

Vehicle Detection Based On Feature Extraction and SVM Classification

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ABSTRACT : Vehicle detection is very much important in avoiding accidents and for surveillance. Various features are used for the detection of vehicles such as edge detection ,corner detection, color transform, etc. The images background is removed using the Gaussian mixture model(GMM).Afterwards we will extract different features of the images using various methods.The extracted features want to be classified as belonging to vehicle or non vehicle. It is an important process so we go for classification task using the Support Vector Machine (SVM)classification, the process can be termed as the training phase since we are training the image as whether it contains the vehicle features or not. Database of the features of vehicle will be created during the training phase .Same procedure will be followed when we give an input image for the detection purpose such as it will undergo background subtraction using the Gaussian mixture model, the features will be extracted and the extracted features will be compared with trained phase to detect whether there will be vehicle pixel or non vehicle pixel available Using the Haar we can eliminate noise and find corners so as to enhance the detection.

Keywords - Edge Detection,EM GMM,HAAR ,SVM

1. INTRODUCTION

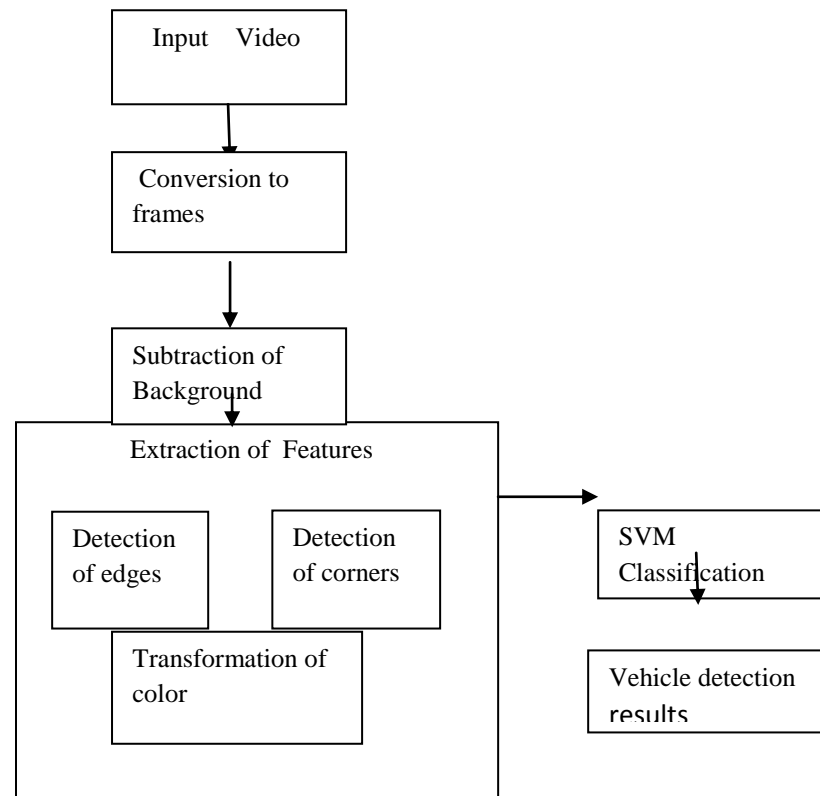
Detection of vehicles is very important in the monitoring scenario such as traffic and in military uses. Through video analysis we are detecting the vehicles. Statistics shows that vehicle accidents are occurring due to collision with other vehicles. A driver assistance system has attracted increasing attention in order to avoid accidents. . Vehicle detection—and tracking —has many applications including vehicles traveling in high speed in highways, and reckless driving. In particular, verification of vehicles is challenging due to variation in color,size etc. Panning, tilting, and rotation of camera motions are the challenges of vehicle detection in surveillance. Due to the flexibility and low cost image analysis has gaining interest. Camera positions, lightning conditions. will vary the view of vehicles. There is no specific vehicle models assumed, making the method flexible. However, when the contrast is weak their system would miss vehicles or when the neighboring objects influences are present. Since car roofs and windshields usually have different colors the major drawback is that a vehicle tends to be separated as many regions. Moreover, nearby vehicles might be clustered as one region if they have similar colors. Mean-shift segmentation algorithms high computational complexity is another concern.. Using cascade [1] classifiers we can identify the vehicles in the surveillance video. The problem here we face is many sample images are required for training and the rotated vehicles will be miss detected.

Stefan Hinz [2] used vehicle features using the hierarchical models. The detection using this method will end in false detection due to low clarity and other vehicles surrounding the corresponding vehicle. Choi and Yang [3] used method base on symmetry but the idea based on this will take the objects such as buildings and other constructed objects. Hoffmann and others [4] generated vehicle hypothesis using the symmetry and shadow but the detection will results in false detection due to the inaccurate hypothesis generation. Shastry A. C and others[5] used some constraints for the detection of objects in the video but the constraints will not accurate for all the videos so false detection will occur. Jon Arrospeide And Luis Salgado[6] used moments in determining the presence of vehicles in video because there are different types of vehicle there structure will be different and lot of images has to be take for comparison purpose.

The proposed system consists of two phases training phase and detection phase. Local edge and corner features were the features which we will extract in the training phase . In the detection phase same feature extraction is also performed as in the training phase. Afterwards the extracted features are used to classify pixels as vehicle pixel or non vehicle pixel using SVM. The detection task is based on pixel wise classification which is the distinguishing feature of the proposed framework . However, neighbourhood region of each pixels features are extracted.

2. VEHICLE DETECTION

The proposed system architecture consists of training phase and detection phase. We will explain each stages in detail .Both are very much important for the overall process. In training and testing process we are using the features of images .The below figure fig 1 gives the proposed workflow.



2.1 Subtraction of Background

The initial process which we are doing in the image sequences is the background subtraction. Gaussian mixture model(GMM) is used in the Subtraction process .Figure 2 gives the steps in GMM A Gaussian Mixture Model (GMM) is represented as a weighted sum of Gaussian component densities which is a parametric probability density function. GMMs are commonly used as a probability distribution of continuous measurements or features which is a parametric model .so in the process we use Expectation-Maximization (EM) algorithm. EM algorithm is often used to language modeling in which a data point is generated that is hidden from us which estimate parameters of a mixture model,. By randomly assigning values to all the parameters to be estimated the Expectation-Maximization (EM) algorithm starts processing. Expectation step and the maximization step will be alternated in the expectation maximization algorithm. In the E-step, expected likelihood will be computed for the complete data (the so-called Q-function) where the the computed conditional distribution of the latent variables is taken for expectation given the current settings of parameters and our observed data. In the M-step, by maximizing the Q-function it re-estimates all the parameters . we can repeat the E-step and another M-step once we have a new generation of parameter values. Until the likelihood converges this process continues, i.e., reaching a local maxima. Intuitively,EM will augment the data iteratively by predicting the values of the hidden variables and to estimate further the parameters by assuming that the true values are guessed. Background will be completely removed in this process and can be efficiently used for comparison between different purposes such as edge detection and for corner detection.

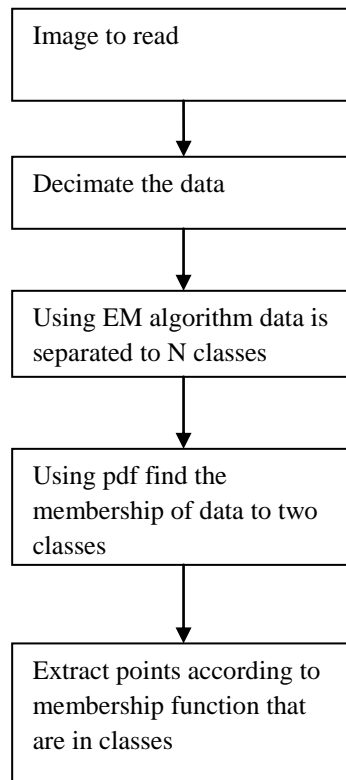


Fig. 2. Steps in GMM

2.2 Extraction of features

Here we extract the local features from the image. Such as edge ,corner detection and color transformation.

2.2.1. Edge and Corner Detection

Classical canny edge detector is used to detect edges Two thresholds are there in classical canny edge detector that is the lower threshold T_{low} and higher threshold T_{high} . Then we use method to find the thresholds according to different scenes using Adaptive thresholds . By following derivation we can find adaptive threshold, consider an image f with m pixels whose gray value at pixel (x,y) is denoted $h(x,y)$

The i th moment n_i of h is defined as,

$$n_i = \sum_j q_j k_j^i \quad (1)$$

Where j is the total number of pixel in image h with grey value k_j and $q_j = m_j/m$. First three moments of image h are preserved in the resulting image g .For bi-level thresholding, we would like to select threshold T .So as to detect edges with magnitude $D(x,y)$ of each pixel. Adaptive threshold found by equation is used as the higher Threshold T_{high} in the canny detector.

$$T_{low} = 0.1 \times (V_{max} - V_{min}) + V_{min} \quad (2)$$

Here V_{max} and V_{min} are the maximum and minimum gradient magnitudes in image. Intersection of two edges can be categorized as the corner detection. Gradient variation in the images can be represented as the corner. Consider a gray scale image I , Making displacement sweep a window $W(x,y)$ (u in x direction and v in right direction). $W(x,y)$ is the windows at position x,y . $I(x,y)$ is the intensity at x,y . $I(x+u,y+v)$ intensity at moved window. Haar Wavelet transform is used to represent image variations at different points. Variation in signal at different scales information can be obtained using wavelet representation. Simplest wavelet function which can be used for fast execution is haar.

2.2.2. Transformation of color

To identify vehicle pixels from background use Color transform model that has excellent capabilities. This color model transforms RGB color components into the color domain (u,v)

$$u_p = 2 Z_p - G_p - B_p / Z_p \tag{3}$$

$$v_p = \text{Max}(B_p - G_p / Z_p, R_p - B_p / Z_p) \tag{4}$$

Where (Rp, Gp, Bp) is the color component of the pixel p and $Z_p = (R_p + G_p + B_p) / 3$ is used for normalization. Vehicle colors are concentrated on less area than non vehicle colors so that we can easily identify the vehicle and non vehicle pixels. Under the u-v color model we can observe that vehicle colors and non-vehicle colors have less crossing regions. So we first obtain u-v components using color Transform and then use a support vector machine (SVM) to classify vehicle colors and non vehicle colors. Consider an \square_p pixel p we extract five types of parameters i.e., T,N,M, A, and E for the pixel p. The first feature S denotes the percentage of pixels in \square_p that are classified as vehicle colors by SVM. The features that we considered last is the size of the connected vehicle-color region and the aspect ratio where the pixel resides $A = \text{length/Width}$, and feature E is the vehicle color region pixel count.

2.2.3. Classification of vehicles using SVM

An SVM model is represented as examples that can be considered as points in space that can be categorized into different categories. A classification system is shown in fig 3. Support vector machine is primarily a classifier method that performs classification task in a multidimensional space that separate cases of different class labels by constructing a hyperplanes. SVM supports both classification tasks and regression and can handle multiple and categorical continuous variables. Dummy variables are created for categorical variables

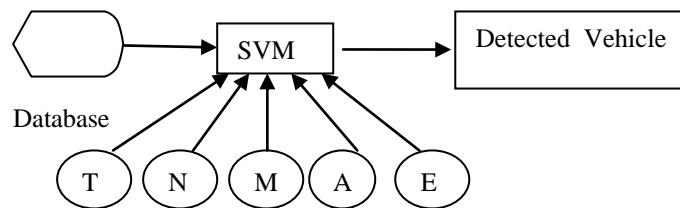


Fig. 3 . Classification using SVM

Here we use T, N, M, A and E which are the extracted features for training Support Vector Machine, during this training phase we create a database of vehicle features. After training phase the stored database is used for detection purpose.

3. RESULTS

For background removal we use GMM which is an efficient method. In log gabor filter method[1] for calculation vehicle pose was taken. Here we are using the edges and corners for the calculation. Video which we are giving will be converted to frames in the first step. The pixels which we obtained through these detection purpose will be used for classification purpose such as vehicle pixel or non vehicle pixel. There were some complexity while using neural networks in the previous method. Background colors are regarded as colors corresponding to the first eight highest bins and are removed from the scene. Each pixel would be transformed to u and v color components using the color transform method. Non vehicle area are taken as the blocks that do not contain any local features without the need of performing classification via SVM



Fig.4. Input Frame

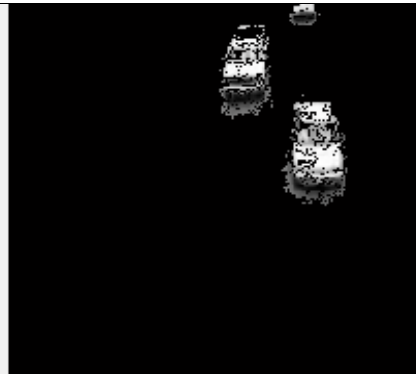


Fig.5. Background Subtracted Image

In fig,4 the input frames which we give for testing is given ,these frame is a video to frame converted image. These frame which are converted will undergo background subtraction using GMM .Using the canny edge detection we will get an edge detected image as in the fig 6.The training samples used to train the SVM classifier are less than the number of training samples required. Vehicle and non vehicle objects are classified based on color. Vehicles are represented by binary 1 and non vehicles are represented by binary 0 in the classification purpose. We need to select the block size to form sample when using SVM. By using GMM shadows will be removed. Each 3 x 4 block will be taken to form a feature vector. Pixels color would be transformed to u and v color components using (3) and (4). The edge detected images used to train the SVM are displayed in Fig. 6. Noise has been removed and the corners has been successfully depicted in fig 7.Notice that without the need of performing classification using SVM blocks that do not contain any local features are taken as non vehicle areas .



Fig.6.Edge Detection



Fig.7. Corner Detection with noise removal

For detection of vehicles we use Support Vector Machine (SVM). For final vehicle classification the parameters T, N, M, A, E which extracted are used to train SVM. Pixel classification yields the best detection accuracy which we can observe in the surveillance scenario. The vehicles which we obtained in the video will be depicted in a box as shown in the fig.8 so that we can identify the presence of the vehicle..Strict vehicle size or aspect ratio constraints is not depended in this work.



Fig. 8 . Detected vehicle

The results demonstrate good generalization ability and flexibility under different heights and camera angles on a wide variety of scenes.

4. CONCLUSION

We have proposed an vehicle detection system for images that does not depends on camera heights, vehicle sizes, and aspect ratios. The proposed detection system uses pixel wise classifications. Proposed detection system uses Gaussian Mixture Models (GMM) for background removal. Here we also use haar wave-let based feature extraction in the corner detection and for noise removal. False detection has been eliminated in this system. Edges are detected accurately so that the vehicle and non vehicle margin is correctly calculated. The experimental results demonstrate flexibility and good generalization abilities of the proposed method on a data set with images .

5. ACKNOWLEDGMENT

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