J Sign Process Syst (2016) 82:357–371
DOI 10.1007/s11265-015-1006-4

Real-Time Automatic Obstacle Detection method for Traffic Surveillance in Urban Traffic

Jinhui Lan[1] · Yaoliang Jiang[2] · Guoliang Fan[3] · Dongyang Yu[2] · Qi Zhang[4]

Received: 3 April 2014 / Revised: 16 April 2015 / Accepted: 20 April 2015 / Published online: 10 May 2015

Abstract Obstacle detection in urban traffic is a hot topic in intelligent visual surveillance systems. In this paper, a real-time automatic obstacle recognition method based on computer vision technology is presented. The proposed method aims at detecting and recognizing the road obstacles such as abandoned objects, accident vehicles and illegally parked vehicles, which can prevent the traffic accident effectively. In the method, the target images are captured by a visible image sensor firstly. In order to avoid the static objects disappearing from foreground in short time when using GMM (Gaussian Mixture Model), background is built and foreground objects are extracted by the proposed algorithm SUOG (Selective Updating of GMM). Relative object speed is used to detect the static obstacles, and FROI (Flushed Region of Interest) algorithm based on the concept of connected domain, is presented to eliminate noises outside road and improve real-time capability. At last, a classification method of adaptive interested region based on HOG and SVM, and a new recognition algorithm of accident vehicles based on multi-feature fusion are proposed to classify the road obstacles. Experiments indicate that the detection rate of the proposed obstacle detection method is up to 96 % in urban road traffic. Through experiment, it is shown that the developed obstacle detection method has low computational complexity, and can fulfill the requirement of real-time applications, and it is correct and effective.

Keywords Video surveillance · Feature extraction · SVM · Obstacle detection

✉ Jinhui Lan
lanjh@ustb.edu.cn; ustblanjinhui@gmail.com

Yaoliang Jiang
beikejyl@163.com

Guoliang Fan
guoliang.fan@okstate.edu

Qi Zhang
zhqi@ustb.edu.cn

[1] Department of Instrument Science and Technology, University of Science and Technology Beijing, 30 Xue Yuan Road, Beijing 100083, People's Republic of China

[2] Department of Instrument Science and Technology, University of Science and Technology Beijing, 30 Xue Yuan Road, Beijing, China

[3] Visual Computing and Image Processing Laboratory (VCIPL), School of Electrical and Computer Engineering at Oklahoma State University (OSU), Stillwater, OK, USA

[4] Department of Intelligent Science and Technology, University of Science and Technology Beijing, 30 Xue Yuan Road, Beijing, China

1 Introduction

Road traffic plays an important role in today's life and many crucial services and human activities are becoming more dependent, either directly or indirectly, upon it. Therefore, efficient management of the road traffic is critical to efficient transportation and it has now become an imperative for those in charge of traffic surveillance. But in the real complex urban traffic scene, kinds of obstacles may be a terrible threat to the traffic system. Some drivers or passengers drop or throw objects from their vehicles to road when they are driving. These objects bring potential security problems to traffic system. Illegally parked vehicles disturb regular traffic order and may cause traffic accidents. Also, Accident vehicles detection in times is very important to prevent second traffic accidents for traffic system. And In the other hand, with current traffic management activities, traffic surveillance by means of monitoring cameras has already been put in place. So the real-time detection of road obstacles in complex traffic scenarios is very necessary and importance to keep the traffic safety and smooth, with intelligent traffic surveillance systems based on computer vision and image processing algorithms.

In this paper, we present a road obstacle detection method by computer vision technology for road surveillance. There are three type road obstacles in this paper, abandoned objects, accident vehicles and illegally parked vehicles. The common features of these obstacles are as follows, causing traffic jam or traffic accident frequently, getting zero speed eventually, and being stopped on road area. In these common features, obstacles'position and speed are useful for obstacle detection with relatively ideal algorithm. In this paper, a real-time obstacle detection method is proposed based on object features such as position, speed and etc. Firstly, we improve the GMM, and present a SUOG algorithm as initial process of road objects to retain static objects in foreground, in which background image updates when static objects appeared on road. Next, road area is determined automatically by FROI algorithm based on the concept of connected domain, eliminating the objects outside the road area to improve the recognition rate. After all road objects tracked and marked, static objects are selected from road objects based on their speed and static objects in ROI, which are determined as road obstacles. Then, we extract the adaptive interested region of the road obstacles, and use HOG (Histogram Orientation Gradient) descriptor to detect the interested region, getting the HOG feature of the obstacles. SVM (Support Vector Machine) classifier is trained and used to distinguish the stopped vehicles including illegally parked vehicles and accident vehicles from abandoned objects. And finally, a new recognition algorithm of accident vehicles based on multi-feature fusion is presented for further classification. Simplified traffic environment of obstacle detection is shown in Fig. 1.

The rest of the paper is arranged as follows: Relevant previous work is given in Section 2. In Section 3, the proposed method is described. Details of foreground detection (Section 3-A), feature extraction and obstacle detection (Section 3-B), and obstacle classification (Section 3-C) are also provided. We present the detection and recognition results with comments in Section 4. The paper concludes with Section 5.

2 Previous Work

Obstacle detection in urban traffic is one of the most crucial tasks in intelligent visual surveillance systems. There has been considerable amount of research related to road obstacle detection and classification. Most researchers used computer vision technology to deal with this problem and the systems for vehicle detection using stationary cameras are the most typical and our system falls into this category.

2.1 A Abandoned Object Detection

There are many papers related to abandoned object detection, the approaches of locating the abandoned objects can be basically grouped into two categories: one is based on the tracking approach [1, 2], and the other is based on the background-subtraction method [3–8]. Most tracking-based approaches need to detect all moving objects accurately. They usually encounter the problem of merging, splitting, occlusion, and identity correspondence, and it is difficult to track all the objects precisely in crowded situations. On the contrary, background-subtraction techniques can work well in these highly-cluttered scenarios. Paper [3] proposed abandoned object detection algorithm based on dual background segmentation. The drawback of this method was background initialization relatively simple, which could affect the final detection result. In [4], adaptive background subtraction (ABS) technique is employed to detect the unknown, changed, or removed objects. Paper [5] proposed a new framework to robustly and efficiently detect abandoned and removed objects based on background subtraction (BGS), the background is modeled by three Gaussian mixtures. In [7], an approach by incorporating background modeling and Markov model is proposed to detect abandoned objects. Paper [8] proposed a pixelwise method that employs dual foregrounds to extract temporally static image regions in the crowded scenarios. Besides, there are also some other methods [9–14]. Paper [9] proposed an approach for detecting abandoned objects and tracking people using the Condensation algorithm. Abandoned luggage detection method based on mask sampling is

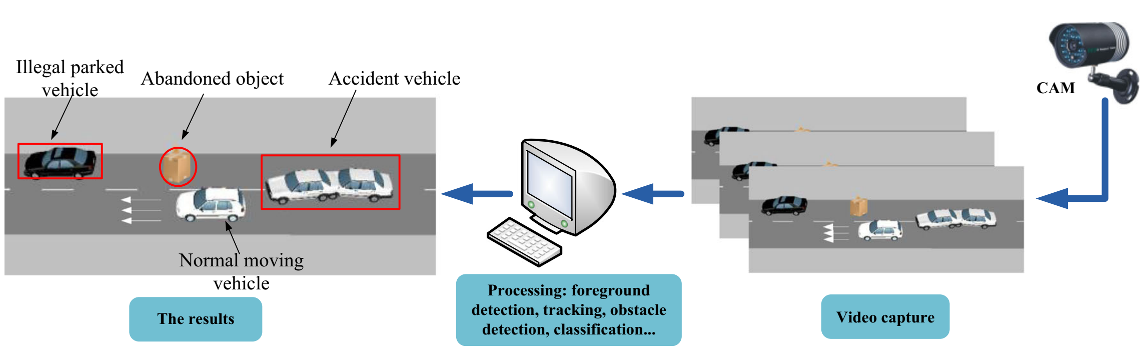


Figure 1 Outline of the developed obstacle detection method.

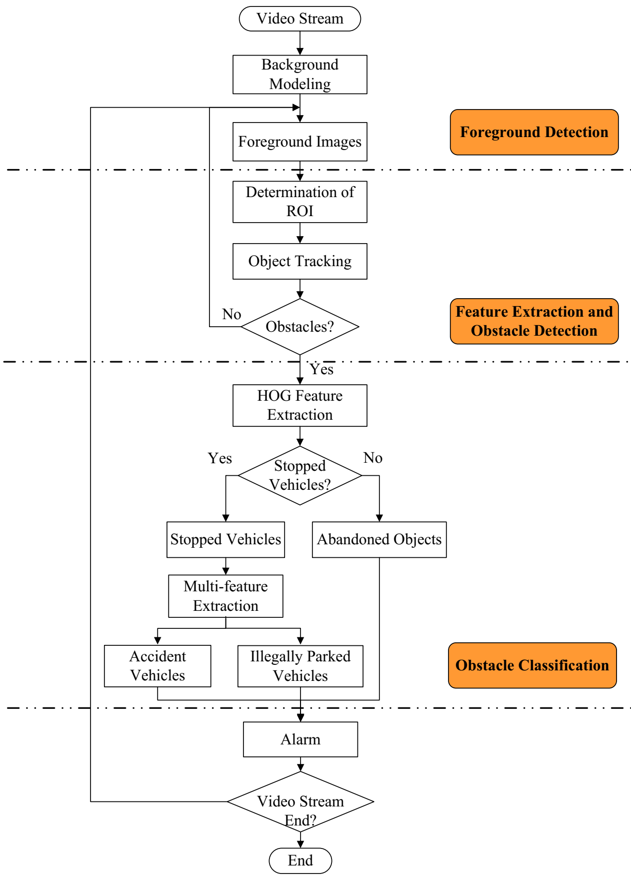


Figure 2 Flow chart of the overall system.

proposed to detect the static abandoned objects using the position information, but it is not useful to retain the static objects in the foreground for all time in [10]. A few papers proposed abandoned object detection algorithm for traffic scene. In [11], Gaussian mixture model (GMM) is used to model the background, and an edge statistics feature is brought to erase the noise to detect the abandoned objects in highway scene, but it was limited in relative simple highway scene. Papers [12, 13] proposed obstacle detection algorithm in road traffic scene, but the goal of them was detection of dynamic events. In [14], the image sequences are acquired with a monochromatic camera placed in each guarded room, and processed by a local PC-based image-processing system, devoted to detecting the presence of abandoned objects.

2.2 B Vehicle Events Detection

For specialized vehicle activities, such as detection of illegally parked vehicles and traffic accident vehicles that we are talking in this paper, have not been studied in depth with several possible exceptions of [15–22]. Paper [15, 16] present two systems that detect and warn of illegally parked vehicles. In [17], a video-camera based method is exploited to detect centers of non-motion through recognizing short stability intervals. These are further connected to build the long stability interval used to measure the overall vehicle stopping time. It can detect the stopped vehicles in real time. Paper [18] proposed a methodology for detecting this event in real-time by applying a novel image projection that reduces the dimensionality of the image data and thus reduces the computational complexity of the segmentation and tracking processes. There are several papers [19–22] related to accident vehicles detection by using machine vision techniques for surveillance. Paper [19] focus the attention on studying the abnormal behavior

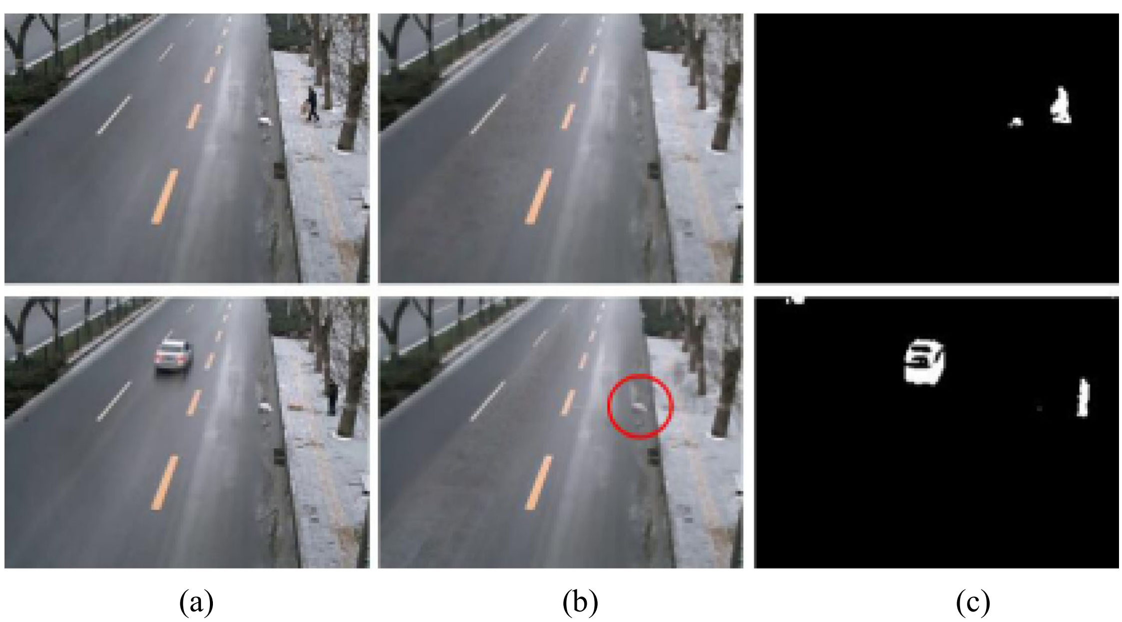


Figure 3 Results of Gaussian Mixture Models, First row: frame=490, second row: frame=550, (**a**) Current frame, (**b**) Background image, and (**c**) Foreground image.

Figure 4 Results of the proposed method, First row: frame=490, second row: frame=550, (**a**) Current frame, (**b**) Background image, (**c**) Foreground image.

of vehicle causing an incident based on the concepts of fuzzy theory. The decision whether an accident occurs or not relies on the behavioral abnormality of some continual image shots. Paper [20] develops a technique for automatic incident detection using D-S evidence theory data fusion based on the probabilistic output of multi-class SVMs. In [21], the authors propose a system for automatic incident detection. The aim of this system is to distinguish between different types of incidents. While in [22], a car detection system based on color segmentation and labeling is proposed, which performs color recognition. However, most of these methods mentioned above give unsatisfactory results. What is more, such methods often employ sophisticated algorithms, creating a barrier to the real-time performance.

2.3 C Obstacle Classification

Obstacle classification is supported in literature by a large number of algorithms and methods [23–27]. However, the issue of obtaining high accuracy obstacle classification results in complex traffic scenarios is not completely solved yet. A neural network is used in [23] in order to classify people, vehicles, and other background clutters. A classifier based on error correction output is proposed in [24] and used for distinguish between bikes, cars, trucks, persons and people groups. A pattern matching approach using 2D image intensity information is used for obstacle classification [25]. Pedestrian detection using dense 3D information as a validation method is described in [26]. In [27], robust illumination independent features are combined in a boosting technique for building a fast Adaboost classifier. Multiple obstacle features are usually extracted in order to train a classifier for obstacle classification in every frame from the video sequence. The classifier is individually applied in each frame on every detected obstacle. Paper [28] use background difference and time difference methods to extract the object, and take speed measurement, object size determination and trajectory measurement as the characteristics to judge on four types of incidents: stopped vehicle, slow vehicle, fallen object and vehicles attempted lane change.

3 Proposed Method

Our proposed method consists of four consecutive processes: foreground detection module, feature extraction and obstacle detection model, and obstacle classification model. After one process is completed, the next step is executed. Flowchart of the overall method is shown in Fig. 2.

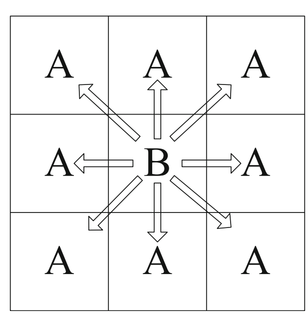


Figure 5 Basic elements of Flushed ROI method.

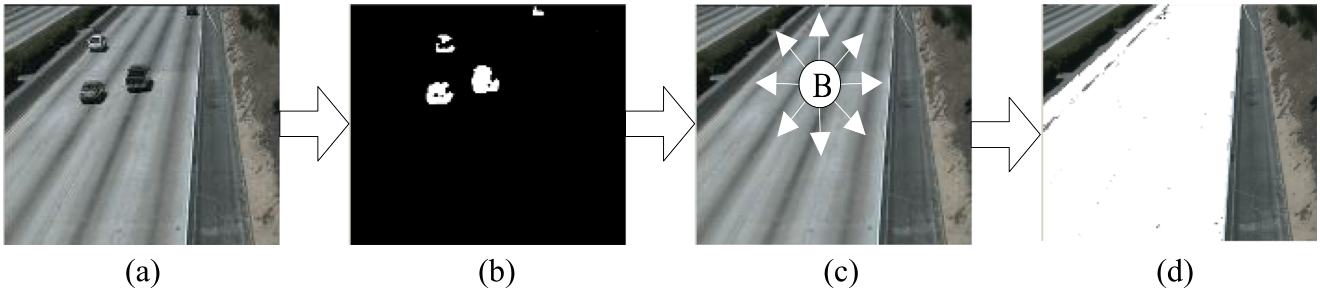


Figure 6 Process of FROI: (**a**) Current frame, (**b**) Moving objects in foreground, (**c**) Background seed points corresponding to moving objects, and (d) FROI area.

3.1 A Foreground Detection Module

The backbone of the method is foreground detection module. Quality of foreground impacts on the accuracy of obstacle detection directly. Foreground detection module based on Gaussian Mixture Model is used to build background and extract foreground.

In recent two decades, researchers have been involved in work that is related to video surveillance to develop more accurate and robust algorithms for foreground object segmentation and extraction. In this paper, GMM is used to model video background based on the papers of [29–31]. The main idea of GMM is on the basis of that recent history of every pixel's gray value can be modeled using a mixture of K Gaussian distributions, and the probability of the current pixel's gray value can be defined as Eq. (1):

$$P(X_t) = \sum_{i=1}^{k} w_{i,t} \times \zeta\left(X_t, \mu_{i,t}, \sum{}_{i,t}\right) \tag{1}$$

Where t is current time, X_t is the gray value of the pixel, K is the number of current Gaussian distribution, which is always from 3 to 5. The bigger its value is, the stronger GMM's anti-interference ability is. $w_{i,t}$ is an estimation of the weight of the i th Gaussian distributions in mixture model at time t, $\mu_{i,t}$ and $\sum_{i,t}$ are the mean value and covariance of the i th Gaussian distributions in mixture model at time t, ζ is Gaussian probability density function, which can be defined as Eq. (2):

$$\zeta(X_t, \mu, \sigma) = 1 \Big/ \left((2\pi)^{n/2}\left(\left|\Sigma_{i,t}\right|\right)^{1/2}\right) \exp\left(-\frac{1}{2}(X_t - \mu_t)^T \Sigma_{i,t}^{-1} (X_t - \mu_t)\right) \tag{2}$$

Where n is the dimension of X_t. Assume that RGB channels are independent and with the same variance, so that one dimensional gaussian mixture model of each color channel is established as Eq. (3) shown.

$$\Sigma_{i,t} = \sigma_{i,t}^2 I \tag{3}$$

Traditional Gaussian Mixture Model need update background to adapt to dynamic environment changes. The weight of K Gaussian distributions is updated when the gray pixels of X_t matches one of K current Gaussian distributions at this pixel as $|X_t - \mu_{t-1}| \le c \times \sigma_{t-1}$. c is a constant in this formula and generally assigned to2.5. The weight of K Gaussian distributions updating are as Esq. (4-7):

$$w_{i,t} = (1-\alpha) w_{i,t-1} + \alpha M_{i,t} \tag{4}$$

$$\mu_{i,t} = (1-\rho)\mu_{i,t-1} + \rho X_t \tag{5}$$

$$\sigma_{i,t}^2 = (1-\rho)\sigma_{i,t-1}^2 + \rho\left(X_t - \mu_{i,t}\right)^T \left(X_t - \mu_{i,t}\right) \tag{6}$$

$$\rho = \alpha / \omega_{i,t} \tag{7}$$

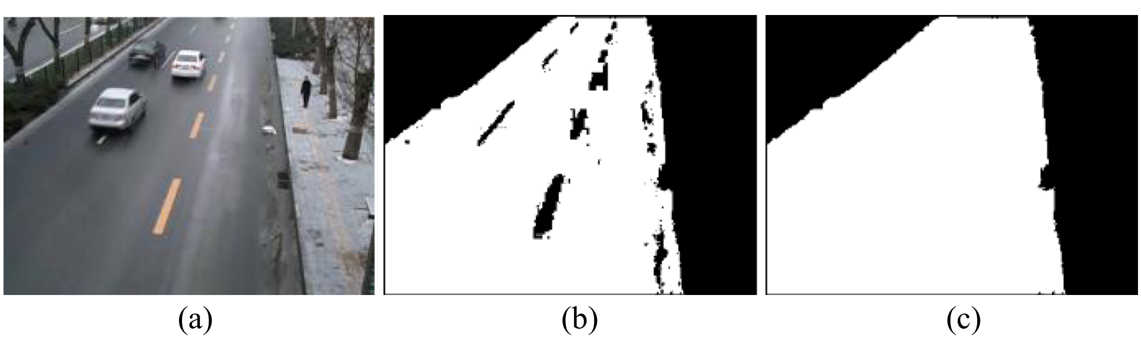
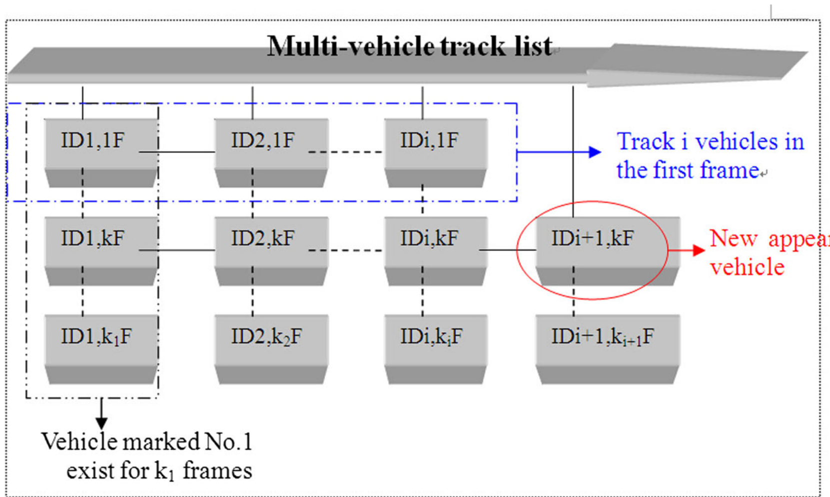


Figure 7 Effects of road marking to road ROI area: (**a**) Current frame, (**b**) The original road ROI area, and (**c**) Final filling result of road ROI area.

Figure 8 Multi-vehicle track list.



Where α is the user defined learning rate, whose value is between 0 and 1. ρ is the learning rate of parameters. The value of $M_{i,t}$ depends on exactly matching process [32]. The value of $M_{i,t}$ is 1 when the pixel matches current distribution, otherwise, it is 0.

The drawback of traditional Gaussian Mixture Model for road obstacle detection is that the pixels of static objects are updated as parts of background. Hence, static objects disappear from foreground quickly. In order to retain the static obstacle objects in foreground for a long time, traditional Gaussian Mixture Model is improved from the aspect of the background updating in this paper.

To solve the problem of background updating, an algorithm named SUOG (Selective Updating of GMM) is presented. In SUOG, background is completely built by traditional GMM through training frames, and background updating depends on whether there are any static obstacle objects in ROI of foreground. If there are any static obstacle objects in foreground ROI, background will not be updated, otherwise, background will be updated with current video frame. The SUOG can be described as Eq. (8):

$$BG_n = \begin{cases} update_{GMM} & obstacleobject = 0 \\ B_{n-1} & obstacleobject = 1 \end{cases} \tag{8}$$

Where BG_n is background for current time, $update_{GMM}$ represents background updating with GMM, B_{n-1} is the background for previous time, $obstacleobject$=1 represents that there are some static obstacle objects in foreground. Results of Gaussian Mixture Model are shown in Figs. 3 and 4 shows

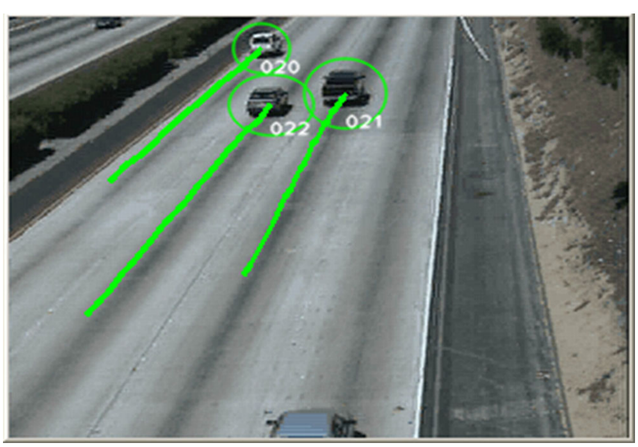


Figure 9 Process of FROI Result of object tracking.

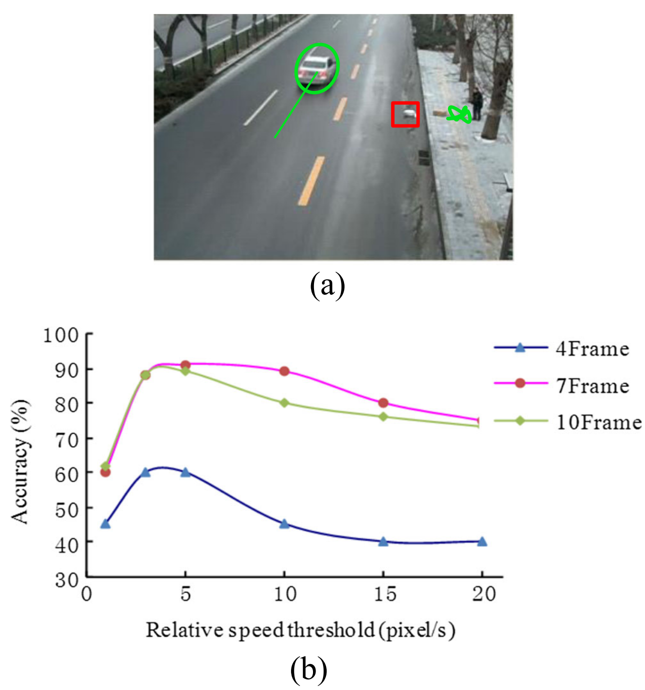


Figure 10 Result of this model: (**a**) Result of obstacle detection, and (**b**) Influence of different relative speed thresholds, frame intervals to detection accuracy.

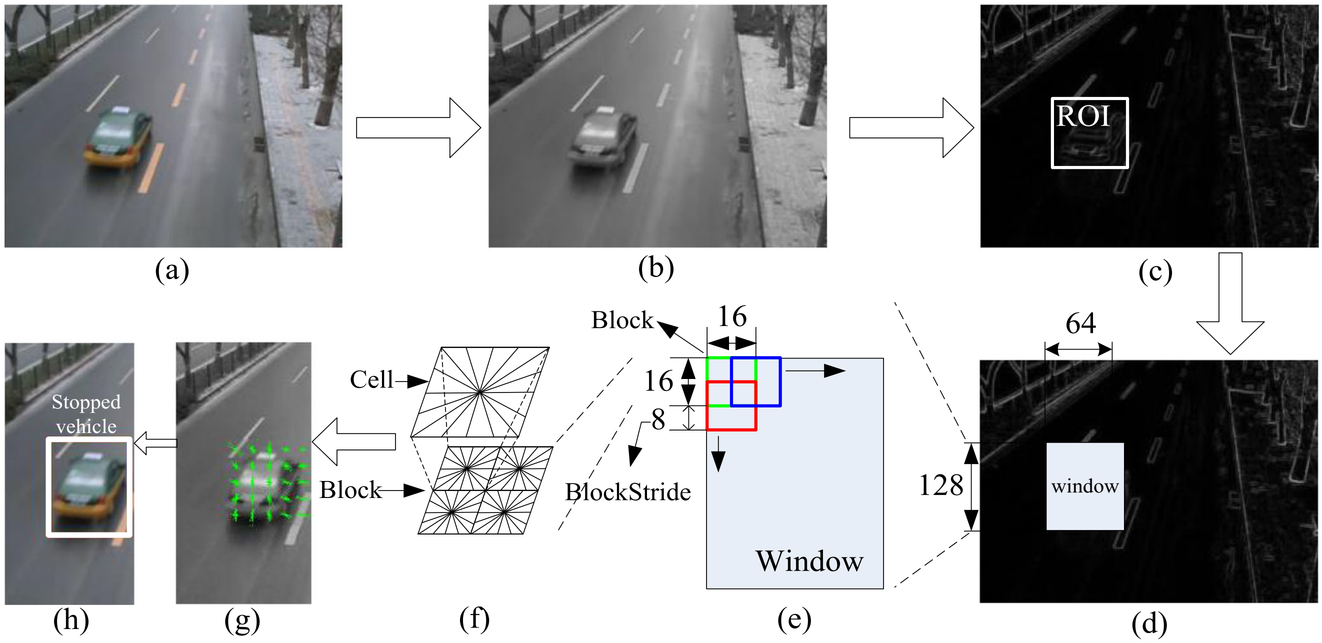


Figure 11 Process of the classification method: (**a**) Current image, (**b**) Gray image, (**c**) gradient image, (**d**) Image and HOG feature window, (**e**) HOG feature window and HOG blocks (relationship), (**f**) HOG blocks and cells, (**g**) HOG feature, and (**h**) Detection and classification.

the results of the proposed method. In the first row of Fig. 3, we can see that the abandoned object appears in the foreground image at 490th frame. But the static object disappears from foreground quickly. And at about 550th frame, the foreground object completely updates to the background which is in red circle as shown in the second row. In comparison, the method proposed in this paper shows a batter result. As shown in Fig. 4, the abandoned object doesn't update to

Figure 12 Sample images: (**a**) Positive samples, and (**b**) Negative samples.

Table 1 Support vector structure of obstacles classifier.

Element Vector	1	2	3	⋯	3779	3780
1	0.003002	0.002066	0.002066	⋯	0.001669	0.000322
2	0.006639	0.002425	0.002066	⋯	0.00447	0.006549
3	0.010137	0.002453	0.002068	⋯	0.004730	0.010052
4	0.010147	0.002531	0.002418	⋯	0.005007	0.010329
5	0.011448	0.003267	0.003672	⋯	0.007064	0.012683
6	0.011726	0.003403	0.003999	⋯	0.008183	0.013255
⋮	⋮	⋮	⋮	⋱	⋮	⋮
69	−0.012688	−0.020697	0.001149	⋯	0.019590	0.016572
70	−0.014112	−0.023566	−0.001149	⋯	0.018725	0.015062
71	−0.014768	−0.024221	−0.001525	⋯	0.018692	0.015018
72	−0.014888	−0.024324	−0.001577	⋯	0.018581	0.014813

the background even at 550th frame, and we can detect foreground object accurately.

3.2 B Feature Extraction and Obstacle Detection Model

In feature extraction and obstacle detection model, FROI algorithm is proposed to improve detection accuracy. After tracking foreground objects by Mean Shift tracking algorithm, objects' relative speed is measured as the feature to recognize the moving objects and obstacle in road.

Due to static objects outside roads having same feature with road obstacles from aspect of speed, road area in frames should be defined as ROI. The definition of ROI also benefits to reduce noise and interference. In this paper, a new ROI definition method is proposed based on connect domain of background color [33] named as FROI (Flushed Region of Interest) algorithm. The two basic elements of FROI are shown in Fig. 5.

In FROI algorithm, foreground moving objects is detected at first. Then, pixels which are corresponding to pixels of foreground moving objects are found in background by coordinate and defined them as seed point B. Absolute difference between gray value of seed point B and gray value of A which is neighbors of seed point B in background is calculated. If the absolute difference less than threshold T, acquired with adaptive threshold algorithm, we flush both of A and B with (a new mark—white color) new color in the copy of background. Otherwise, we just flush B with new (mark) color. If point A is flushed, it is defined as new seed point B until there is no point A flushed. The final new colored flushed areas are considered as ROI.

The FROI method can be described as Eqs. (9-10):

$$dif = |A(x,y) - B(x,y)| \tag{9}$$

$$A = \begin{cases} I & dif < T \\ A & dif > T \end{cases} \tag{10}$$

Where *dif* is the absolute difference between gray value of seed point and gray value of its neighbors, $A(x,y)$ and $B(x,y)$ are neighbors of seed points and seed point in background image. I is new color value and T is the threshold. The threshold can be acquired by previous experiments. The simplified process of FROI is shown in Fig. 6.

The experiment results show that the proposed method can detect road ROI automatically, but cannot eliminate the influence of road marking. In this paper, in order to improve the integrity of the road ROI, further filling of the detected road ROI is proceed. In this step, detect the road contour of the whole road ROI image at first. Then, fill the closed contour. And finally, morphology processing is used to improve the integrity of the road ROI. As shown in Fig. 7, the detection of road ROI area is integrated and accurate.

In order to acquire the relative speed, multi-vehicle tracking algorithm based on CamShift [34, 35] and identity data correlation is proposed to track road objects in real time. As CamShift is single object tracking algorithm, we build a track list and give each moving vehicle a label as the identity data to track multiple vehicles in this paper. When tracked vehicles run out of the search window, we delete the corresponding labeling from track list. For the new entry vehicle, we build

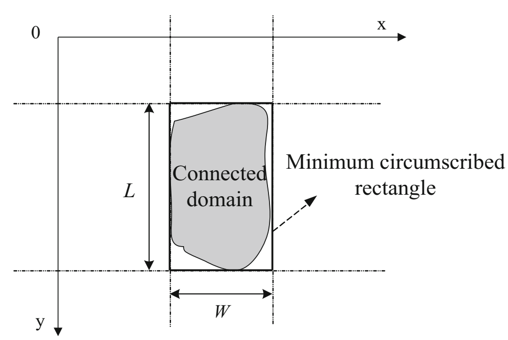
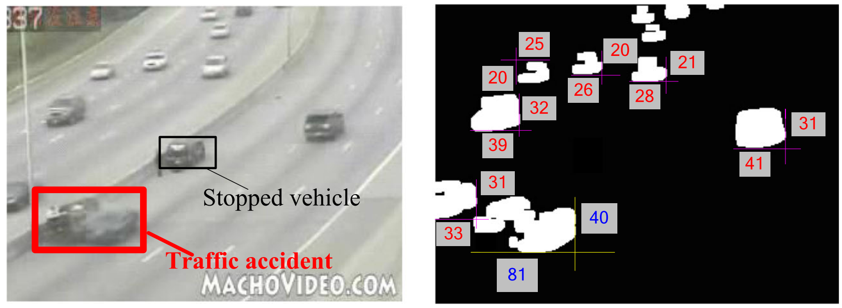


Figure 13 Minimum circumscribed rectangle of vehicle.

Figure 14 Features of each connected domain when vehicle collisions happens: (**a**) Current frame, and (**b**) Binary image.



(a) (b)

label by adding tracker. This method can realize multi-vehicle tracking effectively, and the Multi-vehicle track list is shown in Fig. 8.

Multi-vehicle track list consist of several vehicle tracking sub list, each vehicle is given an ID, F represents the video image frame, the blue rectangle indicates that there are i vehicles tracked in first frame, black rectangle means that the vehicle with ID 1 exists in image sequence for k_1 frames, and red ellipse indicates that the new target appears in the k th frame, which is marked with ID $i+1$. Then, the multi-vehicle tracking algorithm is described as follows.

Step 1 Suppose that there are i vehicles appear in the k th frame. Mark the vehicles with ID $1,2,\ldots,k-1,k$ firstly.
Step 2 Use CamShift to track each of the marked vehicles, respectively.
Step 3 In the next frame, search the same target vehicle with nearest neighbor threshold method, and transfer the target vehicle's ID from k th frame to $k+1$ th frame.
Step 4 If a new vehicle with ID $i+1$ appears, establish a new vehicle tracking sub list in the current frame.
Step 5 If there is no matching label vehicle for T frames, the vehicle can be considered to have left the track area. Then delete the vehicle tracking sub list.

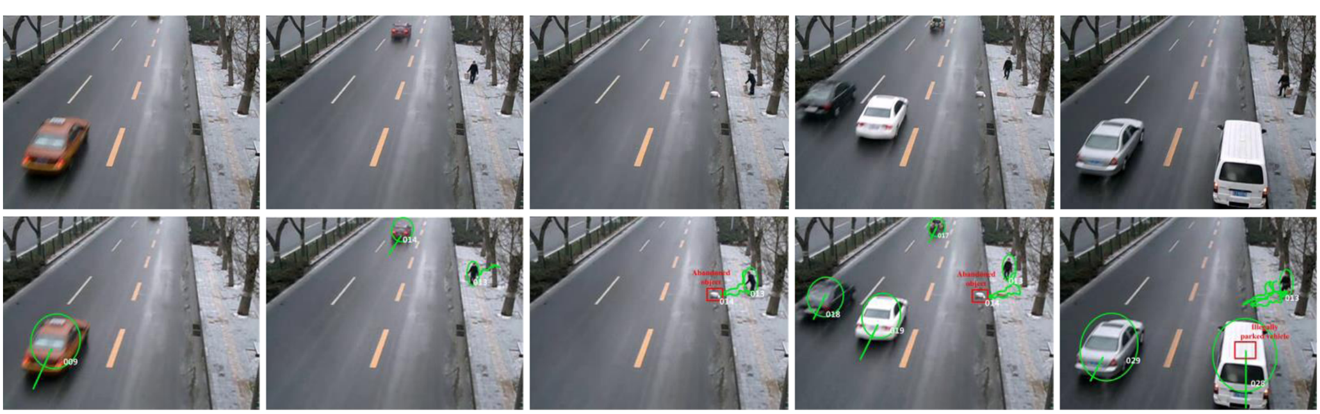
The result of vehicle tracking is shown in Fig. 9.

Final goal of this model is to detect road obstacles quickly and accurately. So it doesn't need to measure real speed of objects. In order to simplify overall algorithm, it is measured relative object speed. Coordinate of object center is acquired by frame interval, and then moving distance of corresponding object is computed in frame intervals. The unit of the distance is pixel. Relative speed of road objects can be acquired through dividing distance by time. Relative speed of objects is described as follows.

$$Rs_i = \sqrt{\|x_i - x_{i+n}\|^2 + \|y_i - y_{i+n}\|^2}\Big/t \tag{11}$$

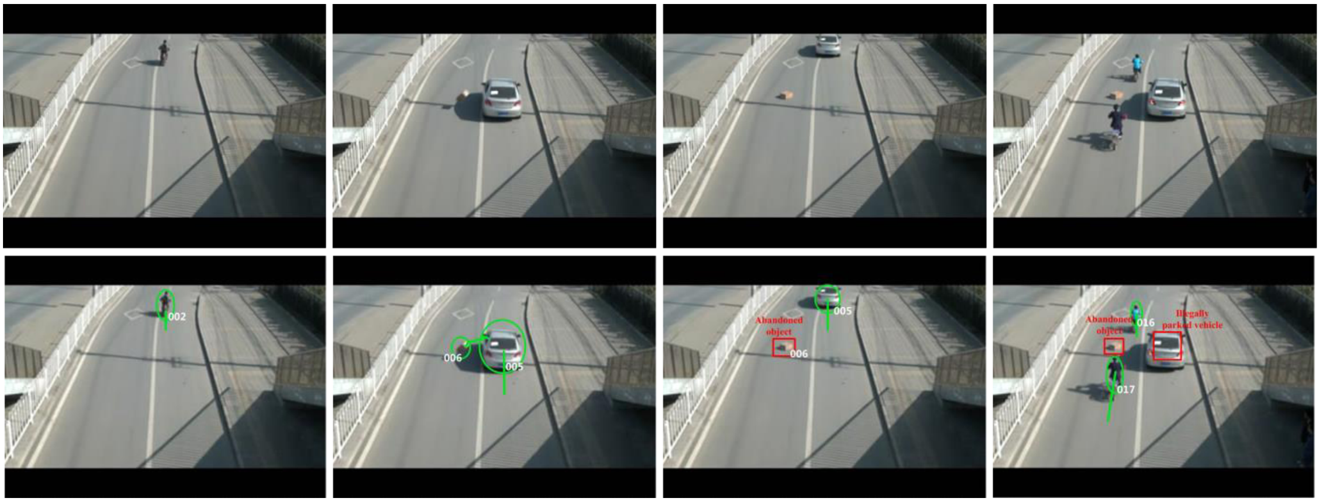
Where Rs_i is relative speed of objects, t is the time which is spend during frame interval, $p_i(x_i,y_i)$ is coordinate of object center in i th frame, $p_{i+n}(x_{i+n},y_{i+n})$ is coordinate of corresponding object center in $i+n$ th frame, n is the frame interval, unit of relative speed is pixel/s. As known from Eq. (10), frame interval n influences relative speed of object Rs_i.

In this paper, road obstacles (abandoned object, accident vehicle and illegally parked vehicle) are mainly recognized by relative speed of objects. Because of kinds of noise such as camera shake and illumination, relative speeds of road obstacles aren't absolute zero. To recognize road obstacles by relative speed of objects,



Frame.153 Frame.379 Frame.504 Frame.720 Frame.1225

Figure 15 Detection result of 6-min-long video sequence we have taken in Beijing.



Frame.27 Frame.73 Frame.100 Frame.265

Figure 16 Detection result of 3-min-long video sequence we have taken in Beijing.

the concept of relative speed threshold T_{rst} is proposed. Obstacles are recognized by Eq. (12).

$$Obstacle = \begin{cases} 1 & Rs_i < T_{rst} \\ 0 & Rs_i > T_{rst} \end{cases} \tag{12}$$

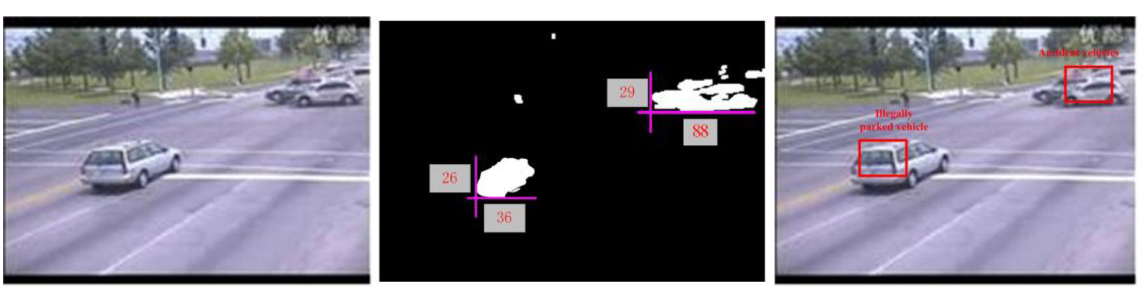
As known from Eq. (12), if relative speed of object Rs_i is smaller than relative speed threshold T_{rst}, the object is regarded as obstacle. Otherwise, the object isn't obstacle. According to contents above, frame interval n influences relative speed of object Rs_i. So the accuracy of obstacle recognition depends on frame interval n and relative speed threshold T_{rst}. According to algorithms described above, road obstacles detection demo is developed for analyzing relationships between detection accuracy and relative speed thresholds T_{rst}, frame intervals n. The result of this model is shown as Fig. 10.

From the Fig. 10 (a) we can see that the abandoned object in the road ROI area can be detected quickly and accurately, while the abandoned object outside the ROI area doesn't be detected. In (b), there shows the influence of different relative speed thresholds and frame intervals to detection accuracy. We can see that when frame interval n is 7 and relative speed threshold T_{rst} is 5, the highest obstacle detection accuracy rate up to 92 %.

3.3 C Obstacle Classification Model

Obstacle classification has important significance to traffic safety, and according to different obstacles, we can take different measures to eliminate potential safety problems. Based on part A and part B, obstacle object in the road can be detected. So in this part, we research on the obstacle classification. Due to the randomness of abandoned object, it is difficult to extract its features and classify. So there are two classification steps in this model. Firstly, separate the abandoned objects from stopped vehicles such as illegally parked vehicles and accident vehicles with the classification method of adaptive interested region based on HOG and SVM. Then, fuse the shape feature, time feature and spatial feature of stopped vehicles, to decide whether the stopped vehicles are illegally parked vehicles or accident vehicles.

In the first step, a classification method of adaptive interested region based on HOG and SVM is proposed as the



(a) (b) (c)

Figure 17 Detection result of 2-min-long video sequence from the Web: (**a**) Current frame, (**b**) Binary image, and (**c**) Detection result.

preliminary classification. In this method, the size of ROI area can be adjusted automatically based on the obstacle size. Therefore, the proposed method has small calculation and good adaptability. The specific process of this method is shown as Fig. 11.

As we can see in Fig. 10 (a)–(c) are the pre-processing of the image, determine the ROI area according to the size of obstacles after getting the edge information (image gradient information). Figure (d)–(f) show the HOG feature detection process by using 64*128 HOG description window to scan the ROI, and get the HOG feature as shown in (g). The road obstacles are finally classified by the trained SVM classifier based on the HOG feature, the final classification results are shown in (h). The training process of the SVM classifier is described in detail as follows.

In this paper, there are 1000 different types of vehicle images as positive samples and 1000 other images as negative samples as shown in Fig. 12. Besides, the HOG feature vector is detected as the sample feature to built and train the linear SVM classifier. The feature vector $f=(x_1,x_2,\cdots\cdots,x_n)$ is made up of all the HOG features detected from the sample images. The detection window's size is 64*128 pixels, the block's size is 16*16 pixels, and the cell's size is 8*8 pixels. As every 2*2 cells form a block, and each cell has 9 features, so that each block contains 4*9=36 features. Take every 8 pixels as the step length, and each detection window will be scanned 7 times in horizontal direction and 15 times in vertical direction. There are totally 36*7*15=3780 features in a sample which form the feature vector $f=(x_1,x_2,\cdots\cdots,x_n)$.

After the training, the SVM classifier is obtained which Consists of 72 support vectors, and each support vector contains 3780 elements. The value of the support vectors is shown in Table 1.

After the first step of classification, we can distinguish abandoned objects from stopped vehicles accurately. In order to classify the stopped vehicles such as illegally parked vehicles and accident vehicles, a new recognition algorithm of accident vehicles based on multi-feature fusion is presented for further classification in the second step. Accident vehicles have different features from illegally parked vehicles, such as shape feature, aspect ratio of connected domain and so on. In this paper, vehicle region area, aspect ratio, stopped vehicle numbers, and residence time are treated as the parameters of traffic accident detection.

Region area is a basic feature of the region. Small interference region can be eliminated by calculating the connected domain area. The vehicle region area A can be defined as Eq. (13).

$$A=\sum_{(x,y)\in R} 1 \tag{13}$$

Here, the area of unit pixel is 1, R is a connected domain.

Table 2 Comparison results of obstacle detection.

Method	Obstacle type	Real residence frames	Correct recognition frames	False recognition frames	Detection rate (%)
Abandoned object detection method in paper [11]	Abandoned objects	856	845	92	89.14
	Illegally parked vehicles	511	Null	Null	Null
	Accident vehicles	406	Null	Null	Null
Illegal parking detection method in paper [17]	Abandoned objects	856	Null	Null	Null
	Illegally parked vehicles	511	502	15	95.44
	Accident vehicles	406	Null	Null	Null
Abnormal incident detection system in paper [28]	Abandoned objects	856	779	17	89.23
	Illegally parked vehicles	511	472	29	87.41
	Accident vehicles	406	367	51	80.31
Proposed method	Abandoned objects	856	841	13	96.78
	Illegally parked vehicles	511	496	20	93.41
	Accident vehicles	406	381	39	85.62

The aspect ratio can be defined as Eq. (14).

$$S = L \Big/ W \tag{14}$$

Where L is the length of the minimum circumscribed rectangle of vehicle, W is the width of the minimum circumscribed rectangle of vehicle, as shown in Fig. 13.

Get the stopped vehicle numbers which is described as Eq. (15), after the segmentation of stopped vehicles.

$$C_s = \sum_i P_B \tag{15}$$

Where P_B is the detection area of stopped vehicles.

Residence time is defined as Eq. (16).

$$t_s = t_2 - t_1 \tag{16}$$

Where t_1 is the first detection time of stopped vehicles, and t_2 is the current time.

When vehicles collided, there will be a connected domain in the binary image, which consists of all the accident vehicles as shown in Fig. 14. The numbers marked in figure (b) represent the length and width of the connected domains, respectively. We can see that the vehicle region area, aspect ratio and stopped vehicle numbers of the accident connected domains are clearly different from the connected domains. Thus, we can determine the abnormal connected domain as the suspected accident vehicles by setting the thresholds of area and aspect ratio. Finally, stopped vehicle numbers and residence time are used as the futures of the accident vehicles for further judgment.

Based on the above analysis, we can distinguish the accident vehicles from illegally parked vehicles, and finally complete the classification of obstacles. The results are shown in part IV.

4 Results

We use two datasets for the experiments: a set of video sequences we have taken in Beijing, China, by traffic video surveillance system. And an accident vehicle detection set which is acquired from the Web. The captured dataset we have taken in Beijing consists of two video sequences. The time durations for two video sequences are 6 and 3 min, and each sequence consists of one illegally parked event and one abandoned object, respectively. The other video is 2 min long and consists of one illegally parking event and one accident vehicle. These datasets have been chosen for testing our system in various environments. Videos are recorded at a sampling rate of 15 fps, at the resolution of 320*240 pixels. The frame rate is high enough for tracking road obstacles because those objects have zero speed. This method is implemented on Visual Studio 2008 with OPENCV.

The detection result of the 6-min-long video sequence is shown in Fig. 15. Figure 15 shows that, between frame 153 and 379, there is no any obstacle in the road area, and moving objects including vehicles and people have been well tracked. At frame 504, an abandoned object, which is left in the road, is successfully detected with an alarm. There is another abandoned object out of the road ROI at frame 720, but the proposed method doesn't detect it as obstacle because of FROI algorithm, as shown in the figure. Illegally parked event occurs at frame 1225. One vehicle comes in a "No Parking" area and stays at a fixed location. The illegally parked vehicle is efficiently tracked, detected and marked in the red rectangle. In order to test the efficiency of our method in various environments, another video sequence is taken into the experiment. The detection result is shown in Fig. 16. The result is acceptable.

The 2-min-long video sequence has been used to verify the validity of the proposed method for accident vehicles. As seen from Fig. 17, the width of the second connected domain is 88 pixels, and the length is 29 pixels. Then the connected domain area is 1745 pixel^2, and the aspect ratio is 0.33. The connected domain in binary image also shows that there is more than one vehicle in this region. Therefore, it is observed that the connected domain is abnormal and it can be regarded as the suspected accident. The proposed method is able to detect abandoned objects, illegally parked vehicles in high accuracy, but not detect the accident vehicles as well in actual traffic scene. Because when the traffic is in congestion, this

Table 3 Time efficiency of this method.

Frames	Total time (s)	Numbers of obstacles	Traffic volume	Processing time (s)
0–100	8.49	1	5	1.82
100–200	8.36	1	4	1.69
200–300	8.70	2	10	2.03
300–400	8.30	2	7	1.63
400–500	7.85	1	3	1.18
…	…	…	…	…
2600–2700	7.42	0	2	0.75

method is not able to segment vehicles that arrive together, it may cause the error detection of accident events in heavy traffic.

To show the effectiveness of the proposed method, we compare the performances of our system with the detection methods proposed in paper [11, 17] and [28]. The comparison results of obstacle detection are shown in Table 2. The detection method proposed in paper [11] uses Gaussian mixture model and object tracking model to detect the abandoned object in highway scene, and it has a high detection rate. But in our video sequence, the existing illegally parked vehicles and accident vehicles may cause some false detection. Paper [17] presents an illegal parking detection method based on 1-D transformation, and the performance of this method is very good. But both of the above methods can only detect one kind of the obstacles which discussed in this paper, and they don't have universality. The detection method in paper [28] takes the speed measurement, object size determination and trajectory measurement as the characteristics to judge on four types of incidents: stopped vehicle, slow vehicle, fallen object and vehicles attempted lane change. As there is no road ROI area in the method, the obstacles outside the road may cause some false detection and recognition. Experimental results show that our method can recognize the obstacles effectively and achieve a higher detection rate.

At last, time efficiency of this method is analyzed with the 3-min-long video sequence, which is recorded at a sampling rate of 15 fps, and the resolution of 320*240 pixels. As shown in Table 3, the method detects road obstacles in 100 frames within 8.7 s, and actual time for record this video is 6.67 s. The processing time of each frame image is from 7.5 to 20.3 ms in this detection method. It implies that the proposed method implement real time detection for road obstacles.

5 Conclusion and Discussion

In order to detect road obstacles in time and prevent traffic accident, a real-time automatic obstacle detection method is proposed for detecting road obstacles based on traffic surveillance videos processing in this paper. SUOG algorithm is proposed to detect static objects, relative object speed is used to detect the static obstacles, and then FROI algorithm is used to define road ROI in frames. In the obstacle classification model, a classification method of adaptive interested region based on HOG and SVM, and a new recognition algorithm of accident vehicles based on multi-feature fusion are proposed to classify the road obstacles. The experiments results show that the detection method achieves a high detection rate and real time detection of road obstacles in actual traffic scene. The proposed detection method can reduce traffic accidents, maintain the traffic safety effectively.

Acknowledgments The authors would like to thank Yiliang Zeng, Jian Li, Min Liu of the School of Automation and Electrical Engineering University of Science and Technology Beijing, for their great help. This paper is supported by National Natural Science Foundation of China (Grant No. 61174181) and Research Fund (Grant No. 9140A05030214QT02070).

Conflict of interests The authors declare that there is no conflict of interests regarding the publication of this article.

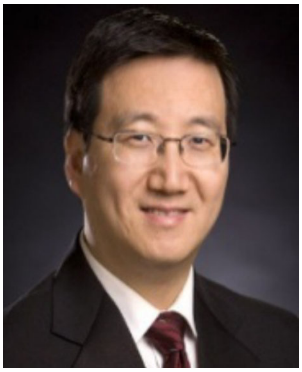
References

1. del Rincon, J.M., Herrero Jaraba, J, Gomez, J.R., et al. (2006). *Automatic left luggage detection and tracking using multi-camera*. IEEE International Workshop on Performance Evaluation in Tracking and Surveillance (pp. 59–66).
2. Krahnstoever N., Tu P., Sebastian T., et al. (2006). *Mutli-view detection and tracking of travelers and luggage in mass transit environments*. 9th PETS, CVPR (pp. 67–74).
3. Singh, A., Sawan, S., Hanmandlu, M, et al. (2009). *An abandoned object detection system based on dual background segmentation*. 6th IEEE International Conference on Advanced Video and Signal Based Surveillance (pp. 352–357).
4. Grabner, H, Roth, P., Grabner, M. (2006). *Autonomous learning of a robust background model for change detection*. IEEE International Workshop on PETS (pp. 39–54).
5. YingLi, T., Feris, R. S., Liu, H., et al. (2011). Robust detection of abandoned and removed objects in complex surveillance videos. *IEEE Transactions on Systems, Man, and Cybernetics Part C: Applications and Reviews, 41*(5), 565–576.
6. Xiya, L., Jingling, W., & Qin, Z. (2012). *An abandoned object detection system based on dual background and motion analysis*. IEEE International Conference on Computer Science & Service System (pp. 2293–2296).
7. Muchtar, K., Lin, C-Y, Kang, L-W, et al. (2013). *Abandoned object detection in complicated environments*. Signal and Information Processing Association Annual Summit and Conference. Asia-Pacific.
8. Porikli, F., Ivanov, Y. & Haga, T., (2008). Robust abandoned object detection using dual foregrounds. *Journal on Advances in Signal Processing*, *30*.
9. Spengler, M., & Schiele, B. (2003). *Automatic detection and tracking of abandoned objects*. IEEE International Workshop on Visual Surveillance and PETS.
10. Liao, H.H., Chang , J.Y. & Chen, L.G. (2008). *A localized approach to abandoned luggage detection with foreground-mask sampling*. IEEE Proceedings of Advanced Video and Signal Based Surveillance (pp. 132–139).
11. Fu, H., Xiang, M., Ma, H., et al. (2011). *Abandoned object detection in highway scene*. 6th IEEE International Conference on Pervasive Computing and Applications (pp. 117–121).
12. Franke, U., & Heinrich, S. (2002). Fast obstacle detection for urban traffic situations. *IEEE Transactions on Intelligent Transportation Systems, 3*(3), 173–181.
13. Nedevschi, S., & Danescu, R, et al. (2004). *High accuracy stereo vision system for far distance obstacle detection*. IEEE Intelligent Vehicles Symposium (pp. 292–297), Parma.
14. Sacchi, C., & Regazzoni, C. S. (2013). A distributed surveillance system for detection of abandoned objects in unmanned railway environments. *IEEE Transactions on Vehicular Technology, 49*(5), 2013–2026.
15. Morimoto, K. (1994). *System for detecting and warning an illegally parked vehicle*. U.S. Patent 5343237.

16. Boragno, S., Boghossian, B., Black, J., Makris, D., & Velastin, S. (2007). *A DSP-based system for the detection of vehicles parked in prohibited areas*. In Proc. IEEE Int. Conf. Advanced Video Signal Based Surveillance (pp. 260–265).
17. Lee, J.T., Ryoo, M.S., Riley, M. & Aggarwal, J.K. (2007). *Real-time detection of illegally parked vehicles using 1-D transformation*. In Proc. IEEE Int. Conf. Advanced Video Signal Based Surveillance (pp. 254–259).
18. Bevilacqua, A., & Vaccari, S. (2007). *Real time detection of stopped vehicles in traffic scenes*. In Proc. IEEE Int. Conf. Advanced Video Signal Based Surveillance (pp. 266–270), London.
19. Kimachi, M., Kanayama, K., & Teramoto, K. (1994). *Incident prediction by fuzzy image sequence analysis*. In Proc. IEEE int. Conference Vehicle Navigation and Information Systems (pp. 51–57).
20. Zeng, D., Xu, J., & Xu, G. (2008). Data fusion for traffic incident detection using D-S evidence theory with probabilistic SVMs. *Journal of Computers, 3*(10), 36–43.
21. Ikeda, H., Matsuo, T., Kaneko, Y., & Tsuji, K. (1999). *Abnormal incident detection system employing image processing technology*. Proc. of the IEEE Conference Vehicle Navigation and Information, Systems (pp. 748–752), Tokyo.
22. Meler, M. (2006). *Car color and logo recognition*. CSE 190A Projects in Vision and Learning. University of California.
23. Toth, D., & Aach, T. (2003). *Detection and recognition of moving objects using statistical motion detection and Fourier descriptors*. 12th International Conference on Image Analysis and Processing (pp. 430–435).
24. Zhang, L., Li, S.Z., Yuan, X., & Xiang, S. (2007). *Real-time object classification in video surveillance based on appearance learning*. IEEE Conference on Computer Vision and Pattern Recognition (pp. 1–8).
25. Gavrila, D. (2000). *Pedestrian detection from a moving vehicle*. Proceedings of the 6th European Conference on Computer Vision-Part II (pp. 37–49).
26. Gavrila, D.M., Giebel, J., & Munder, S. (2004). *Vision-based pedestrian detection: the PROTECTOR system*. IEEE in Intelligent Vehicles Symposium (pp. 13–18).
27. Khammari, A., Nashashibi, F., Abramson, Y., & Laurgeau¸ C. (2005). *Vehicle detection combining gradient analysis and AdaBoost classification*. IEEE Proceedings in Intelligent Transportation Systems (pp. 66–71).
28. Ikeda H., Kaneko, Y., Matsuo, T., et al. (1999). *Abnormal incident detection system employing image processing technology*. Towards the New Horizon Together. Proceedings of the 5th World Congress on Intelligent Transport Systems (pp. 748–752), Seoul.
29. Bhargava, M., Chia-Chih, Chen., Ryoo, M.S., & Aggarwal, J.K. (2007). *Detection of abandoned objects in crowded environments*. IEEE Conference on Advanced Video and Signal Based Surveillance (pp. 271–276), London.
30. Stauffer, C., & Grimson, W.E.L. (1999). *Adaptive background mixture models for real-time tracking*. IEEE Conference on Computer Vision and Pattern Recognition (pp. 246–252).
31. Xuehua, S., Jingzhu, C., Chong, H., & Xiang, Z. (2010). *A robust moving objects detection based on improved gaussian mixture model*. International Conference on Artificial Intelligence and Computational Intelligence (pp. 54–58), Sanya.
32. Zivkovic, Z., & van der Heijden, F. (2004). Recursive unsupervised learning of finite mixture models. *IEEE Transaction on Pattern Analysis and Machine Intelligence, 26*(5), 651–656.
33. Khudeev, R. (2005). *A New flood-fill algorithm for closed contour*. IEEE International Siberian Conference on Control and Communications (pp. 172–176), Tomsk.
34. Bradski, G.R., Clara, S. (1998). Computer vision face tracking for use in a perceptual user interface. *Intel Technology Journal,* 1–15.
35. Comaniciu, D., Ramesh, V.,& Meer, P. (2000). *Real-time tracking of non-rigid objects using mean shift*. IEEE Conference on Computer Vision and Pattern Recognition (pp. 142–149), Hilton Head Island.

Jinhui Lan received the PhD degree from Beijing Institute of Technology, China in 1998. She joined Tsinghua University, China, as a lecturer in the same year. From August 2002 to February 2004, she was a Visiting Academic at Deakin University, Australia, working on multi-sensor systems. Since July 2008, she has been a Professor at the University of Science and Technology Beijing, China. In 2013, she was a visiting scholar at University of Wisconsin-Madison, USA. In cooperation with other researchers, she has successfully completed more than 30 projects and solved some key technical problems. So far, she has published over 80 refereed papers in the areas of image processing, remote sensing, ITS, measurement and instrument, and multi-sensor data fusion.

Yaoliang Jiang received B.S. degree in automation from University of Science and Technology Beijing (USTB), China, in 2012. Currently, he is pursuing a Master's degree in Department of Instrument Science and Technology at the University of Science and Technology Beijing, Beijing, China. His research interests focused on machine learning, image and video signal processing, object detection and tracking in ITS.



Guoliang Fan received the B.S. degree in Automation Engineering from Xi'an University of Technology, Xi'an, China, M.S. degree (with honor) in Computer Engineering from Xidian University, Xi'an, China, and Ph.D. degree in Electrical Engineering from University of Delaware, Newark, DE, USA, in 1993, 1996, and 2001, respectively. Since 2001, he has been with the School of Electrical and Computer Engineering at Oklahoma State University (OSU), Stillwater, OK, where currently he is a Professor and also holds the endowed Cal and Marilyn Vogt Professorship of Engineering. His research interests include image processing, pattern recognition and computer vision.He is an associate editor of IEEE Transactions on Image Processing,IEEE Journal of Biomedical and Health Informatics, and EURASIP Journal on Image and Video Processing.Dr. Fan is a recipient of the 2004 National Science Foundation (NSF) CAREER award, the Halliburton Excellent Young Teacher Award in 2004, the Halliburton Outstanding Young Faculty Award in 2006 from the College of Engineering, Architecture and Technology (CEAT) at OSU, the Outstanding Professor Award from IEEE-OSU in 2008 and 2011, and the Distinguished Young Alumni Award from the ECE department of University of Delaware in 2015.

Dongyang Yu received B.S. degree, University of Science and Technology Beijing (USTB), Beijing, China in 2012. Now, he is pursuing a Master's degree in Department of Instrument Science and Technology at the University of Science and Technology Beijing, Beijing, China. His research interests focused on pattern recognition, machine learning and target tracking.

Qi Zhang received the M.S. degree in Institute of Systems Engineering from Tianjin University, Tianjin, China, in 1985, and the Ph.D. degree from Osaka city university, Japan, in 1998. From April 1998 to March 2007, he worked in Japan Pacific International Consulting Group and any other companies related to ITS. And since 2007, he has been an Associate Professor in the Department of Intelligent Science and Technology, University of Science and Technology Beijing, China. He focus his research on ITS, electronic information and systems engineering.