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MOVING VEHICLES EXTRACTION IN TRAFFIC VIDEOS

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Abstract- In this paper we propose two different approaches to segment and extract moving vehicles in traffic videos. Background subtraction is used to extract foreground frames. Different types of moving vehicles are then segmented by first proposed hybrid approach which combines a connected component analysis and a semi-supervised thresholding. In the second proposed approach, Gabor filtering method is used for segmentation of moving vehicles. The robustness and efficacy of our proposed approaches are elaborated by experiments conducted on real traffic videos captured under complex background, variations in illumination, motion, position of a camera and different moving directions during day time. The presented results are as well compared with 2 well-known methods of GMM and W^4 used in extraction of moving vehicles.
Key words - Moving vehicles extraction, Background modeling, Background subtraction, Connected component analysis, Semi-supervised thresholding, Gabor filtering, GMM, W^4.

INTRODUCTION

In this era, employing video surveillance systems for traffic monitoring has demonstrated assure over the conventional loop detectors. Video systems are less disturbing and less costly to install than loop detectors. Consequently, building and using large on-line camera networks enables us to screen various aspects of traffic such as traffic congestion, traffic jam, traffic speed, road accidents, lane occupancy, individual lane speed along with the ability to detect and track individual cars, recognizing suspicious vehicles, and other anomalous situations in real time. However, conventional traffic monitoring involves watching traffic situation across a range of times on different screens concurrently. Gazing at 5-10 screens at the same time would make an operator to lose his attention, get bored or simply look at the "wrong screen" when something happens. Consequently, reliable traffic monitoring system is required. The reliable traffic monitoring should be adaptive to changes in the real world environments, easy to set up, capable of operating independently of human operators and making intelligent decision. It should facilitate in automatically identifying the events of our interest and sending a warning to the operator in real time.

As a remedy, vision-based traffic video monitoring systems are broadly brought into usage in intelligent transportation systems. Vision-based traffic video monitoring systems reduce the cost of traffic monitoring with increase in quality. Moreover, confidence and precise automated traffic analysis and control techniques are obtained. In addition to vehicle counts, a set of traffic parameters such as vehicle labels, lane changes, illegal U-turns, posture, speed and moving direction can be measured. Vision-based traffic video monitoring systems help us in gathering statistical data on traffic activity through monitoring the density of vehicles and also assist us in taking intelligent decisions in any abnormal conditions by analyzing the traffic information.

In this direction, to have an effective vision-based traffic surveillance tool in real time, a video image processing system (VIPS) should automatically segment and extract correctly all different types of road vehicles from the background under low, moderate and heavy traffic conditions with a wide range of traffic video parameters such as complex background, motion, illumination changes in a scene, position of the camera and vehicles direction. Indeed, precise detection of moving vehicles in VIPS makes vehicle tracking more reliable and faster which substantially supports correct classification of vehicles too. Further a set of traffic parameters like traffic status and vehicles trajectory such as lane changes, illegal U-turns and vehicles speed can also be measured accurately. However, current VIP systems suffer from the existence of shadows and ghosts in a scene where the detected ghosts are considered as moving vehicles and segmentation of vehicles with cast shadows created occlusions among vehicles as well as destroy the shape of vehicles. Moreover, existing well-known algorithms are not able to segment and extract moving vehicles from the background under different real traffic videos captured in an uncontrolled environment. In addition the traffic congestion also creates the problem of occlusion which makes the VIPS not to detect and track moving vehicles individually.

In this paper, we propose the approaches that are able to segment and extract moving vehicles under different traffic videos captured under uncontrolled environment. We utilize the segmentation methods which are more applicable in extraction of moving vehicles and removal of ghosts or cast shadows detected along with traffic vehicles. The proposed segmentation algorithms also preserve the shape of the segmented vehicles.

The rest of the paper is organized as follows. In the related work section, we present different approaches proposed in literature to extract and detect moving vehicles in traffic videos. Our proposed hybrid and Gabor filtering approaches are introduced in the proposed approach section. Experimental results detail the experimentation carried out on different types of traffic videos along with the illustrated results conducted on our proposed approaches as well the well-known algorithms GMM and W^4. Conclusions drawn from this study are summarized in the conclusion section.

RELATED WORK

Detection of moving vehicles is the first step in information extraction from traffic videos. The most widely adopted approach is based on background subtraction. In literature, a median filter method for background modeling can be found in [1, 2]. Toyama et al. [3] developed a three-component system that was the combination of the pixel, region and frame level algorithms to model a background of a video. Wren et al. [4] applied a single Gaussian model to each pixel over a sequence of frames to extract a background image. Typically, each pixel was modeled using a Gaussian distribution built up over a sequence of individual frames and segmentation was then performed using an image differencing strategy. A single Gaussian model is appropriate for scenes with almost static background. An adaptive background modeling for real time tracking based on Gaussian mixture model was used in [5-9]. In their work, they represented each pixel in a sequence of frames with a mixture of Gaussians. Stauffer and Grimson (2000) also used motion information along with the color information to model dynamics of background. Elgammal et al. [10] used non-parametric prediction algorithm instead of Gaussian mixture model to estimate probability density function of each pixel. Even though this technique is better in modeling the behavior of each pixel, several thresholds are needed which make it impractical. Haritaoglu et al. [11] employed a kernel density estimation method to cope with varying background such as waving trees. They used three values for each pixel: minimum intensity, maximum intensity and maximum intensity difference between consecutive frames observed during training period. A pixel wise median filter over time was then applied to each pixel to distinguish between stationary and moving pixels.

It is well-known that background modeling should reflect the real background as accurately as possible, allowing the system to detect the accurate shape of moving vehicles. The detection accuracy can be measured in terms of correctly and incorrectly classified pixels during normal conditions of the vehicle's motion, i.e., the "stationary background" case. Besides, the background modeling should immediately reflect sudden scene changes such as the start or stop of vehicles, so as to allow detection of only the actual moving vehicles with high reactivity, i.e., the "transient background" case. If the background model is neither accurate nor reactive, then the background subtraction causes the detection of false vehicles, often referred to as "ghosts" [7, 11]. In addition, moving vehicle segmentation with background suppression is affected by the problem of shadows [10, 12] which on the other hand makes the appearance and geometrical properties of vehicles getting distorted. Besides, the existence of shadows may cause the close moving vehicles to be segmented as one.

In this paper, we propose two simple methods that efficiently provide segmentation and extraction of moving vehicles as well removal of ghosts and shadows detected along with moving vehicles. We propose hybrid approach that combines foreground frame extraction, connected component analysis and a semi-supervised thresholding for segmentation of different types of moving vehicles and ghosts or shadows elimination, named as false vehicles in this paper, as the first method. In the second proposed method, a Gabor filtering method is exploited on an enhanced extracted foreground frame to segment moving vehicles and removal of ghosts or cast shadows detected along with moving vehicles after background subtraction.

PROPOSED APPROACH

In this paper, background subtraction is used to extract moving vehicles in traffic videos. Some fragments of the background (often referred as "ghosts") are detected and vehicles are also extracted along with cast shadows. Segmentation of vehicles with cast shadows could create occlusions among the vehicles as well as destroy the shape of the vehicles. In this direction, to segment moving vehicles and to remove the detected ghosts and shadows, false vehicles, in various traffic videos captured by stationary cameras under uncontrolled environment, hybrid approach is applied that is the integration of knowledge of detected vehicles, extraction of connected component and a semi-supervised thresholding. Gabor filtering method is used as another technique to segment vehicles and to remove ghosts or cast shadows detected along with moving vehicles. Fig. 1 shows the stages of the proposed approach.

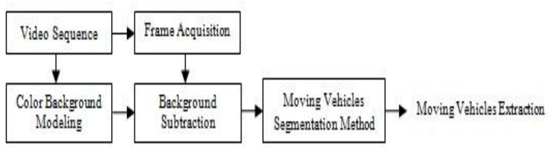

Fig. 1- Stages in the Proposed Model.

Color Background Modeling

In a traffic video, the intensity of the pixels of a moving vehicle will sharply vary. Thus, by applying a pixel wise median filter on each pixel of a sequence of frames, it could be possible to model a background image without any moving object. This procedure is applied on every channel of RGB color space of the frames to generate a background image in respective channels. For a frame, a background subtraction is applied to extract moving vehicles. However, moving vehicles are detected along with false vehicles.

Fig. 2- (a) Generated Background image. (b) A sample frame of a video sequence. (c) Extracted foreground frame

Fig. 2 illustrates an example of background modeling and subtraction approach. After background subtraction, vehicles are segmented. Hybrid approach utilized for segmentation of traffic vehicles is explained in hybrid approach section. Moreover, details on a Gabor filtering method employed to segment moving vehicles as the second approach are given in a Gabor filtering approach section.

Hybrid Approach

After background subtraction and extracting the foreground frame, Canny edge detector is applied on the extracted foreground frame to segment moving vehicles in a frame. A dilation operator is then used to create a single component for each vehicle. Next, every vehicle is thresholded locally to remove the cast shadow of a vehicle. To eliminate the cast shadow of a vehicle, mean 'm' and standard deviation 's' of a vehicle's region located in its corresponding main frame is computed and then the region of the vehicle is thresholded locally by 'm-k×s' [13]; where the value of 'k' is constant and it is fixed empirically. Fig. 3 illustrates examples of moving vehicles segmentation with cast shadow removal.

Gabor Filtering Approach

This approach is done through enhancing the intensity values of the foreground frame followed by Gabor filtering method. After background subtraction, variations in lighting may cause low resolution for a number of the pixels in the extracted foreground frame.

On the other hand, segmentation of vehicles can be significantly improved by means of an intensity-adjusted technique where the intensity values of the pixels of the foreground frame are enhanced by contrast stretching method as shown in Fig. 4(c).

To segment the detected vehicles as well as removal of false detected vehicles, we apply Gabor filtering function proposed by Bovik et al. [14]. Gabor filtering function is a complex sinusoid modulated by a rotated Gaussian. An input image is filtered with the 2D Gabor filter described in G by the parameters S, F, W and P to create the output filtered image. This version of the 2D Gabor filter is basically a bi-dimensional Gaussian function centered at origin (0,0) with variance S modulated by a complex sinusoid with polar frequency (F,W) and phase P. Fig. 5 demonstrates the segmentation of the vehicles of a foreground frame shown in Fig. 4(c).

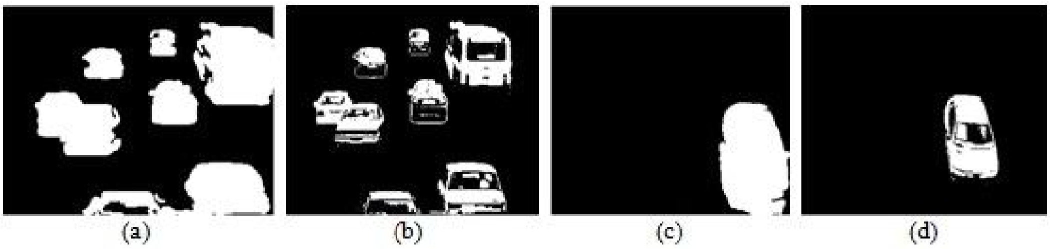

Fig. 3- (a)(c) Vehicle Extraction in a frame. (b)(d) Vehicle cast shadow removal.

Fig. 4- (a) Main Frame. (b) Foreground frame. (c) Enhanced frame.

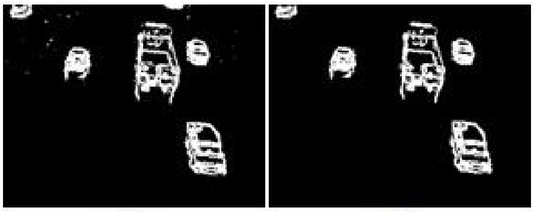

Fig. 5- (a) Vehicle extraction in a frame. (b) Small specks and detected false vehicles are eliminated in the extracted frame.

EXPERIMENTAL RESULTS

Experiments are conducted on real traffic videos captured under different complex background, illumination, motion, position of a camera and moving directions. The route motion of vehicles is either towards or away from the camera. In the experiment, 200 frames (about 8 seconds of a video) are taken to model the background image. In the hybrid segmentation approach, the value of 'k' used for thresholding the region of a vehicle so as to remove the cast shadow is set to 0.2. Gabor filtering applied in this experimentation is the summation of filtering through different directions W= 0°, 45°, 90° and 135°. It is applied with the variance S=0.7, modulated by a complex sinusoid F= 0.2 and phase P= 0. This technique is implemented in Matlab 10 on Intel® Core™ 2 Duo CPU 2.20 GHz with 1 GB RAM and 32-bit operating system. We compare our simple proposed approaches with 2 well-known methods of GMM and W^4. Table 1 displays the segmentation results on a frame of few traffic videos using hybrid approach, Gabor filtering method, GMM and W^4.

Conclusion

In this paper, vehicles are detected by background subtraction and segmented using hybrid approach which combines foreground extraction, connected components analysis and a semi-supervised thresholding. Gabor filtering method is as well utilized as another approach to segment moving vehicles and to eliminate ghosts and cast shadows detected along with moving vehicles. Our proposed approaches can be run under varied complex background, illumination, motion, position of a camera and clutter. Results show robustness, simplicity and efficiency of our segmentation approaches and it can be well adapted for real time implementation of a prototype system. However, the background modeling fails to model a background image for heavy traffic videos. From the experimental results, it is observed that a single vehicle might be segmented into more than one part and conversely a number of vehicles may be segmented as a single vehicle. In our future work, we focus on blending the segmentation methods to overcome the above mentioned limitations as well as capability to segment and extract traffic vehicles in congested traffic videos.

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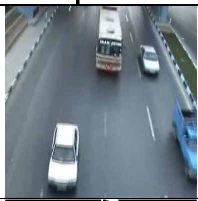
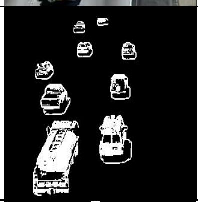
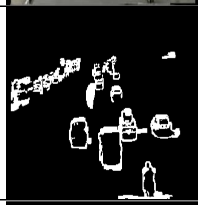
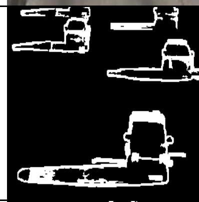
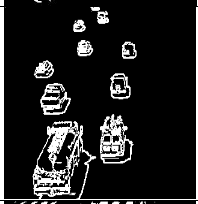
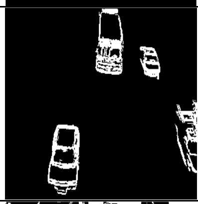
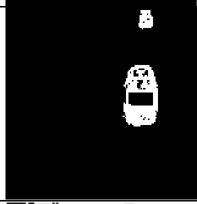
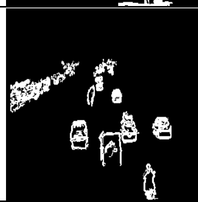
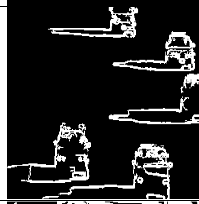
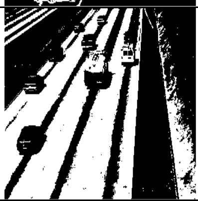
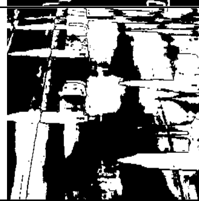
Table-1 - *Results of four segmentation algorithms for different traffic video sequences.*

	Sequence 1	**Sequence 2**	**Sequence 3**	**Sequence 4**	**Sequence 5**
Original Image					
Hybrid Approach					
Gabor Filtering					
GMM					
W4