Abnormal Traffic Events Detection Based on Short-time Constant Velocity Model and Spatio-Temporal Trajectory Analysis

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Abstract

A novel algorithm is presented in this paper to detect anomalous vehicle behaviors such as abnormal stop and vehicle crashing. After objects detection, spatio-temporal trajectory of multiple objects can be obtained to construct the regional short-time constitute velocity model. Then gray model theory is adopted to estimate the motion model parameters. With the definition of abnormal traffic events patterns, individual vehicle movement can be judged as an abnormal or normal vehicle behavior. Experimental results show the proposed method can detect the abnormal traffic events effectively.

Keywords: Abnormal Traffic Events; Constant Velocity Model; Gray Theory Model; Trajectory Analysis

1 Introduction

Traffic abnormal events refer to the abnormal traffic flow in highway caused by occurrence of highway events (such as crash, car retrograde, stop anomaly etc.). Because of the random and unpredictable properties of traffic abnormal events, video-based traffic abnormal detection has become a popular problem in the research field of traffic safety.

The major difficulties of traffic anomaly detection include two aspects: motion modeling of abnormal traffic events and behavior classification. Hidden Markov Model (HMM) and 3D model \cite{1-3} are widely used for motion modeling. Multiple observations HMM are adopted in \cite{1, 2} to describe object movement, but the validity of model depends on the quantity and quality of observational data, the accuracy of events characteristics associated. Weiming Hu \cite{3} use the
3D model for vehicle motion tracking and modeling, but 3D model is difficult to be obtained accurately form the video. Also the 3D model calculation costs large computation. In behavior classification aspects, neural network and clustering method are widely used recently. Hu [4] etc. employ the self-organizing fuzzy neural network to learn the motion patterns of vehicle trajectory for anomaly identification and prediction. But a lot of abnormal event samples are required to ensure the accuracy of this method. Patino [5] classify the vehicle trajectories with hierarchical clustering method, but the classification results may be affected due to the errors caused by decomposition or combination in certain clustering level.

For event detection, both unsupervised [6] and supervised [7, 8] classification methods have been developed. Since unsupervised methods are commonly used to detect anomaly activities instead of some predefined classes of events, supervised anomaly event detection remains prime choice. Common supervised classification models applied to intelligent systems include Artificial Neural Networks (ANNs) and dynamic probabilistic network models such as Hidden Markov Models (HMMs). Hierarchical data mining approach in [9] is adopted for trained anomalies rules. Although an ANN has the advantage of being flexible and being able to model accident sequence consisting of a large number of random processes, HMMs are considered to be more robust against observation sequences with variable length compared to ANN methods.

In trajectory based anomaly detection applications, these two types of traffic anomaly detection methods above both need large amount of anomaly samples to calculate the anomalies model parameters or to train the classifier rules. While in intelligent traffic CCTV system, the traffic anomaly samples are not easy to get, also the samples vary widely because of many factors such as variant environment, vehicle behaviors and so on. It is difficult to ensure the efficiency and performance of different methods. The difference of samples also brings high complexity and real time applicability to anomaly detection process. Therefore, a supervised anomaly detection method combined with linear motion model and spatiotemporal context is proposed in this paper.

For realizing the traffic anomaly detection without essential need of large amounts of abnormal samples, it should be feasible to get a large amount of traffic normal samples from practical highway CCTV system under a relatively fixed condition. These normal samples can provide enough normal motion parameters. Those moving objects with obvious different parameters in the same highway region can be determined as anomaly by human observer with certain prior knowledge. This kind of prior knowledge contains description of traffic movement, composition of different traffic movements and traffic law description and so on. Therefore, need of traffic abnormal samples and classification can be substitute with traffic normal samples and behaviors patterns definition.

According to this thought, a regional short time linear motion model is proposed in this paper first to find abnormal vehicle motion. Then according to the traffic rules, related prior knowledge and spatial -temporal parameters of highway regional motion, object behavior of anomaly stop, retrograde, crash and other abnormal patterns are defined to classify different vehicle behaviors. In this paper, the algorithm mainly focuses on two parts: motion modeling and behavior patterns definition. A regional continuous velocity motion model is presented to describe short term regional movement based on motion information of multiple objects in the same region. Then traffic anomaly behavior patterns are defined here based on spatial and temporal motion characteristics. Behavior descriptions combined with trajectory analysis is feasible to identify common abnormal vehicle behaviors without complex training operations in practice. The proposed anomaly detection method is tested with actual highway video that it improves the efficiency of motion modeling
and needs less learning calculations.

2 System Framework

Video-based traffic anomaly detection mainly includes two parts: target detection and tracking, motion behavior analysis and anomaly detection. Target detection and tracking includes 4 parts: background modeling, differential detection, feature extraction and motion tracking. Motion analysis and anomaly detection depends on the accuracy of motion information extracted in target detection and tracking procedure such as trajectories, orientation and velocity of vehicles. This extraction is combined with the definition of anomaly behavior to achieve the target motion discrimination. This system framework is shown in Fig. 1.

![Algorithm framework](image)

Fig. 1: Algorithm framework

**Multiple Features Extraction.** Highway surveillance video is highly compressed format, which has a serious loss of color information. In this condition a single feature is difficult to reflect the characteristic of vehicle objects. Therefore, features of object centroid, area, perimeter, aspect ratio, degree of saturation and irregularity [1] are chosen as the spatial characteristics of the vehicle, while features of trajectory, velocity and orientation are selected as temporal characteristics.

**Multiple Target Matching Based on Spatial-temporal Continuity Constraints.** In object tracking procedure, the same moving object in adjacent frames has the characteristics of short-time motion continuity. Based on this continuity constraint, motion continuity, shape continuity and regional and relative position continuity are used in this paper to match multiple objects. Minimum distance principle is adopted, match assurance is defined as:

$$
\xi_{li} = \frac{s_{li}}{s_{li} + q_{li}}
$$

(1)

where $s_{li}$ and $q_{li}$ are similarity and difference of different objects $O_i$ and $O_l$, the confidence threshold is taken as 0.6.
3 Motion Modeling

3.1 Linear Motion Model

In several frames, vehicle motion has the short-time regional continuity, which can be assumed as linear motion. While anomaly behavior of single vehicle is random, event [10], sudden change of spatial and temporal motion feature, its fitness to linear motion declines.

Therefore, in this paper a simplified constant velocity model is proposed to model the object motion, which is defined as below:

\[
\begin{align*}
    x_{i,k} &= \alpha x_{i,k-1} + \beta + \delta_i \\
    y_{i,k} &= \alpha y_{i,k-1} + \beta + \delta_i
\end{align*}
\]  \hspace{1cm} (2)

where, \(x_{i,k}\) and \(y_{i,k}\) are centroid coordinates of the \(i\)-th object in the \(k\)-th frame, \(\alpha\) and \(\beta\) are linear regression coefficients, \(\delta_i\) is Gaussian noise distribution with parameter of \( \mathcal{N}(0, 1) \).

3.2 Learning of Model Parameters

Regressive parameters of continuous velocity model can reflect the spatial orientation of the target movement. But the raw data may be subject to noise interference. Therefore GM(1, 1) gray model in [11] is adopted here to calculate the short time regional motion direction features to further quantitative prediction of the directional parameters.

The differential equation of GM(1, 1) model is shown as:

\[
\frac{dU_1}{dt} + aU_1 = b
\]  \hspace{1cm} (3)

in which, \(U_0 = [u_0(1), u_0(2), \ldots, u_0(n)]\) is the original observation sequence, \(U_1 = [u_1(1), u_1(2), \ldots, u_1(n)]\) is the accumulation new sequence, which is generated by:

\[
u_1(k) = \sum_{i=1}^{k} u_0(i), \quad k = 1, 2, \ldots, n \]  \hspace{1cm} (4)

The unknown parameter \(a, b\) can be estimated by the least squares method. With the predefined value of \(a\) and \(b\), the predict model can be express as:

\[\hat{\nu}(k + 1) = [\mu - \nu u_0(1)]e^{-\nu(k-1)}\]  \hspace{1cm} (5)

in which, \(\mu = \frac{a}{1 + 0.5a}, \nu = \frac{b}{1 + 0.5a}\).

4 Traffic Abnormal Detection

4.1 Definition of Traffic Abnormal

From a statistical point of view, traffic abnormal is defined as the significant difference of a moving target in the time, spatial distribution or the space-time joint distribution from the average statistical characteristics of the entire video sequence. The moving target has an abnormal motion performance in time, space, or space-time joint distribution.
4.2 Classification of Traffic Abnormal Event

The abnormal behavior of a single vehicle movement can be divided into two categories: one abnormal behavior refers to the velocity of moving vehicle does not meet the road provision of speed, such as excessive speed, too slow, abnormal parking or stop and other acts. The variation of speed can be reflected by its changing rate of motion direction. The other abnormal behavior refers to the abnormal changes of vehicle direction, such as the vehicle driving route anomalies which due to human operating, the external impact or road surface water and so on. The route anomaly can be detected by the mutation of abnormal direction of motion. Therefore, according to the local short-term local trajectories, the motion distribution of current target is analyzed to determine the existence of a motion direction exception in order to achieve the detection of abnormal traffic incident.

4.3 Detection of Traffic Abnormal Incident

Traffic abnormal rules [12] based on motion orientation of trajectories and local region orientation pattern description is defined in this paper. According to these rules, an abnormal behavior of vehicle target can be detected if its motion characteristics meet one of the following behavior patterns.

(1) Abnormal parking. When position of the $k$-th moving target in the $i$-th frame stays the same or changes a little in the continuous several frames, the target can be as abnormal parking or stop.

\[
\begin{align*}
|x_{i,k} - x_{i-m,k}| &\rightarrow 0 \\
y_{i,k} - y_{i-m,k} &\rightarrow 0
\end{align*}
\]  

(2) Retrograde. When the orientation parameter of current target is significantly different from the orientation of multiple targets in adjacent region, which can be described in the opposite sign of regressive coefficients $\alpha$ and $\beta$. Then the target can be judged as retrograde.

\[
\begin{align*}
\left| \frac{\sum_{i=1}^{N} \alpha_{ik}}{N} - \frac{\sum_{j=1}^{obj\_num} \sum_{k=1}^{2N} \alpha_{jk}}{2N} \right| &> Thre_{\alpha} \quad \text{OR} \\
\text{sign} \left( \frac{\sum_{i=1}^{N} \alpha_{ik}}{N} \right) \times \text{sign} \left( \frac{\sum_{j=1}^{obj\_num} \sum_{k=1}^{2N} \alpha_{jk}}{2N} \right) &= -1
\end{align*}
\]
\[
\begin{align*}
\left\{ \sum_{i=1}^{N} \frac{\beta_{ik}}{N} - \sum_{j=1}^{\text{obj.num}} \sum_{k=1}^{2N} \beta_{jk} \right\} > \text{Thre}_\beta \quad \text{OR} \\
\left\{ \text{sign} \left( \sum_{i=1}^{N} \frac{\beta_{i;k}}{N} \right) \times \text{sign} \left( \sum_{j=1}^{\text{obj.num}} \sum_{k=1}^{2N} \beta_{j;k} \right) \right\} = -1
\end{align*}
\]

(3) Crash. If the trajectories of the \( k \)-th target and the \( l \)-th target has an intersection, and in the following multiple frames the motion orientation of these two targets has obvious polyline offset, then a crash can be detected between these two targets.

\[
\begin{align*}
\left\{ \left| x_{i;k} - x_{i;l} \right| \rightarrow 0 \right\} \text{AND} \left\{ \left| y_{i;k} - y_{i;l} \right| \rightarrow 0 \right\} \left\{ \left| \alpha_{i;k} - \alpha_{i-m,k} \right| > \text{average}(\alpha)/N \right\} \left\{ \left| \beta_{i;k} - \beta_{i-m,k} \right| > \text{average}(\beta)/N \right\}
\end{align*}
\]

in which, \( \alpha_{i;k} \) and \( \beta_{i;k} \) are the orientation parameter of the \( k \)-th object motion, \( (x_{i;k}, y_{i;k}) \) is the centroid of this object. \( m \) is set in the value range 3-5. \( \text{average}(\alpha)/i \) and \( \text{average}(\beta)/i \) are continuous parameters of the short-time local orientation pattern, which can be calculated by the average of regressive coefficients of multiple objects appears in the same region of continuous \( N \) frames.

### 5 Experiments and Analysis

The algorithm presented in this paper is carried out in the platform of CPU 2.5 GHz, 2.0 GB memory and MATLAB 7.1. Actual highway monitoring video of Henan Province Zhong Yuan Highway Co. Ltd is selected for test. This video is selected as a car accident record due to the slippery road surface because of rainy weather. The video is MPEG-4 encoded format, frame rate 25 f/s, resolution of 320 × 240.

The highway traffic scene is shown in Fig. 2. The blue area is artificially set as the detection area. When a vehicle object enters in this area, the exact entering time will be recorded and the vehicle will be numbered. For example, the 3-th white vehicle enters the detection zone in 181-th frame and the 4-th black vehicle appears at the 195-th frame in the test video. The vehicle detection result is shown in Fig. 2 (a). Fig. 2 (b) is the partial enlarged result of Fig. 2 (a) to show the predicted motion trajectory of the detected 3-th and 4-th vehicle objects.

Initial state values are calculated by the motion parameters of all the moving vehicles under current regional motion orientation. With these initial motion parameters, the motion of a new vehicle target can be detected as normal or abnormal motion pattern. Also the next step of target motion can be predicted. With the method presented, the statistical short-time regional motion parameters in the 205-th frame is \((-0.66, 186.63)\), the movement orientation parameter of No. 3 vehicle is calculated as \((-0.58, 172.57)\). No. 3 vehicle is judged as normal driving with
Fig. 2: Motion trajectory of moving vehicle in highway

our method, which can be. When No. 4 vehicle enters into the detection region, its movement parameters is detected as (0.04, 53.5) in the 205-th frame. Comparing to the predicted motion parameters of (-0.48, 161.67) calculated by the consecutive 10 frames before, there are significant difference between the motion of No. 4 vehicle and that of all the local moving vehicles. This difference shows the anomaly of the motion of No. 4 vehicle. If this vehicle target continues its original motion state, it is predicted to be in a risk of potential accident by our method. While noticing the actual video, in the 228-th frame, No. 4 vehicle runs into the highway fence and causes a crash. In the 247-th frame, No. 4 vehicle runs and stops after collision.

The time-spatial trajectory of No. 4 vehicle is shown in Fig. 3. In the 195-th frame to the 205-th frame in the video, the motion parameter of No. 4 vehicle is (0.04, 53.5). Its minimum distance from the short-time local motion parameter of (-0.66, 186.63) is far beyond the threshold. According to this difference, 4# vehicle is judged as abnormal motion orientation. From the 225-th frame to the 238-th frame, the 4# vehicle runs into the highway fence and stops after collision. After collision, it can be calculated from the real motion video that the position of the 4# vehicle is substantially constant and its motion parameters changes from (0.04, 53.5) to (0, 0) while its vehicle velocity changes from 1.23 pixels / frame to 0.00 pixels / frame. It can be judged combined

Fig. 3: The space-time trajectory of vehicle in traffic abnormal process
with our abnormal detection model that the 4# vehicle has stopped abnormally. From the 239-th to 260-th frame, the 4# vehicle runs to the other side of the road on the reverse direction. Its motion parameters changes from (0, 0) to (−0.39, 141.38). According to this parameter change the 4# vehicle can be judged as be retrograde. The real vehicle trajectory in short-time term is contrasted with the trajectory predicted by short-term linear model by the proposed linear model for the purpose of traffic incident detection. In the experimental video, the 4# vehicle is judged as traffic anomaly object with the incident type of abnormal route, abnormal parking and retrograde.

6 Conclusions

This paper presents a model based on short-term continuous velocity and trajectory analysis for traffic detection method. By trajectory analysis, vehicle movement in short-time regional can be modeled and the regional motion parameters can be found out by linear motion model. Combining motion parameters of interested targets and regional objects, a few traffic anomaly patterns can be described based on the prior knowledge to achieve automatic abnormal detection of target motion. Highway actual surveillance video is used in experiment for algorithm verification. Experimental results show that the proposed method can accurately detect abnormal traffic events of parking, collision and retrograde. Collision event prediction also can be realized by this method. Motion vehicles in a limited number of continuous frames in a short period of time are adopted in the proposed method to model the regional linear motion. Based on the prior knowledge, the motion orientation information can be applied to describe the unusual motion behavior patterns.

With the presented method the anomaly detection can be realized without large amounts of abnormal traffic incident samples and training computation. This improvement of detection based on anomaly pattern rules put forward a viable way for automatic traffic abnormal detection. Future work will focus on the quantitative characteristics of abnormal incident severity for describe its impact on the overall traffic condition of a highway.

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