SVM CLASSIFIER FOR VEHICLE SURVEILLANCE UNDER NIGHTTIME VIDEO SCENES

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Abstract: Vehicles type classification during the night time is an important emerging research area for intelligent transportation system. Video during the night time may have less clarity as such in the day time. Especially, Vehicle in the road at the night time is difficult to identify. This paper presents an effective traffic surveillance system for detecting and tracking moving vehicles in nighttime traffic scenes using SVM classifier. Existing systems identifies vehicles by using TI DM642 kit for capturing live video for detecting vehicles. The light intensity of the vehicles is extracted and classified based on the level of light intensity. It uses the vehicle front headlight only for identification and they measure the distance between the lights. Based on measurements, it provides the result about the vehicle type as it suggest. The proposed system uses stored compressed video which is taken from the ordinary camera. Since ordinary camera less cost than TI DM642 Kit to use and maintain. Stored compressed video are input for the proposed system. The proposed system filters the video for getting the noiseless video and exhibits the SVM classifier to provide clear vehicle classification than the existing system. SVM are the classifier algorithm to store the data into the set and it refers when light intensity is measured and given to the system. It compare and check the data with the recorded one and provide the result if both matches. If not matches, it alerts the user to identify the vehicle. This paper mainly focuses on tracking vehicle clearly and applied to the different video for the good result.

Index Terms: Tracking vehicle, SVM classifier and Traffic surveillance.

1. INTRODUCTION

Recognizing and classification of the vehicles during the night time in an important emerging area for intelligent transportation. It may uses for security purposes to recognizing authorized vehicles. Previous studies on the vehicle identification and tracking on traffic surveillance, driver assistance systems and autonomous vehicle guidance and road traffic information system. In traffic surveillances, cameras, loop detector and other sensors are used to obtain the information about moving vehicles such as number of vehicles passed on the particular portion of the road. Among the devices which mentioned earlier, Camera based system is the best one for the traffic surveillance and vehicle analysis including vehicle classification, vehicle speed and traffic flow.

Recently, vehicle lights have been used as salient features for nighttime vehicle detection applications for traffic monitoring systems and driver assistance systems. For traffic surveillance applications, these methods use morphological operations to extract candidate headlight featured objects and then perform shape analysis, template matching, or pattern classification to find the paired headlights of moving vehicles. Moreover, most of the aforementioned methods are unable to deal with vehicles with single headlights, such as motorbikes.

This paper presents effective nighttime vehicle detection, tracking, and identification approaches for traffic surveillance by locating and analyzing the spatial and temporal features of vehicle lights using the SVM classifier. By improving our previous work, this paper presents a system comprising the following processing stages for efficiently detecting and classifying moving vehicles at night. Some of the sample videos are taken for the processes which are taken in the highways. These sample video depict that, in typical nighttime traffic scenes, there are moving cars and motorbikes on the road, and under poorly or brightly environmental illuminated conditions, vehicle lights are the only valid salient features. In addition to the vehicle lights, some lamps, traffic lights, and signs are also visible sources of illumination in the image sequences of nighttime traffic scenes. First, Compressed video are filtered using median filter to extract the noise-less video for the process. The advantage of the median filter is easier to apply for the video and can get most accuracy than the other filter. Then, a fast bright-object segmentation process based on automatic multi-level histogram threshold is performed to extract pixels of bright objects from the captured image sequences of nighttime traffic scenes. The advantage of this automatic multi-level threshold approach is its robustness and adaptability when dealing with various illumination conditions at night. Then, to locate the connected components of these bright objects, a connected-component analysis procedure is applied to the bright pixels obtained by the previous stage. A spatial clustering process then groups these bright components to obtain groups of vehicle lights for potential moving cars and motorbikes. Next, a feature-based vehicle tracking and identification process is applied to analyze the spatial and temporal information of these potential vehicle light groups from consecutive frames using SVM classifier. This step includes collecting the data set from the compressed video and compare with the stored set, to classify the vehicles. This step also refines the detection results and corrects for confusions caused by noise and errors during the segmentation and spatial clustering processes. Thus, actual vehicles and their types can be efficiently detected and verified from SVM classifier to obtain accurate traffic flow information. We also implemented the proposed system on a compressed video which is taken from ordinary camera shot on roadside during the night time. Experimental results show that the proposed traffic surveillance system is feasible and effective for vehicle detection and identification in various nighttime environments.

II. FILTERING COMPRESSED VIDEO

Stored compressed video are mainly use to send the data as quick as possible. Compressed video may comprise with some noise during the transmission. There are some of the filtering methods to reduce noise during transmission. Low-Pass filter, High-pass filter and median filter are some of them used to various fields. Since aforementioned filtering methods are easy to handle and gives good result. Among aforementioned methods, this paper uses Median filter method to reduce noise in compressed video. Median filtering is very widely used in digital image processing because, under certain conditions, it preserves edges while removing noise. The main idea of the median filter is to run through the signal entry by entry, replacing each entry with the median of neighboring entries. The pattern of neighbors is called the "window", which slides, entry by entry, over the entire signal. For 1D signal, the most obvious window is just the first few preceding and following entries, whereas for 2D (or higher-dimensional) signals such as images or video, more complex window patterns are possible (such as "box" or "cross" patterns). Note that if the window has an odd number of entries, then the median is simple to define: it is just the middle value after all the entries in the window are sorted numerically. For an even number of entries, there is more than one possible median. Fig.1 (a) shows the video taken from the ordinary camera and stored in the compressed manner. Fig.1 (b) shows the video which is filtered from the compressed stored video using the median filter.

Fig 1(a) Input compressed video (b) Filtered video from the input compressed video

III. LIGHTING OBJECT EXTRACTION

The first step in detecting and extracting moving vehicles from nighttime traffic scenes is to segment the salient objects of moving vehicles from traffic image sequences. As Section I mentions, most recent studies on vehicle detection adopt edge maps, frame differencing, and background subtraction techniques to extract the features of moving vehicles from traffic scenes. However, edge feature extracted and fore ground object image extracted techniques, which are effective for vehicle detection in daytime, become invalid in nighttime illumination conditions. This is because the background scenes are greatly affected by the varying lighting effect of moving vehicles. The edge features of moving vehicles extracted from nighttime traffic scenes are mostly adjoined and blurred. Therefore, performing vehicle detection and recognition for nighttime traffic surveillance requires an effective approach for correctly and rapidly locating and extracting the salient features of vehicle lights under poorly illuminated conditions. This would enable the efficient extraction and segmentation of the object regions of moving vehicles. Therefore, this section presents a fast bright-object segmentation process based on automatic multi-level histogram threshold. The proposed method extracts the bright-object pixels of moving vehicles from image sequences of nighttime traffic scenes.

By applying the multi-level threshold technique, the lighting object regions of moving vehicles can be efficiently and adaptively segmented under various environmental illumination conditions in different nighttime traffic scenes.

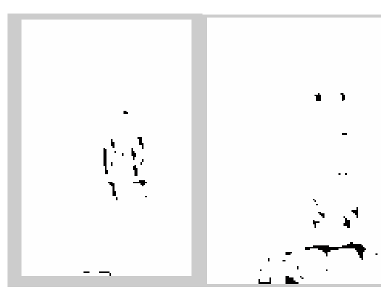


Fig.2 Background subtraction for the particular region.

As a result, lighting objects can be appropriately extracted from other objects contained in nighttime traffic scenes. Fig.2 illustrates the light object extraction in the moving vehicle from the lights exhibits by the stationary object in the video scenes. Accordingly, as bright object extraction, performing this lighting object segmentation process successfully separates the lighting objects of interest into threshold object planes under different environmental illumination conditions in nighttime traffic scenes.

III. SPATIAL CLASSIFICATION PROCESS OF LIGHTING OBJECTS

To extract/obtain potential vehicle light components from the detection zone in the bright-object plane, a connected component extraction process can be performed to label and locate the connected components of the bright objects. Extracting the connected components reveals the meaningful features of location, dimension, and pixel distribution associated with each connected component. The location and dimension of a connected component can be represented by the bounding box surrounding it.

Since various non-vehicle light components, such as traffic lamps, road signs, road reflector plates, reflected beams, and some other illuminant objects, coexist with actual vehicle lights, we applied a spatial classification process to preliminarily detect potential vehicle lights and filter out non-vehicle components. These detected potential vehicle lights are then processed by the following vehicle light tracking and identification process to identify the actual moving vehicles.

The connected component extraction and spatial classification processes are only performed on the bright objects located in the detection area. Fig. 3 (a) and (b) shows the spatial classification using the bounding box approach to detect the light object in the video

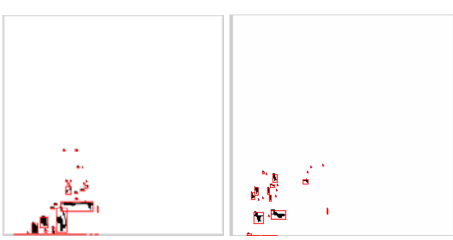


Fig.3 (a) and (b) Tracking the vehicles with different intensities.

IV SUPPORT VECTOR MACHINES

Support vector Machine is a subfield of artificial intelligence that focuses on extracting useful information from images Combining many of descriptors and giving them as input to a learning classifier such as a support vector machine (SVM) has been shown to lead to very good results. Since, video are the sequence of the images link with each other. These video are used SVM classifier taking single images (frames) to process which are described in following discussion topics.

A. SPATIAL PYRAMID APPROACH

The multi-resolution approaches in uses a pyramid representation to capture the spatial correspondence between histograms. A multi-resolution image was constructed using four levels of the Burt-Adelson pyramid. In this method, each level is obtained by filtering with a Gaussian kernel and sub-sampling. After that, computing the histogram of each of the four levels has been done. The distance between two multi-resolution histograms is the sum of the four individual Level1 distances between pairs of histograms corresponding to the same pyramid levels. In contrast with this approach, the spatial pyramid approach uses the fixed partitioning scheme to combine several levels of histograms. Combining multiple levels using this approach has been shown to improve recognition performance compared to using a single level. In this paper this spatial pyramid scheme is used.

V. COMBINING MULTIPLE FEATURES

The main idea of combining multiple evidences is that repeated evidences of the same object would increase the probability of relevant features in the object. We used this for several reasons:

(1) The features can be computed easily and efficiently.

(2) The system preserves the spatial information of images by simply combining local histograms at multiple levels.

(3) The histogram itself has many merits, such as invariance to image rotations and robustness to image translations around the viewing axis, and it varies slowly with the angle of view.

(4) Each level in the spatial pyramid presents different information for recognizing the image.

However, we still have to combine all local histograms in a classifier. In this paper, we used two-layer stacking spatial pyramid classifier for the classification of the vehicle in SVM classifier.

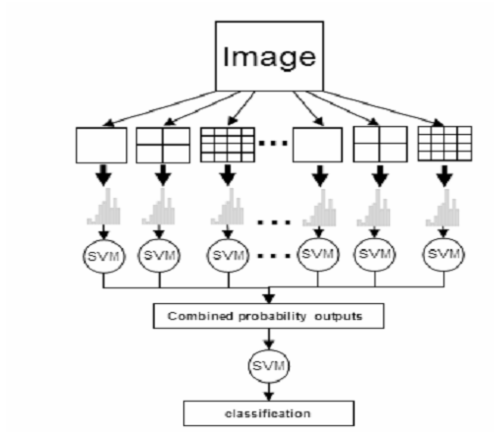
A. TWO-LAYER STACKING SPATIAL PYRAMID CLASSIFIER

While exploring a two-layer stacking method, it reduces the size of input vectors and at the same time replaces the fixed weighting scheme. This method can reduce the size of the large feature vectors and improve the generalization performance of the spatial pyramid classifier. The two-layer spatial stacking method combines outputs from different classifiers of the spatial pyramid approach. It uses the fact that the probability estimates or outputs from each classifier can be combined and used for recognizing images with many different descriptors.

The system first trains a set of SVM classifiers on the histograms of each level with a single different descriptor in the pyramid. In this case, each classifier estimates the posterior class probability values or class predictions of a given image. The posterior probabilities contain important information about the predicted classes and can be used instead of the feature vectors of the descriptor to train the final classifier. After that, the outputs of these SVM classifiers are concatenated into a feature vector for each image. Then, this feature vector is used to learn another SVM classifier. In our implementation, an SVM classifier with the RBF kernel using the one-vs.-all approach is used to provide probability outputs on the decision values. Fig. 3 shows the 2-layer stacking spatial pyramid approach.

VI. FEATURE EXTRACTION AND REPRESENTATION

One of the most important features of our visual system is the construction of edge features, and using such edge orientation information it is possible to describe shapes. For this reason, edge-based descriptors such as SIFT and histograms of oriented gradients have become popular and are nowadays widely used in image recognition systems. Therefore, like many other researchers, we have chosen to concentrate on various edge descriptors to represent the image content. These descriptors are applicable to real-world images and provide significant relationships between lines or contours and have enough power for shape discrimination.



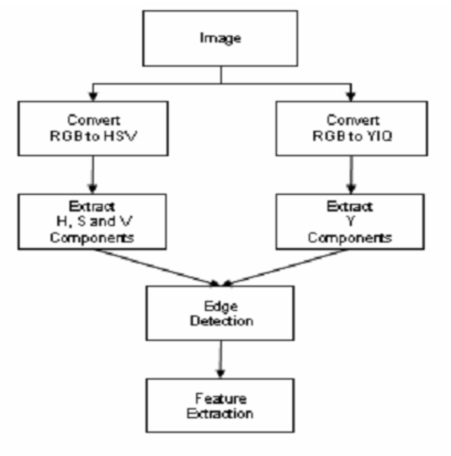


Fig. 4 (a) The 2-layer stacking spatial pyramid classifier. (b) The overall feature extraction process for computing edges-based on color and intensity perception.

VIII EXPERIMENTAL RESULT

Fig. 5 shows experimental scene of a congested nighttime highway at rush hour under a light environmental illumination condition. These images were obtained by a closed-circuit television (CCTV) camera. This figure shows that even though multiple vehicles are stopped or moving slowly close to each other in this congested traffic scene [particularly in Fig. 5(a) and (c)], the proposed method still successfully detects and tracks almost all vehicles. Thus, the vehicle light sets of some few detected cars may be occluded and misclassified as single-light motorbikes.

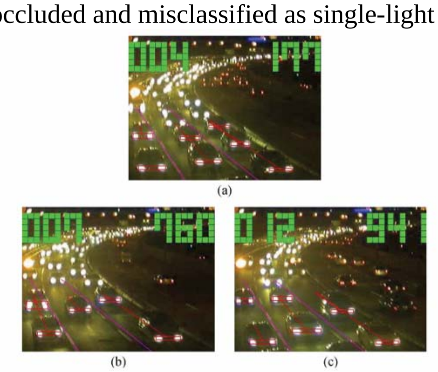


Fig.5 Results of vehicle detection and classification for a congested highway traffic scene under a light environmental illumination condition.

Fig. 6 shows the alternative experimental samples of vehicle detection on a nighttime urban road in a rainy day. In the rainy condition, the most significant difficulty is the numerous scattering glares caused by reflected lights on the ground. As Fig. 6 shows, the proposed system is able to avoid most of the reflected glares and appropriately detect, classify, and track most cars and motorbikes. Table I depicts the results of vehicle detection in the rainy traffic scene.

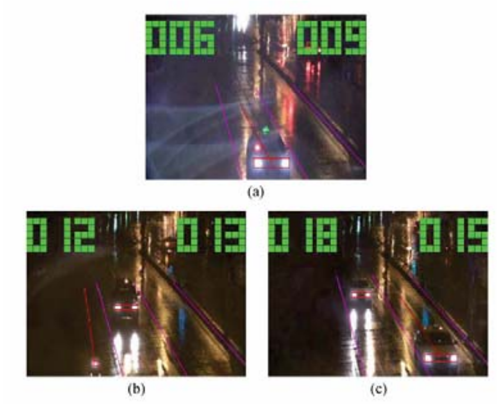


Fig. 6 Snapshots of different car/motorbike detection and classification results for a nighttime urban traffic scene in a rainy day.

The following part evaluates the performance of the proposed system and compares it to the contrast-based method of Huang et al.[15], the background-subtraction-based method of Wu et al.[10], and the pairing-light-based method of Wang et al.[16].

TABLE – I EXPERIMENTAL DATA OF T H E PROPOSED APPROACH FOR TEST SEQUENCE 4 OF THE RAINY ROAD IN FIG.6

Lane	Detected Vehicles	Actual Vehicles
Lane 1	4	4
Lane 2	7	7
Lane 3	6	6
Total No. Cars	17	17
Total No. Motorbikes	22	20
Detection Score *J* of Cars	100%	
Detection Score *J* of Motorbikes	90.91%	
Time span of the video	15 minutes	

VI. CONCLUSION

This paper has proposed effective nighttime vehicle detection and tracking system for identifying and classifying moving vehicles for traffic surveillance using SVM classifier. The proposed approach uses an efficient and fast bright-object segmentation process based on automatic multi-level histogram threshold to extract bright objects from nighttime traffic image sequences. This technique is robust and adaptable when dealing with varying lighting conditions at night during the rainy season. The proposed nighttime vehicle detection and classification approaches were also implemented and tested with real highway nighttime traffic scenes. Experimental results and comparison with existing methods have shown that the proposed system is effective and offers advantages for vehicle detection and classification for traffic surveillance in various nighttime environments. For further studies, the vehicle type classification function can be further improved and extended by Platt's SMO algorithm, including vehicle lights and vehicle bodies, to further enhance the classification capability on more detailed vehicle types, such as sedans, buses, trucks, Lorries, and light and heavy motorbikes.

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