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DETECTING AND TRACKING MOVING VEHICLES FOR TRAFFIC SURVEILLANCE

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ABSTRACT

Traffic surveillance has become an important issue in traffic monitoring. In general, to observe the traffic flow, vision based traffic surveillance is one of the most popular methods. This paper presents an efficient method for detecting and tracking vehicles that aims to locate and segment interesting vehicle from a video with occlusions in traffic surveillance. Initially background subtraction is used for detecting moving vehicles from static cameras using frame differencing method. This method detects the foreground objects based on the difference between the reference frame and the original frame. Then the shadows in the foreground are eliminated by the edge extraction and the edge of the moving vehicle is detected. Finally the vehicle is detected using Histogram of Oriented Gradient (HOG) and Relative Discriminative Histogram of Oriented Gradient (RDHOG) method which represents the shape and magnitude of the vehicle and by generating trajectory of the moving vehicles. This method can detect the vehicle with any shape, color and with occlusion. After the detection of vehicles in the frame, the detected vehicle is tracked using a particle filter which is based on the likelihood estimation of the probability density function. This method can detect and track vehicles with occlusions effectively.

Keywords: background subtraction, edge extraction, histogram of oriented gradients (HOG), particle filter.

INTRODUCTION

Traffic surveillance has become an important issue in traffic monitoring. Due to prompt development of urbanization, traffic congestion, incident and violation provide great challenges for traffic management systems. Sensing vehicles ahead and traffic situations during driving are important attributes in safe driving, accident avoidance and automatic driving and pursuit. Traffic monitoring is needed to reduce the traffic congestion on highways, to reduce the road accidents, to identify suspicious vehicle, etc. In this the video is obtained using static cameras.

Detection and tracking of moving vehicles is an important issue in traffic surveillance. It is used to locate the moving objects in the video sequence and hence avoid collisions during traffic congestions. This process is important for services such as intelligent parking systems, auto-driving systems, measurement of traffic parameters or estimation of travel times. The most widely used technique for detecting moving objects with static background is background subtraction. The background subtraction is used to separate the foreground objects from the background. Then RDHOG is applied to track the vehicle.

This paper is organized as follows: Section I gives an overview of previous works on detection and tracking of the moving objects and vehicle. The system overview of the proposed system is presented in Section II. Experimental results are demonstrated in Section III. Finally, conclusions will be presented in Section IV.

RELATED WORKS

There are different methodologies proposed for detection and tracking in this literature. S. Chen, J. Zhang, Y. Li, and J. Zhang (2012) proposed a hierarchal background model of background subtraction for segmenting the background images. This method generates the region and pixel model by MoGs and HOG which is used to detect the foreground objects. This method generates several false positive and it is more complex. Y. L. Chen, B. F. Wu, H. Y. Huang, and C. J. Fan (2011) proposed a technique for detecting moving vehicles by locating and examining the spatial and temporal features of the vehicle lights. The tracking of the detected vehicle is done based on component on consecutive frames and the grouping is applied to estimate the motion information on consecutive frames. This method is not suitable for congested and complicated traffic scenes.

L. Maddalena and A. Petrosino (2008) presents a detection method based on self-organizing model. This method does not solve camouflage problem. B. F. Wu and J. H. Juang (2012) proposed a histogram extension technique for extracting moving vehicles from complex environments. The drawback of this method is the detection ratio is low and the accuracy ratio is low during rainy and night conditions. M. Vargas, J. M. Milla, S. L. Toral, and F. Barrero (2010) proposed a new approach for detecting moving vehicles by background subtraction using sigma-delta method. This technique degrades under slow or congested traffic conditions. W. Kim and C. Kim (2012), has presented a simple and robust method for background subtraction which is a popular approach for detecting moving vehicles in temporally dynamic texture scenes. In this paper the background subtraction is based on the Fuzzy Color Histogram. B. Han and L. S. Davis (2012) proposed a new approach for background subtraction based on discriminative technique which is performed using support vector machine. SamYong Kim, Se-Young Oh, Jeong Kwan Kang and Young Woo Ryu Kwangsoo Kim, Sang-Cheol Park and Kyong Ha Park, presents a novel vehicle detection and tracking algorithm that can be functional to the general road condition in the day and night times using vision and sonar sensors. The drawback of this method is that when it is applied to driver assistance system without proper distance information it produces collision. Burcu Aytekin and Erdinc Altug (2010), presents vehicle detection and tracking system based on treating the monochrome images caught by a single camera. The tracking of the detected vehicle is done by Kalman filter. It is used to predict and update the states of the linear and Gaussian models. The drawback of this method is that the shadow indication for vehicle detection is scenes with low sun making the cast long shadows. This is not applicable for tracking vehicles in the congested traffic with occlusions.

W. Zhang, Q. M. J. Wu, X. Yang, and X. Fang (2008), presents a multilevel framework to detect and handle vehicle occlusion from the video sequence taken by a stationary camera. This model consists of three levels namely intra-frame level, inter-frame level and tracking level. The detection process is performed in the first two levels. Then the tracking is done to detect the occlusion by using bidirectional occlusion handling algorithm. Zehang Sun, George Bebis, and Ronald Miller (2005) proposed an on-road vehicle detection based on clustering algorithm by employing a set of Gabor filters. This method provides better performance. Ronan O'Malley, Edward Jones, and Martin Glavin (2010) proposed a different image processing system to detect and track vehicle's rear-lamps pairs in frontward facing color video. The vehicle is detected by color threshold. The tracking is performed by Kalman filter. Bin Tian, Ye Li, Bo Li, and Ding Wen (2014) proposed a rear-view vehicle detection and tracking based on higher solution camera. The detection is performed by Markov Random Field model and the tracking is performed by Kalman filter. Garcia. J, Gardel. A, Barvo. I, Lazaro. J. L, Martinez. M, and Rodriguez. D (2013) also presents the tracking by particle filter. Sam Yong Kim, Se-Young Oh, Jeong Kwan Kang and Young Woo Ryu Kwangsoo Kim, Sang-Cheol Park and Kyong Ha Park presents a tracking method based on sonar sensors. It is a template based tracking. It improves the drift problem. Y. Lao, J. Zhu, and Y. F. Zheng (2009) provide a unique probabilistic tracking system which includes a sequential particle sampler and a fragment-based measurement model. This method is applicable in difficult tracking scenarios, either fast motion or dense occlusions. X. Mei and H. Ling (2011), presents a robust visual tracking method by object tracking as a scarce approximation problem in a particle filter framework. C. Y. Chang and H. W. Lie (2012), presents a simple effective method of image processing to capture the dynamic movements of an overhead crane by fuzzy sliding mode controller. This method increases the computational speed. The particle filtering technique and its various types and there comparison is given in Bouaynaya. N and Schonfeld. D (2009),Hossein Tehrani Niknejad, Akihiro Takeuchi, Seiichi Mita (2012),Khan. Z. H, Gu. I. Y. H, and Back house. A. G (2011), Maggio. E and Cavallaro. A (2005) and Pan.P and Schonfeld. D (2011). This method is used to track vehicles with occlusions. J. Scharcanski, A. B. de Oliveria, P. G. Cavalcanti, and Y. Yari (2011), developed a new particle filtering technique for handling both partial occlusions and total occlusions in vehicular tracking situations. This proposed method is known as the adaptive particle filter. This method uses two modes of operation. When the vehicle is not occluded it uses bivariate normal probability distribution function to generate the new parameters. When the vehicle is occluded it uses Rayleigh distribution for generating the new parameters. The main drawback of this method is that it is not suited with concentrated traffic situations where the roadway can be jam-packed and the vehicles can be very close to each other. Amirali Jazayeri, Hongyuan Cai, Jiang Yu Zheng, Mihran Tuceryan (2011) presents a tracking method based on hidden Markov model. The drawback of this method is that it is not applicable for distant vehicle.

SYSTEM OVERVIEW

This paper presents an effective approach for detection and tracking of moving vehicles in the crowded scene with occlusion detection using RDHOGPF. The main objective of this method is to detect and track vehicles with occlusions for traffic surveillance, to detect and track vehicles at various lightning conditions and weather conditions and to reduce false positive and improve efficiency. The first step of this system is to generate set of information relating to the location. This information is generated by the detection of the vehicle. The detection of the vehicle includes background subtraction. Then the shadow in the interest region is eliminated by the edge extraction. Then RDHOG is computed which forms the vehicle descriptor to detect the vehicles. Then the trajectory is generated when the vehicle appears in the consecutive frames or more than one frame. The detected vehicle is then tracked using particle filter which is based on the estimation of the posterior probability density function. The similarity degree between the detected particle and the template is found using the Bhattacharyya distance of the HOG features and the RDHOG features. The occlusions can be detected by updating the estimated trajectory. The proposed methodology is used in this paper is shown in Figure-1.

A. Background Subtraction

Background Subtraction is used to detect the vehicles entering the region of interest (ROI). The background subtraction technique used in this paper is the frame differencing method. Videos usually consist of sequence of images which are called as frames.

Videos usually consist of sequence of images which are called as frames. Frame differencing is a pixel-wise differencing between two or more consecutive frames in an image sequence to sense regions analogous to moving objects such as human and vehicles. In this approach the background subtraction is done by subtracting the current image from a reference image. This

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is known as frame differencing method. The background subtraction is obtained using (1).

$$F(t) = I_c(t) - I_r(t) \quad (1)$$

where, F(t) represents the background subtracted image using frame differencing method at time 't', $I_c(t)$ represents the current or original frame and $I_r(t)$ represents the reference frame.

Frame differencing is a very adaptive technique to dynamic environments, but often holes are developed inside moving entities which are removed by structuring element or mask.

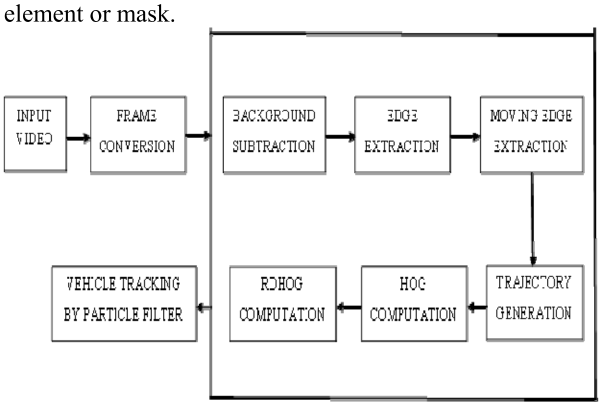

Figure-1. Workflow of the proposed method.

B. Edge Extraction

The main aim of edge detection is to diminish the amount of data in an image, while conserving the structural properties to be used for further image processing. It refers to the process of recognizing and tracing sharp discontinuities in an image. The discontinuities are the sudden changes in the pixel intensity which characterizes the boundaries of object in the scenes. Edge detection involves convolution of the image with an operator.

The edge feature is integrated in this system to detect vehicles correctly. The edge extraction is used to remove the shadows, headlight reflections of the vehicles. There are various methods for edge extraction. The method used for detecting the edge in this paper is canny edge detection.

The canny edge detection is a multistage algorithm used to identify wide range of edges in an image. It is used to find the discontinuities. It is used to remove the shadows that are generated due to the vehicles. It is used to find the optimal edges. It is a four step process. The algorithm for canny edge detection is as follows

a. Smooth the image with a Gaussian filter
b. Find the intensity gradient of the image

$$G = \sqrt{G_x^2 + G_y^2} \quad (2)$$

$$\theta = \arctan 2(G_y, G_x) \quad (3)$$

c. Thin the images by non-maximal suppression
d. Detect and link the edges by double thresholding

The first step smoothing is used to remove the noise in the original image before detecting and locating the edges. In the second step the image gradient is calculated to find the strength of the edges by finding the magnitude and direction of the edges. Then the non-maximal suppression is applied to remove the unwanted pixel in the images. Double thresholding is used to reduce the number of false edge detected. This edge detection technique can adapt to various environments.

C. Moving Edge Extraction

It is used to extract only the edges of the moving objects by comparing the background image and edge extracted image. When the pixel is present in the edge extracted image and absent in background image then that pixel corresponds to the moving edge and all other pixels are removed.

D. Trajectory Generation

The trajectory is established when the vehicle is detected more than twice and it overlaps in the consecutive frames [Bing-Fei Wu, Chih-Chung Kao, Cheng-Lung Jen, Yen-Feng Li, Ying-Han Chen, and Jhy-Hong Juang (2014)]. It is used to detect the vehicles correctly by finding the overlapping areas. The trajectory is generated after the detection of the vehicle and it is used to track the vehicles in the consecutive frames by the older trajectory information. The correct detection for the passing vehicle must include the relationship between the frames at time t, t-1 and t-2. The detected regions overlap if the regions are related to the same vehicle.

Let A_1, A_2 and A_3 represents the detected vehicles at time t, t-1 and t-2 respectively. a_1, a_2 and a_3 represent the area of the detected vehicles A_1, A_2 and A_3 respectively and $a_{1,\,2}$ and $a_{2,\,3}$ are the corresponding overlapping areas. The trajectory is generated if the corresponding overlapping areas are larger than half the size of the respective areas a_1 and a_2.

E. HOG Computation

HOG are feature descriptor used in image processing for the purpose of object detection. The Gradient histograms measure the orientations and strengths of image gradients within an image region. For finding the HOG first compute the gradient of the image by convolving the image with the horizontal and vertical kernel that is [-1 0 1] and $[-1\ 0\ 1]^T$. Normalize the image into 32 x 32 and then divide the normalized image into equal cells of 8 x8.

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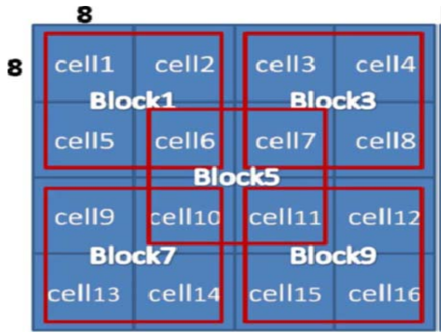

Figure-2. Diagram of cell and block used in the normalized image.

The 32 x 32 image consists of 9 blocks and each block containing 36 bins spaced over 0 to 180^0 . Figure-2 represents the cell and block used in the normalized image. All the histograms are combined to form the feature descriptor. Therefore there are a total of 324 HOG bins which forms the feature descriptor to detect the vehicles. It is used to describe the shapes and magnitude of the target vehicles.

F. RDHOG Computation

This is used to enhance the HOG description of the target [Bing-Fei Wu, Chih-Chung Kao, Cheng-Lung Jen, Yen-Feng Li, Ying-Han Chen, and Jhy-Hong Juang (2014)]. In addition to the HOG features it also takes the features by considering the relationship between the central block and the surrounding block. Therefore the difference between the HOG bins in the central block and the blocks around the central block is given by

$$RDb_j(i) = b_5(i) - b_j(i), j=1, 2... 9; j\neq 5 \quad (4)$$

where b_j (i) is the i^{th} bin of the j^{th} block, b_5 (i) is the i^{th} bin of the central block and RDb_j (i) is the i^{th} RDHOG bin of the j^{th} block. Now there are 288 RDHOG bins in each descriptor. Then the HOG and RDHOG features are combined to form a total of 612 descriptors.

G. Particle Filter

Particle filters are also called Sequential Monte Carlo (SMC) filter [Bing-Fei Wu, Chih-Chung Kao, Cheng-Lung Jen, Yen-Feng Li, Ying-Han Chen, and Jhy-Hong Juang (2014)]. The goal of a particle filter is to estimate the posterior density of the state variables given the observation variables. This particle filtering method involves two steps namely prediction and updating. In the prediction the posterior estimate of the state variable is given as

$$\hat{x}_k = \arg\max_{x_k} w_k^{(j)} \quad (5)$$

where $w_k^{(j)}$ is the weight of the jth particle $x_k^{(j)}$. The weight of the particle is calculated based on the similarity between the HOG weight of the particle and the RDHOG weight of the particle. Therefore the jth particle weight $w_k^{(j)}$ at time k can be computed as follows

$$w_k^{(j)} = p(y_k/x_k^{(j)}) = h_k^{(j)}/d_k^{(j)} \quad (6)$$

where

$$h_k^{(j)} = \sum_{i=1}^{N} \sqrt{d^{(j)}(i)\, d^T(i)} \quad (7)$$

and

$$d_k^{(j)} = \sum_{i=1}^{M} |RDb^{(j)}(i) - RDb^T(i)| \quad (8)$$

where $h_k^{(j)}$ is the jth HOG weight particle at time k and is computed using Bhattacharyya distance. $d^{(j)}(i)$ and $d^T(i)$ are the ith elements of the HOG feature of the jth particle and the target respectively and N is the total length of the HOG descriptor which is equal to 324. $d_k^{(j)}$ is the jth RDHOG weight particle at time k and $RDb^{(j)}(i)$ and $RDb^T(i)$ are the ith elements of the ith elements of the RDHOG features of the jth particle and target.

As $h_k^{(j)}$ increases, the similarity between the target and the particle increases. As $d_k^{(j)}$ becomes lower the difference between the central block and the surrounding block in the target and the particle is lower. The updating is done by resampling in which the lower weight particles are ignored and the strong weight particles are retained.

RESULTS

This chapter explains about the experimental results obtained for detection and tracking of the vehicles. The input chosen for the process is a real time video obtained from the website. The implementation process is done using MATLAB 13.0. The video format is MPEG.

The input is a real time video which consists of number of frames. First the video is converted into frames using MATLAB. Figure-3 shows the input frame obtained after converting the video into frames.

Figure-3. Input Frame.

The background subtraction is used to separate the foreground objects from the background. It is a widely used approach for detecting objects in videos obtained from static camera. Figure-4 shows the background subtracted image for the input frame shown in Figure-3.

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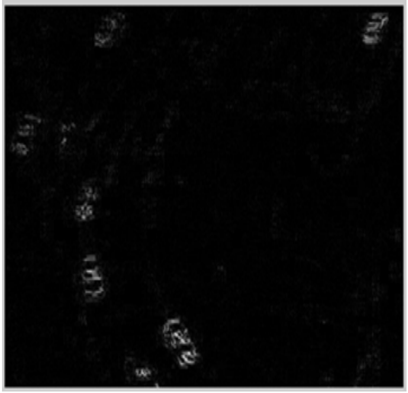

Figure-4. Foreground Image.

Region property is used for labeling each moving object. Labeling will reduces the computation loading. The moving edges can vertically distinct two vehicles. Edge features are found by applying a canny operator to the image. The edges formed by lane marks and road marks may have an impact on the shapes of vehicle edges. Therefore, the edge generated by the background, lane marks and road marks can be removed using the edge in the background image. Finally the shapes of the objects are obtained. Figure-5 shows the edge extracted image which removes the shadows present in the background subtracted output and Figure-6 shows only the moving vehicle detected output.

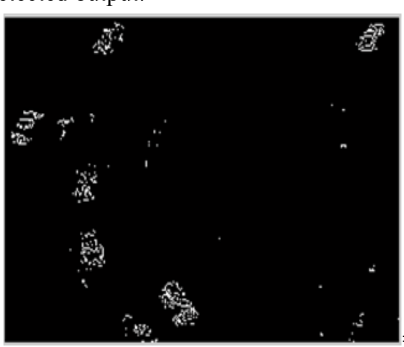

Figure-5. Edge extracted output.

Figure-6. Moving object obtained after shadow elimination.

Particle filter is called Sequential Monte Carlo method which is used to track the vehicles. The tracking is done when the movement of the vehicle is continuous in successive frames. The tracking object should have relationship between the frames at time t, t-1 and t-2. This relationship generates the trajectory by finding the information about the areas of the detected vehicle at time t, t-1 and t-2.

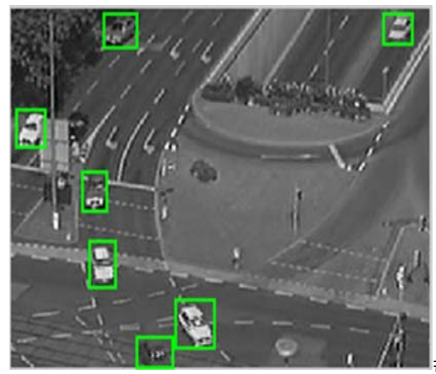

Figure-7. Vehicle tracking using particle filter.

It is used to track the vehicles by finding the probability density function of the state variable. The particle is obtained by finding the maximum value from the set of weighted particles. The weight of the particle is obtained by finding the ratio between the Bhattacharyya distance between the weight of the HOG features of the jth particle and the target at particular time k to the difference between RDHOG features of the jth particle and the target. Figure-7 shows the output of the vehicle tracking using particle filter. To solve the degeneracy problem resampling is performed in which the lower weight particles are deleted and retains only the strong weight particles.

CONCLUSIONS

Thus this paper presents a new approach for detection and tracking of vehicles. The foreground objects are first separated from the background using background subtraction. The input video is obtained using the static camera. The background is a static background and the background subtraction method used here is frame differencing method. Then the shadows are removed using edge extraction. The trajectory of the moving object is detected and then the shape and the magnitude of the vehicle is found using the HOG and RDHOG features so that the vehicle is detected correctly. Then the detected vehicle is tracked using the particle filter which tracks the vehicle by finding the posterior probability density function of the ratio of HOG and RDHOG weight of the particles. Then the blobs or occlusions are removed by eliminating the particles with lower weights while generating newer trajectory from the estimate of the older trajectory. Thus the particle is detected and tracked using background subtraction and RDHOGPF.

In future works, we intend to progress this method to find the traffic parameters like number of vehicles passing on the road for a specific time, speed of the vehicle, classification of the vehicle, traffic density, etc. for traffic surveillance system. In addition we will do the performance comparison with the existing methods.

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