. According to the vehicle operation and phase timing, the situations of two vehicle's relative movement on four phase intersections are summarized. The motion vectors of the conflicting vehicle are quantized on the basis of vehicle tracking. Then, the HMM is used to classify the traffic conflicts of the intersection. Finally, numerical experiments verify that the algorithm is able to classify the conflict when the traffic is normal. Furthermore, the algorithm can forecast the traffic accidents (such as bumping, tandem, and stop) which occurred in the intersection.

Key Words: intelligent transportation; incident detection; hidden Markov model; intersection; traffic conflict

1 Introduction

In recent years, the rate of urban road traffic accidents remains high, especially in urban intersections. Except for the complicated intersection designs, the other factor is that the travel condition is often congested. For example, vehicles always travel freely to different directions at multilane intersections, yet the driver may park their cars illegally in the middle of the road when an accident occurs. The car will need to be parked in a safe position in order to allow traffic to return to its normal status. Moreover, because of this, the ambulance and police have to work for a long time to deal with the accidents. These obstructions makes it difficult for the traffic incident detection of the intersection[1].

Until now, several research institutions abroad have investigated the simulation experiment of collision detection at intersections. They used data mining technology to find a traffic flow mode suitable for various intersections. They also contrasted the traffic flow conditions of the intersection to predict the incidents[2]. Cuchira *et al*.[3] utilized the traffic rules' inference to reflect a simple traffic condition on a one-way street. Jung *et al*.[4] adopted computer technology to track vehicles from a traffic image and to enhance the accuracy of traffic information detection. Oikawa *et al*.[5] identified traffic congestions based on the video sequence. In China, current research on intersection traffic conditions is in the design stage of traffic controllers. Moreover, building the detecting coil and predicting incidents via the direct usage of the highway traffic flow mode must still be designed. In view of the lack of intersection traffic incidents detection in China, this study designs a set of traffic conflict detection systems suitable for urban intersections.

2 Analysis of the relative motion between two vehicles with conflict at the intersection

Fig. 1 displays the intersection plan for Huaihai South Road and Jiefang Road in Huai'An city. The signal is controlled by four phases. According to the vehicle running and phase timing, this paper summarizes the relative motion condition between two conflicting vehicles at the intersection controlled by four phases, as shown in Fig. 2. Fig. 2(a) indicates north-south and east-west through vehicles; Fig. 2(b) indicates north-south and east-west left-turn vehicles; Fig. 2(c) indicates the traffic conflict between two adjacent direction's vehicles; one is the through vehicle, and the other is the right-turn vehicle; Fig. 2(d) indicates the traffic conflict between two vehicles of north-south or east-west direction; one is the left-turn vehicle, and the other is the right-turn vehicle, as shown in Fig.3.

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3 Feature extraction

3.1 Feature extraction about relative motion vectors

This paper designs an algorithm that was suitable for a variety of intersections with different factors, such as geometry of the intersection, angle of video camera and location of the accident. Here, the intersection controlled by four phases is used as an example. In this study, vehicles run in multiple directions and conflicts may occur in every image frame. Therefore, such geometric dependencies increase the amount of training data for HMM algorithm. Thus, in order to avoid this scenario, the algorithm tries to avoid using image intensity as the features, because it depends on the color of vehicles consequently, the processing image is gray. First, the algorithm extracts the motion vectors feature from vehicles[6-8]. The process is shown in Fig. 4 and Fig. 5.

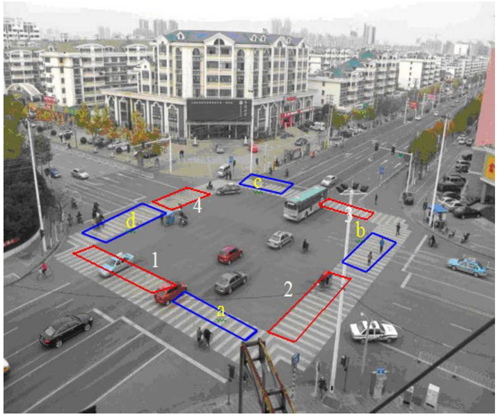

Fig. 1 The plane figure of intersection

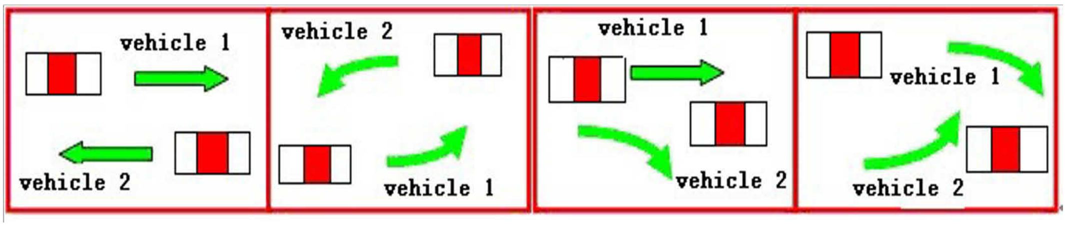

Fig. 2 The relative motion of two vehicle with conflict(supposing vehicle 2 is before vehicle 1)

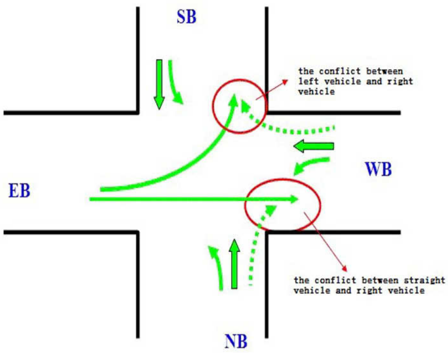

Fig. 3 The schematic diagram of conflict

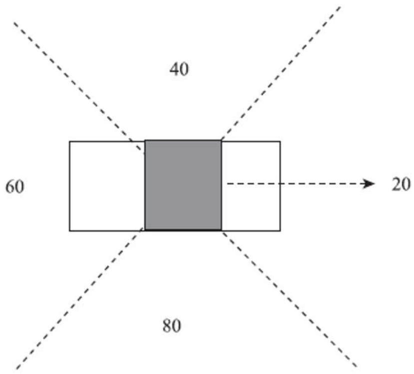

Fig. 5 Feature extraction of relative location

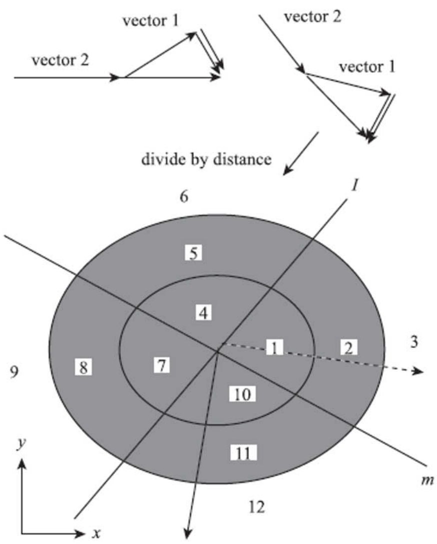

Fig. 4 Feature extraction of relative motion vector

Deductive process for feature extraction of relative motion vector

(1) Estimate the difference of motion vectors between the two objects, which is the motion vector of Vehicle-1 minus the motion vector of Vehicle-2.

(2) Rotate the differential motion vectors to different locations, so that the differential motion vector $\vec{V}_d$ rotates along the dotted line pointer in Fig. 4, counterclockwise to the position of the solid line cursor. The differential motion vector $\vec{V}_d$ to $\vec{V}_r$ form a circular arc and distribute in four areas, which can then be divided by the geographic coordinates.

(3) Divide the rotated vector by the distance between the two objects. Here, the distance is measured by the nearest blocks between the two objects, because the nearest distance directly affects the collision time of the two objects. As shown in Fig. 4, the three circular arcs with different radius sizes are

on behalf of the distance between two vehicles.

In order to classify situations with respect to a pair of vehicles, relations between the locations of the vehicles are needed, as well as relative motion vectors of the vehicles. At this time, such relative location between a pair of vehicles is called 'relative locations', as shown in Fig. 2. Although the relative motion vector between Vehicle-1 and Vehicle-2 in Fig.2(a) is equal to the one in Fig. 2(b), conflict situations are different between the two figures. Furthermore, although there are right-turn motion vectors both in Fig. 2(c) and Fig. 2(d), conflict situations are different between the two figures. Suppose Vehicle-2 is located behind Vehicle-1, the observation with respect to a location of Vehicle-2 relative to Vehicle-1 is '60', and when Vehicle-2 is located on the left side of Vehicle-1, the observation of Vehicle-2 against Vehicle-1 is '40', and so on. The marked relative locations are shown in Fig.5.

3.2 Feature extraction about relative location

Even if the relative motion vectors are equal, conflict situations differ depending on the relative locations. Therefore, in order to classify four conflict situations in Fig. 3, it is necessary to consider features obtained from both relative motion vectors and relative locations. A combination of different observation numbers as summation observation numbers, which are obtained from relative motion vectors and relative locations. Here, the observation numbers obtained from relative motion vectors are from ‘0’ to ‘12’, as shown in Fig. 4. Since the total observation is the combination of motion vectors and relative location vectors therefore, the total numbers are multiples of 20. Each combined observation are guaranteed to stand for a unique situation.

4 Traffic conflict recognition of intersection based on HMM

4.1 HMM theory

For a random event, one observation sequence is as follows: $Y=Y_1, Y_2, \cdots Y_T$, the event implies a state sequence: $X= X_1, X_2, \cdots X_T$. A HMM is composed of five elements: $\lambda = (X, Y, A, B, \pi)$.

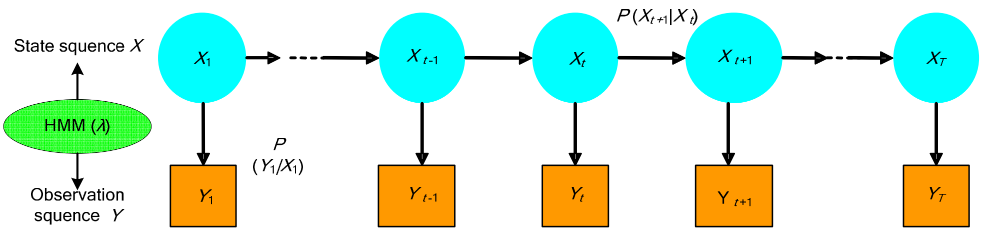

Fig. 6 The diagram of HMM theory

4.2 Model definition

According to the HMM theory chart in Fig. 6, the identification for observed sequence of city intersections can be described using the HMM. There are limited hidden states in the model and these states represent abstract numbers, such as: the traffic operation combination of through, left-turn, and right-turn in four directions. The probability distribution with the similar observed value is in accordance. The paper then applied simple left-to-right HMM for accident detection, and the transfer process is shown in Fig. 7.

T= the length of the image sequence;

$X = \{X_1, \cdots, X_T\}$: the finite set of states;

$Y = \{Y_1, \cdots, Y_T\}$: the finite set of observation values;

$A = \{a_{ij}\}$, $a_{ij} = P(X_t = S_j | X_{t-1} = S_i)$: the matrix of state transition probability;

$B = \{b_{ik}\}$, $b_{ik} = P(Y_t = O_i \mid X_t = S_i)$: the matrix of observation value probability distribution;

$\pi = \{\pi_i\}$, $\pi_i = P(X_1 = S_i)$: the probability distribution of initial state;

$$A = \begin{bmatrix} a_{11} & a_{12} & \dots & a_{1n} \\ 0 & a_{22} & \dots & a_{2n} \\ 0 & 0 & \dots & a_{nn} \end{bmatrix}$$

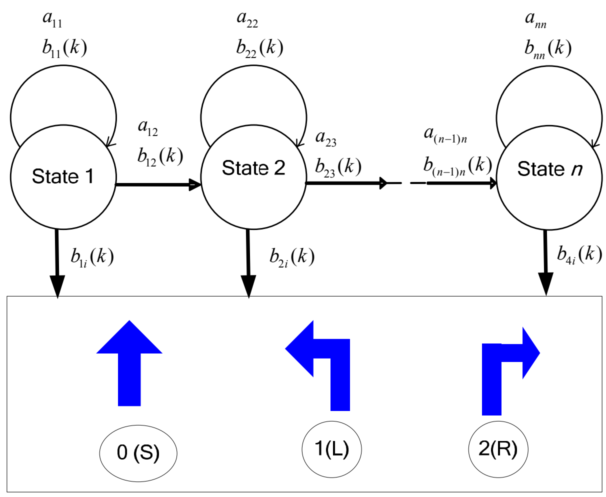

Fig. 7 Left to right HMM

b_{ik}: the probability that output observation value is O_i when the state is S_i. In this algorithm, the forward variable $\alpha_t(i)$ and backward variable $\beta_t(i)$ are defined. $\alpha_t(i)$ is the probability of observation sequence, from 1 to t, at time t and state i, under a given λ, e.g. $\alpha_t(i) = P(Y_1, Y_2, \cdots Y_t, X_t = S_i | \lambda), 1 \le t \le T$. $\beta_t(i)$ is the probability of the partial observation sequence, from t+1 to the end, at time t and state i, under a given λ, e.g. $\beta_t(i) = P\left(Y_{t-1}, Y_{t-2}, \cdots Y_T, X_t = S_i \middle| \lambda\right)$, $1 \le t \le T-1$.

4.3 Algorithm implementation

4.3.1 Flow chart of HMM

HMM algorithm implementation is an output process which makes time series images into symbols or digital sequences. The detailed process is further shown in Fig. 8.

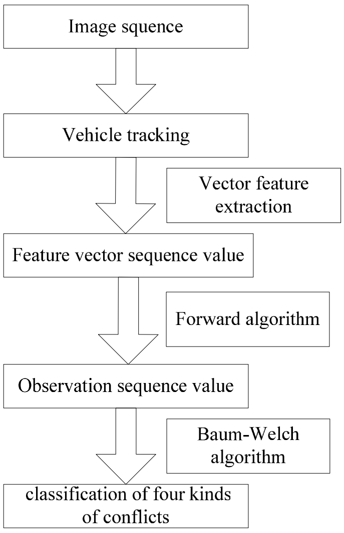

Fig. 8 The flow chart of HMM

4.3.2 Forward algorithm

If the probability of being in each state before time t is known, then the probability of the state S_i on time t is recorded as: $\alpha_t(i) = P(Y_1, \cdots, Y_t, X_t = S_i \mid \lambda)$.

The algorithm process is explained in the following steps:

Step 1: $\alpha_1(i) = P(Y_1, X_1 = S_i \mid \lambda) = \pi(i) b_i(Y_1)$ (1)

Step 2: $\alpha_{t+1}(j) = (\sum_{i=1}^{N} \alpha_t(i) a_{ij}) b_j(Y_{t+1})$ (2)

Step 3: $P(Y \mid \lambda) = \sum_i^N \alpha_T(i) = \sum_{j=1}^{N} \left\{ \left[\sum_{i=1}^{N} \alpha_{T-1}(i) a_{ij} \right] b_j(Y_T) \right\}$ (3)

4.3.3 Baum-Welch algorithm

Step1: initialize π_i, a_{ij}, b_{ik};

Step2: *EM* step;

***E* step**: compute $\xi_t(i,j)$ and $\gamma_t(i)$:

Given HMM and observation sequence, $\xi_t(i,j)$ is the probability of being in state i at time t and in state j at time t+1:

$$\xi_t(i,j) = P\left(X_t = i, X_{t+1} = j \mid Y, \lambda\right) = \frac{a_t(i) a_{ij} b_j(Y_{t+1}) \beta_t(i)}{P(Y \mid \lambda)} = \frac{a_t(i) a_{ij} b_j(Y_{t+1}) \beta_{t+1}(i)}{\sum_{i=1}^{N} \sum_{j=1}^{N} a_t(i) a_{ij} b_j(Y_{t+1}) \beta_{t+1}(i)} \quad (4)$$

Given HMM and observation sequence, $\gamma_t(i)$ is the probability of being in state i at time t:

$$\gamma_t(i) = \sum_{j=1}^{N} \xi(i,j) \quad (5)$$

***M* step**: Utilize the expectations obtained from E step, re-estimate $\lambda = (\pi_i, a_{ij}, b_{ik})$, and obtain the new $\bar{\lambda} = (\bar{\pi}_i, \bar{a}_{ij}, \bar{b}_{ik})$.

$$\begin{cases} \pi_i = \gamma_1(i) \\ \bar{a}_{ij} = \dfrac{\sum_{t=1}^{T-1} \xi_t(i,j)}{\sum_{t=1}^{T-1} \gamma_1(i)} \\ \bar{b}_{ik} = \dfrac{\sum_{t=1}^{T} \gamma_t(j)\, \delta(\mathrm{Y}_k, k)}{\sum_{t=1}^{T} \gamma_t(j)} \\ \bar{\lambda} = (\bar{\pi}_i, \bar{a}_{ij}, \bar{b}_{ik}) \end{cases} \quad (6)$$

$\sum_{t=1}^{T-1} \xi_t(i,j)$: expected number of transitions from state i to j;

$\sum_{t=1}^{T-1} \gamma_1(i)$: expected number of transitions from state i to another state (including state i);

$\sum_{t=1}^{T} \gamma_t(j) \delta(Y_k, k)$: expected number of times in state j output k;

$\sum_{t=1}^{T} \gamma_t(j)$: expected number of times from X to j.

Step3: i=i +1; repeat EM step, until π_i, a_{ij}, b_{ik} close to convergence value.

5 Traffic event forecasting

5.1 Bumping event forecasting

Model λ=$f(A, B, \pi)$ classifies each of the identified events. In order to exactly recognize a bumping event in ordinary situations, observation sequences of every pairs of vehicles will be examined by a classification method HMM to determine which class (such as aforementioned pas-00, pas-11, pas-02 and pas-12) they belong to. The observation sequences of vehicles that are involved in bumping accidents will vary from those of ordinary situations. The system is expected to detect bumping accidents by distinguishing obtained observation sequences of bumping accidents from those of ordinary situations by using HMM. Combined with the total observation sequence when the intersection is under conflict, then the typical observation sequences of bumping accidents are expected to be as follows. Here, observation numbers as 61, 62, 63 and 27, 28, and 29. This observations means a vehicle is getting closer to another vehicle. Observation numbers, such as 60 and 20, entails the moment of a bump, and observation numbers of 69, 68, 67 or 23, 22, and 21 denote reactions after the bump.

For example: consider a rear-end accident that Vehicle-2 bumped Vehicle-1. The observation sequence of Vehicle-2 relative to Vehicle-1 denoted as tdm-0, and the observation sequence expectation value are: 61, 62, 63, 60, 69, 68, and 67; The observation sequence of Vehicle-1 relative to Vehicle-2 denoted as tdm-1, and the observation expectation value are: 29, 28, 27, 20, 23, 22, and 21.The details are show below.

[tdm-0] 61 62 63 60 60 60 69 68 67

[tdm-1] 27 28 29 20 20 20 23 22 21

5.2 Car-following forecasting

However, consider the case of car-following, which is defined when a vehicle comes closer to another, but no impact occurs. The observation sequence of car-following is similar to that of a bumping accident. When observation numbers equal 9 and 3, the relative motions represent a dangerous situation where the relative motion vector is large and distance is close between a pair of vehicles. However, the appearance of 7, 8, and 9 depend on the absolute value of the relative motion vector or relative distance of the two vehicles. Therefore, it seems to be very difficult to distinguish bumping and car-following through observation sequences alone. The former belongs to the event, and the latter belongs to the normal situation. In order to resolve this problem, the traffic rules can be used to distinguish these different situations.

Rule 1: An observation sequence of a pair of vehicles is defined as TDM-01. This pair of vehicles is likely to cause a bumping accident;

Rule 2: Applies to a vehicle stopping inside an intersection due to normal reasons such as a shut down. Based on the stop location, if the other vehicle proceeds through the intersection, it is not an accident, but just a car-following situation. On the other hand, if the other vehicle also stops inside the intersection, the pair of vehicles is likely to have caused an accident.

Rule 3: If other vehicles bypass the stopped vehicle, it is more likely to be involved in an abnormal event. Bypass can be judged through the vehicle trajectories.

Through the above analysis, traffic accidents can be divided into three types.

Type 1: pumping accident;

Type 2: car-following;

Type 3: hard shutdown.

6 Experimental results and analysis

6.1 Traffic conflict identification

In order to verify the validity of the HMM's observation sequence, the paper took three groups intersection video images. Each video lasts three minutes, and each group velocity is 10 frames per second. Each group video has a through, left-turn, and right-turn moving vehicles. The three set of video images are tested respectively, e.g., identify vehicles of through [pas-0], left-turn [pas-1] and right-turn [pas-2]. Each set of observed sequence is composed of 12 observation values, and the observed values for the feature values of the two conflicted cars. The experimental observation sequence values are shown in table 1.

Table 1 Observed sequence value

Type	Video series	Observation sequence
[pas-0]	1	27 27 88 88 89 87 87 87 87 67 67 67
	2	27 28 88 88 88 88 87 87 87 67 67 67
	3	27 27 20 27 28 87 88 88 88 88 87 67
[pas-1]	1	27 27 47 47 47 47 47 47 47 67 67 67
	2	27 27 27 28 47 48 48 48 48 47 47 67
	3	27 27 27 48 48 48 49 68 68 68 68 67
[pas-2]	1	61 61 42 42 43 41 41 41 41 21 21 21
	2	61 60 60 61 62 41 42 42 42 42 41 41
	3	62 62 62 43 43 43 42 22 22 22 22 22

Table 1 illustrates three examples for each type of observation sequences; pas-0, pas-1, and pas-2. Each sequence out of three examples appears slightly different than each other, because disturbance conditions in the three group videos are different. In other words the classification result is stable. After this experiment, it shows that the robust method against such disturbances is considered to be appropriate to classify such sequences, when the videos are under different interference conditions.

Based on the above three types of observation sequences, pas-0, pas-1 and pas-2, situations between a pair of vehicles can be classified as follows:

[pas-00]: The conflict between through and through vehicles, see Fig.9(a);

[pas-11]: The conflict between left-turn and left turn vehicles, see Fig. 9(b);

[pas-02]: The conflict between straight and right-turn vehicles, see Fig.9(c);

[pas-12]: The conflict between left-turn and right-turn vehicles, see Fig. 9(d).

In order to verify the recognition effect on the four types of conflicts by HMM, the real traffic video is adopted to verify the traffic incident detection method. The video location is the signalized cross intersection between Huaihai South Road and Jiefang Road in Huai'An city. This intersection is composed of two main roads, and controlled by four phases.

(a) pas-00

(b) pas-11

(c) pas-02

(d) pas-12

Fig. 9 Recognition results of pas-00, pas-11, pas-02 and pas-12

Four images in Fig. 9 show results of classifying combined observation sequences of many pairs of vehicles into classes. The classes are designated as pas-00, pas-11, pas-02, pas-12 by using HMM. In Fig. 9(a), through vehicle of ID-25 was detected as pas-00 with respect to the through vehicle of ID-23, and they were indicated in a light colored rectangle. Fig. 9(b) left-turn vehicle of ID-26 was detected as pas-11 with respect to the opposite direction left-turn vehicle of ID-27, and they were indicated in a light colored rectangle. Fig. 9(c) through vehicle of ID-29 was detected as pas-02 with respect to the adjacent direction left-turn vehicle of ID-27, and they were indicated in a light colored rectangle. Fig. 9(d) left-turn vehicle of ID-11 was detected as pas-12 with respect to the opposite direction right-turn vehicle of ID-9, and they were indicated in a light colored rectangle.

6.2 Traffic accident forecasting

Due to the limited traffic accident data in intersections, it is difficult to record traffic accidents by a video camera. Therefore, only one case video is utilized to verify the algorithm, e.g. the conflict between through and right-turn vehicles. Fig. 10 shows the car-following and bumping accident that be detected by the algorithm. According to Fig.10, we can see that the algorithm has detected a situation which seems to be an accident by classifying the observation sequence of a pair of vehicles. Although the sequence was classified into TDM-01, it is difficult to completely determine this situation as a bumping accident by only the sequence itself. The video is short, and therefore has no other conflicting vehicle.

Fig. 10 The event of car following

The situation in Fig. 10 should be further identified by the traffic rules. The algorithm successfully detected an accident which is caused by the vehicle of ID-21 and the vehicle of ID-22. The detection steps are as follows: (1) the algorithm detected an observation sequence related to this pair of vehicles as a class of TDM-01; (2) these vehicles stopped for a large amount of time; (3) since several vehicles have passed by these two vehicles, the algorithm decided that vehicle of ID-21 and the vehicle of ID-22 have caused a bumping accident.

In addition, according to the same algorithm and detection rules, a pair of vehicle of ID-9 and vehicle of ID-11 in Fig.9(d) meet the Rule 1 and 2, but have no other vehicles passing by the two vehicles. So, it does not meet the Rule 3, therefore this pair of vehicles should be discarded from candidates for bumping accidents.

7 Conclusions

This paper reviews the state-of-the-art intersection event detection. An analysis of the relative motion of two conflicting cars at an intersection is applied. In order to improve the detection rate of accidents, ease traffic jams, and reduce traffic accidents, a proposal of traffic incident prediction algorithm based on HMM is proposed. Through a numerical example by using the HMM algorithm, we can conclude the following:

(1) HMM based incident detection algorithm is applicable to intersections with multiple types of geometry. This algorithm is used to observe the relative motion of two conflicting cars at an intersection;

(2) Combined with the observation sequence numbers from the relative motion vector and the relative location, the HMM algorithm can effectively classify the two conflicting cars into four types of conflicts;

(3) HMM model can successfully predict potential accidents, such as bumping accident, and hard shutdowns.

Acknowledgements

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