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Abstract

Real time traffic surveillance using computer vision system is an emerging research area. Many new algorithms are being developed to perform the surveillance in the most effective manner. The first and critical step in these road traffic monitoring systems is to detect and track the vehicles. In this paper, we provide a brief review on the night time vehicle detection techniques that have been used in the recent years. The detection of vehicles in the night time can prove to be challenging because the usual features of the vehicles like the vehicle shadows, horizontal and vertical edges that helps in the identification in day time cannot be used during the night time. The only salient features that are visible in the night time are headlights, rear-lights and their beams, street-lamps, horizontal signals such as zebra crossings and traffic scenes with reflectors. Thus, in night time surveillance the target objects are the vehicle headlights and rear lights.

1. Introduction

The data for the real time traffic monitoring systems can come various sources like the loop detectors, ultrasonic detectors, microwave sensors, radar sensors or video cameras. Due to the recent advancement in computer vision and image processing techniques, the video cameras have been found to be an efficient means to collect and analyze the traffic data. Video based camera systems are more sophisticated and robust because the information that is associated with the image sequences present in the video allows us to identify and classify the vehicles in the most effective manner. The temporal continuity of data in video stream helps in improving the accuracy during vehicle detection. A video based monitoring system must be able to handle various weather and illumination conditions.

The vehicle detection in day time can be done using various methods which can be motion based, knowledge based or appearance based. The various techniques that are commonly employed in day time vehicle detection is comprehensively reviewed in [1]. The methods mostly use the edges in the vehicle to identify the moving objects in the screen through frame differencing methods. Stauffer and Grimson [2] in 1999 published a novel method to detect the moving vehicles using background subtraction. In this method each pixel was modeled as mixture of Gaussians and based on the variance and persistence, the Gaussians which corresponds to the background colors were determined. The pixel values that do not fit the background distributions were considered to be foreground. This method was able to handle very slow illumination changes and the multimodal distributions caused by swaying trees. This method was further improved in [2] where an algorithm was proposed to learn the descriptive mixture of the first few frames and the result of this algorithm was used in the Gaussian mixture model. In [3], a spatial temporal technique was used to detect the vehicles. This method exploits the information in the moving points, which can be gathered by the difference between the successive frames and the variations in the luminance in these points. The SVM classifiers can also be used after extracting the required features as suggested by [3]. The vehicle detection can also be obtained by using Gabor filter and Kalman filter to predict the next position [4]. Apart from these common methods, the vehicles can also be detected using the changes in the optical flow as reviewed in [5] and all these methods try to accommodate the illumination changes and weather conditions.

The methods used for the day time vehicle detection cannot be used for the night time vehicle detection due to various factors. In the night time, the bad illumination causes strong noise which increases the complexity of the detection task. The reflection of the beams of headlights and rear lights can cause lots of false alarms during the detection process. The moving reflections of the headlights can introduce a lot of foreground or background ambiguities. Moreover, at night the camera images have very low contrast and a weak light sensitivity thus making it difficult to use the normal day time detection methods. An effective method is to use infra-red thermal cameras as night vision sensors to collect the traffic data during the night.
time. This way the normal detection techniques can be used. But unfortunately, this method is very expensive and can be rarely seen in the real time scenarios and moreover installing two different cameras for night and day time is futile.

The night time environment can be classified into two types. The unlit scene where there are no street lights and the only features visible are the headlights and their reflections. The headlights appear as a bright round blob in contrast to the dark surroundings. The second type is the lit scenes where the streets are illuminated by the public light poles like most of the urban areas. In this type of scenes, the background, pedestrians and other objects are also visible. Here the headlights are not clearly visible, especially when the vehicles are also in white or some light colors. Hence the complexity of extracting the headlights from the images is increased.

In this paper, Section II gives the general description of the night time vehicle detection algorithms. Section III sheds light on the various methods used in feature extraction and Section IV provides an insight into various methods used for headlight pairing and verification. Section V elucidates the conclusion and references.

2. Night Time Vehicle Detection

Most of the night time detection algorithms use the headlights and tail lights as the main features in the detection of vehicles. The general template of the night time vehicle detection algorithm as shown in Fig.1 consists of mainly four phases namely the preprocessing phase, feature extraction and classification to detect the vehicles.

![General Algorithm for night time vehicle detection](image)

The preprocessing phase is optional and is responsible for the offline configuration of the traffic scene as specified in [6]. This phase mainly consists of the calibration of the camera and collecting the required information about the background, lanes and camera parameters which can be used in later stages to judge the traffic flow and vehicle status. The preprocessing stage also removes the noise using smoothing filters and making the image easy to process.

3. Feature Extraction

The main features that can be used in the night time vehicle detection are headlights, rear lights and windshields. The various methods that can be used in the extraction of these features are described in this section.

3.1. Headlight Detection

Headlights are strong and consistent features which can be used to reveal the presence of a vehicle at night. The major difficulty lies in segmenting the headlights pixels from the other bright pixels that are present in the scene. Usually, the contrast between the headlights and their surrounding is very high and the histogram of the images of the night environment is bimodal. The headlights can be identified based on the reflection identity map and the reflection suppression map as used in [7] but the method is complex and is not used frequently. Most of the algorithms have two main steps to detect the headlights namely bright pixel extraction and headlight identification.

3.1.1. Bright Pixel Extraction

Third-order headings, as in this paragraph, are discouraged. However, if you must use them, use 10-point Times, boldface, initially capitalized, flush left, preceded by one blank line, followed by a period and your text on the same line.

3.1.1.1. Non-linear Luminance

The bright pixels can be extracted by extracting the connected pixels that maximize the value of V/S ratio (value on saturation) on the different color channels (R, G, B). This can be done using the non-linear luminance as the threshold value [8]. This can be followed by white top hat transform to detect the presence of vehicles.

\[
L = \frac{1}{2} (\text{MAX}(R,G,B) + \text{MIN}(R,G,B))
\]  

Eq. (1)

3.1.1.2. Canny Edge Detection

The first step is to smoothen the image using Gaussian filter. The smoothened image is then differentiated along the X and Y directions and non-maximum suppression is performed as suggested in [8]. Finally
double thresholding is performed to get the edges of the image. The binary image \( b(x, y) \) is created from an intensity image \( I(x, y) \) according to the Eq. (2).

\[
b(x, y) = \begin{cases} 
1 & \text{if } I(x, y) > T \\
0 & \text{otherwise}
\end{cases} \quad \text{Eq. (2)}
\]

where \( T \) is the thresholding level. The thresholding is done on the obtained region of interest. This method used in [9] is very effective because the edges are not missed in this detector and there will not be an image without any edges present. However, the canny edge detector can be improved by using the fuzzy enhancement algorithm instead of smoothening the image using simple Gaussian filter [10]. Before performing the fuzzy enhanced canny edge detection, the spatial homomorphism can be performed to eliminate the illumination effects [10].

### 3.1.1.3 Multilevel Thresholding

The bright pixels can be extracted using the thresholding. Ostu [11] has determined the optimal threshold by maximizing the between class variance of bright and dark regions. This method is improved in [12]. The normalized probability is calculated as \( P_l \).

The image \( I \) is split into \( k+1 \) classes using \( k \) threshold values. Here \( T \) is taken as the threshold set and \( C_i \) represents the classes that the pixels are grouped into using the thresholds. The between class variance and within class variance can be calculated using the Eq. (3) and (4) respectively.

\[
\nu_{bc}(T) = \sum_{n=0}^{k} w_n (\mu_n - \mu_T)^2 \quad \text{Eq. (3)}
\]

\[
\nu_{wc}(T) = \sum_{n=0}^{k} w_n \sigma_n^2 \quad \text{Eq. (4)}
\]

Where \( \nu_T \) denotes the total variance and the overall mean is denoted by \( \mu_T \).

\[
w_n = \sum_{i=n+1}^{n+1} P_i \quad \text{Eq. (5)}
\]

\[
\mu_n = \frac{\sum_{i=n+1}^{n+1} i P_i}{w_n} \quad \text{Eq. (6)}
\]

The values \( w_n \), \( \mu_n \) and \( \sigma_n \) represents the cumulative probability, mean and standard deviation of class \( C_n \). The separability factor can be calculated as follows:

\[
SF = \frac{\nu_{bc}(T)}{\nu_T} = 1 - \frac{\nu_{wc}(T)}{\nu_T} \quad \text{Eq. (7)}
\]

When the separability factor approaches to 1, the classes of gray levels are completely separated. When the following condition is satisfied, the largest threshold value is used and the bright objects are separated.

\[
SF \geq Th_{SF} \quad \text{Eq. (8)}
\]

### 3.1.2. Headlight Identification

The bright pixel extraction extracts all the bright pixels in the particular frame. But not all of these pixels correspond to the headlights. They can be street lights, reflections or other nuisance lights. To separate the headlights from the other lights the following methods are used:

#### 3.1.2.1 Morphological Filtering

The morphological filtering can be used to remove false positives. These functions can be used to remove objects fewer than 'p' pixels. The erosion and dilation operations can be performed with the same structuring element as mentioned in [9]. The default connectivity is 8 for two dimensional image.

\[
A \circ B = (A \ominus B) \oplus B \quad \text{Eq. (9)}
\]

#### 3.1.2.2 Temporal Information

After the bright pixels are extracted, temporal information can be used [13]. The past car light is used to predict the next light position thus narrowing down the area in which the headlight can be detected. This method suggested in [14] helps in finding the vector of light positions.

#### 3.1.2.3 White Top Hat Transform

This method used in [15] is a powerful method for detection of contrasted objects on non-uniform background. The white hat transformation is defined as the residue between the original image and its opening [16]. The top hat transform is basically used to modify the contrast of the image but the false regions can also be removed using this principle.

\[
WH_T = (f - f \circ B) \quad \text{Eq. (10)}
\]

### 3.2. Rear Light Detection

A rear light can be detected effectively with the help of red light filters. The threshold here is set using HSV color space and the lights are detected [17] - [18]. Many different color spaces with widely varying parameters have been used to segment red-color light regions from images. The luminance(Y) and the red component (Cr) can be combined to form a single
component RGC. This RGC can be used as a threshold to extract the lights \[19\].

\[ I_{RGC} = \frac{Y + Cr}{Y + Cb + Cr} \quad \text{Eq. (11)} \]

3.3. Windshield Detection

Along with the headlights, windshield detection can also aid in the detection of vehicles in the night time. In the night time, the vehicle consists of a dark windshield and pair of bright headlights. After determining the position of windshield (between two headlights), the median value of all the pixels in the windshield is calculated. If the median is a dark value, then the presence of vehicle can be confirmed. In [20] for each pixel in the image, it is assumed that it is the center of a front windshield and then a 3D windshield model is projected to the position of that pixel. The probability of the vehicle presence is calculated using the shape and edge matching likelihoods.

4. Vehicle Identification

After the identification of the features, the features should be analyzed and the vehicles should be identified as a whole. The methods that can be used to analyze the features are as follows:

4.1. SVM Classification

Many of the vehicle detection algorithms use SVM Classifier to confirm the presence of vehicle in the scene [21]-[23]. The group of pixels can be combined together and the eigenvalues are found. These values are given as the input to the classifier [24]. The SVM classifiers can be trained with many attributes of the vehicles like the

- Area in component in pixels
- Coordinates \((u,v)\) of the object’s centroid
- Estimated Distance of the Object’s Centroid
- Hat Value
- Rectangularity
- Aspect Ratio
- Length of the object’s contour
- Circularity
- Angle value of each light object’s centroid
- An input vector was defined for the classifier.

The output of the support vector machine is simply the distance from the hyper plane. This distance will help in the making the decision of whether the analyzed object corresponds to a vehicle or not and this can also be used as a threshold for separating nuisance light sources and vehicles. For creating the training and test sets, the ratio between positive (vehicles) and negative (mainly reflections of traffic signs and headlights) must be set to an appropriate value in order not to produce wrong learning or a high percentage of false positive detections (signs classified as vehicles) during the tests. With the help of the training and testing data sets, the vehicle presence can be estimated accurately using the support vector machines.

4.2. Rule Based Component Analysis

A The identified vehicle headlights can be paired with each other if certain rules are satisfied as mentioned in [12],[26], [27]. These rules are based on the statistical features of the vehicle headlights. The rules that can be used in the estimation are

- The components must be horizontally close to each other and the vertical and horizontal positions should be considered.
- They have highly overlapped vertical projection profiles.
- The components are of similar size.
- The width to height ratio of the bounding box enclosing the two components must be greater.
- Area of the pixels must be similar.
- The symmetry condition must be satisfied.
- The components should have a high horizontal projection profile.

4.3. Symmetry Based Identification

Symmetry can be used to filter potential vehicle candidates and make light pairs. The light pairs which belong to the same vehicle are always symmetrical in size, shape and intensity in normal conditions. This property can be used to detect the vehicles in night time environment. The correlation factor between two lights can be calculated and if the result is within the allowed threshold then it is concluded that both the lights belong to the same vehicle as mentioned in [27]. The correlation between two components can be calculated using

\[ \gamma = \sum_{x,y} \frac{(T(x,y) - \bar{T})(I(x,y) - \bar{I})}{\sigma_T \sigma_I} \quad \text{Eq. (12)} \]

Where \(\bar{T}\) and \(\sigma_T\) are the mean and standard deviation of the component \(T\) and \(\bar{I}\) and \(\sigma_I\) are the mean and standard deviation of the component \(I\). The correlation factor is calculated for different color channels to utilize the color value and to get a better accuracy in grouping headlights together as a single vehicle. This method is mainly used to identify the vehicle in back view after the rear light identification. Apart from the correlation factor, the intensity of the pixels on either side of the symmetrical axis can also be compared to observe the symmetry between two regions.
The below table provides the accuracy of various vehicle detection methods based on the previous experiments conducted in [6]-[28].

<table>
<thead>
<tr>
<th>S.No</th>
<th>Vehicle Detection Methods</th>
<th>Accuracy</th>
<th>False Alarms</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Rule Based Identification</td>
<td>98%</td>
<td>Low</td>
</tr>
<tr>
<td>2</td>
<td>Symmetry Based Identification</td>
<td>92%</td>
<td>Medium</td>
</tr>
<tr>
<td>3</td>
<td>SVM Classification</td>
<td>95%</td>
<td>Low</td>
</tr>
<tr>
<td>4</td>
<td>Hypothesis Generation and Verification</td>
<td>94%</td>
<td>Low</td>
</tr>
</tbody>
</table>

5. Conclusion
This paper presented a critical review on the techniques used in the night time vehicle detection based on the data obtained from the stationary video surveillance camera. These detection techniques coupled with the tracking algorithms can increase the accuracy and efficiency in great detail. Today many kinds of robust tracking algorithms are available to aid vehicle detection and traffic surveillance [29]. With the reducing cost of the hardware and the increasing demand for the intelligent transportation systems, vehicle detection especially in the night when there is heavy traffic flow will continue to be one of the hottest research areas.

6. References


