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Survey on Vehicle Detection techniques

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***Abstract*—Vehicle detection is the foremost step in monitoring the speeding vehicles in a highway. The video sequences captured by a stationary camera show us that there's a need for a vehicle detection algorithm which handles sudden illumination change and also the scenarios where the foreground merges into the background. This paper provides us a survey of various background subtraction techniques that are used for detecting the vehicles efficiently.**

***Index Terms*—Vehicle Detection, video sequences, foreground, background.**

I. Introduction

In many image processing applications, foreground detection is a very important step. Proper detection and identification of these foreground objects only will lead to other processing like tracking. In order to monitor the vehicles in the highway, we have to take into consideration the changing weather conditions and foreground objects that might merge into the background later.

The views of the camera will be different from different positions of the camera which must also be considered in the detection process. There is front view, back view, side view and top view. The height at which the camera is placed will also affect the output of the detection algorithms. The camera specifications, the frame rate and range or distance covered by this fixed camera also should be taken into account for efficient vehicle detection. And as the camera is going to be fixed and is prone to lot of disturbances to noises, there will be noise in the videos which should be removed for efficient vehicle detection.

Several methods have been proposed for vehicle detection. Vehicle detection can be done using background subtraction algorithms and vehicle model based techniques. Each algorithm has its own advantages and disadvantages. But all of these methods try to detect vehicles robustly and efficiently.

Using any detection algorithm first the background and the foreground are separated. In real-time vehicle detection, first the shadow of the vehicles must be removed in order to avoid mistakes in the detection process. This paper provides a survey on the existing algorithms that work on overcoming the problems mentioned earlier. Section (II) provides a survey on the method which uses both color and texture for vehicle detection. Section (III) describes a method that uses color transformation. Section (IV) gives a survey of the Block matching algorithm. Section (V) describes vehicle detection using Gaussian mixture model which is a background subtraction algorithm. Section (VI) describes a method which combines both motion detection and background subtraction algorithm and section (VII) gives a comparison of all the algorithms discussed in this paper.

II. Color and texture based Vehicle Detection

Color and texture are two most important attributes in image processing application. Visual color contrast is used to filter information present in each color component. (Tremeau *et al*. [15]) and to distinguish among similar gray-scale intensities (Barilla-Perez & Spann [15]). There have been both color based and texture based vehicle segmentations. But integration of these both will yield us better results in vehicle detection. The color of the road is homogenous and they have the same texture throughout. You can easily detect vehicles making use of this fact. The color of the vehicle will show a huge variation when compared with the color of the road. But problem comes when the color of the vehicle is similar to the color of the road which can be solved by taking the texture into account. The first step in this method would be creating a background model. A background model can be created using recursive or non-recursive techniques. Since noise is involved, you can use median filter. The differences between the current frame and the background can be calculated using the features of texture and the L* intensities component of L*u*v* color space. This method is based on a change detection technique that will combine both the intensity and texture differences between the current frame and the previous frame. This methods works good for static backgrounds where there is no much difference in the texture of the background.

III. Color and edge based vehicle detection

Luo-wei Tsai, Jun-wei hsieh, Kuo-chin fan *et al*.[2] proposed an approach for detecting vehicles using color and edges. Unlike most of the traditional methods that uses the motion features to detect vehicles, this method introduces a new color transform model to find the possible vehicle candidates. As the same vehicle can have different colors in different weather and illumination conditions, vehicle detection based on colors weren't encouraged much. This proposed method, regardless of the varying lighting conditions, is capable of identifying the vehicle pixels from the background. First, all the colors of the input pixel are projected on a color space. Then using Bayesian network, vehicle colors can be identified from the background. A vehicle will have different size and also different orientation so several vehicle hypotheses are generated from each pixel. The hypotheses can be verified using three important features which are corners, edges and coefficients of wavelet transforms. This method can be used to robustly detect vehicles in case of static backgrounds.

IV. BLOCK MATCHING ALGORITHM

Luigi Di Stefano, Enrico Viarani *et al.* [7] decribed a vehicle detection based on block matching algorithm [8](BMA). BMA was used in applications aimed at estimating the turning rates at crossroads. BMA does not alone provide vehicle detection but also motion estimation. This makes it different from the traditional spatio-temporal derivatives [9] [10] and background subtraction [11] and also increases the power in case of partially occluding vehicles. This algorithm partitions each frame of a given video sequence into blocks of fixed size. It then detects the block displacements between the current and the previous frame. It gives a field of displacement vector (DVF) associated with it. Each partitioned block in every frame encloses a part of the image and can be considered as a matrix containing the grey tones of that part. Each block defines a scan area in the previous frame. And e this block is moved pixel-by-pixel in the scan area and calculating the match measure at each shit position. The similarity between the blocks in each frame of the video can be calculated on the basis of several matching measures [8]. In [7], the author has adopted the Normalized cross correlation function:

$$NCCF = \sum_{i,j} \frac{[P(i,j).q(i,j)]}{\sqrt{[\sum_{i,j} P^2(i,j)].[\sum_{i,j} q^2(i,j)]}} \qquad \text{Eq. (1)}$$

Where "." represents the product between corresponding elements of the matrices.

The BMA usually produces noisy DVFs due to fluctuation in the grey tone in successive frames. A vector median filter is used to smooth the DVF. This approach has been employed for regularization of velocity [12] and optical flow fields [13] as well as DVFs [16]. This regularization by the vector median filter removes the noise and also produces sets of blocks with similar displacement vectors. After getting the cleaned DVF we can detect the vehicles by grouping together 8-connected clusters of blocks with similar displacement vectors

V. IMPROVED ADAPTIVE GAUSSIAN MIXTURE MODEL

With a camera that's stationary, different objects might appear at the same pixel position over time. Friedman and Russell modeled each pixel that is present in a frame as an adaptive mixture model of three Gaussians distribution [1].Koller et al used a Kalman filter to track the changes that happen the background for every pixel [2]. These methods handled the illumination changes efficiently but couldn't cope up with the objects which were newly introduced or removed from the scene. Grimson et al used an adaptive non-parametric mixture model to solve the above problems [3, 4, 5]. A common optimization scheme used to fit a Gaussian mixture model is the *Expectation Maximization* (EM) algorithm. There are many online algorithms which have been introduced which can be classified into two groups. The first group was based on the parametric estimation of probability density functions (*pdfs*). To update the values using the new data without actually affecting the model. The procedure was first introduced by Nowlan [14] and explained based on the results that were obtained by Neal and Hinton [17]. Later, Traven derived an *N* most recent window version of the procedure [18]. McKenna *et al* [19, 20, 21] extended the result of Traven [18] to an *L* most recent window of the results from *L* batch EM runs and used it for tracking a multi-color foreground object.

P.KaewTraKulPong and R. Bowden *et al.* [6], presented a method which improved the adaptive mixture model by verifying the update equations again.
In this method [6], each pixel is modeled using a mixture of K Gaussians. K will have a value from 3 to 5. The probability that a certain pixel has a value $\mathbf{x}_N$ at time N can be expressed as

$$p(\mathrm{x}_N) = \sum_{j=1}^{K} w_j \, \eta(\mathrm{x}_N; \theta_j) \qquad \text{Eq. (2)}$$

Where w_k is the weight parameter of the k[th] Gaussian component. $\eta(x;\theta_k)$ is the normal distribution of the component k which is expressed by

$$\eta(x;\theta_k) = \eta(x;\mu_k,\Sigma_k) = \frac{1}{(2\pi)^{\frac{D}{2}}|\Sigma_k|} e^{\frac{-1(x-\mu_k)^T \Sigma_k^{-1}(x-\mu_k)}{2}} \qquad \text{Eq. (3)}$$

These K distributions are then arranged based on the fitness value which is given by w_k/σ_k. The first *B* distributions are used as the background model of the given scene and this *B* is estimated as

$$B = arg_b min\left(\sum_{j=1}^{b} w_j > T\right) \qquad \text{Eq. (4)}$$

Background subtraction is performed by marking any pixel which is 2.5 standard deviations away from the *B* distributions.

The Gaussian distribution that matches the test value will be updated using the following update equations

$$\hat{w}_k^{N+1} = (1-\alpha)\hat{w}_k^N + \alpha\hat{p}(\omega_k|\mathrm{x}_{N+1}) \qquad \text{Eq. (5)}$$

$$\hat{\mu}_k^{N+1} = (1-\alpha)\hat{\mu}_k^N + \rho\mathrm{x}_{N+1} \qquad \text{Eq. (6)}$$

$$\hat{\Sigma}_k^{N+1} = (1-\alpha)\hat{\Sigma}_k^N + \rho(\mathrm{x}_{N+1} - \hat{\mu}_k^{N+1})(\mathrm{x}_{N+1} - \hat{\mu}_k^{N+1})^T \qquad \text{Eq. (7)}$$

$$\rho = \alpha\eta(\mathrm{x}_{N+1}; \hat{\mu}_k^N, \hat{\Sigma}_k^N) \qquad \text{Eq. (8)}$$

$$\hat{p}(\omega_k = \begin{cases} 1; & if\ \omega_k \text{ is the first match Gaussian component} \\ 0; & \text{otherwise} \end{cases} \qquad \text{Eq. (9)}$$

If none of the *K* distributions match that pixel value, the least probable component is replaced by a distribution with the current value as its mean, an initially high variance, and a low weight parameter. Gaussian mixture models can handle sudden illumination changes but the only drawback in this algorithm is the speed of the algorithm.

VI. COMBINING MOTION DETECTION AND BACKGROUND SUBTRACTION

This method combines both motion detection and background subtraction to detect vehicles. The detection line is perpendicular to the road. And motion detection and the background subtraction are used for different parameters. The motion detection is used for creation of intervals. Intervals are created when the vehicle crosses the detection line and the intervals are closed when the vehicle leaves the detection line. This method can be used without specifying the road lanes. Absolute value of the inter frame difference of the detection line is found and then thresholded. This inter-frame difference may be obtained for several adjacent lines. And the differences of these lines are combined into one single line. This combined line is also again thresholded. The background subtraction methods are used to detect both stopped and also uniformly painted vehicles. Several parameters are used to find foreground objects like color, edge and intensity.

Table -1

Name Of the vehicle detection technique used	ACCURACY RATE	False alarms
Color and texture based vehicle detection (A)	97%	Low
Color and edge based vehicle detection (B)	95%	Low
Block matching algorithm (C)	90%	High
Improved adaptive Gaussian mixture model (D)	97%	High
Combining motion detection and background subtraction (E)	95%	High

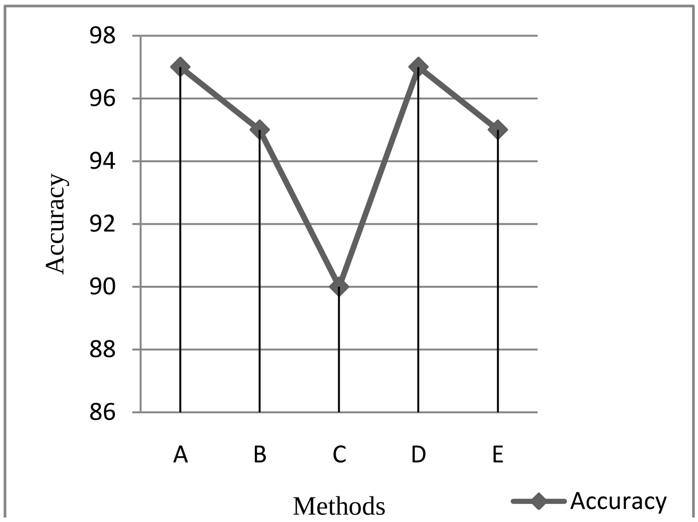

FIG 1: DETECTION ACCURACY

VII. CONCLUSION

This paper has given a complete survey on the various methods that available for vehicle detection in the day time with the image sequence obtained from a stationary CCTV camera at different views. Table 1 gives the accuracy in detection accuracy produced by applying each of the five methods.

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