Vehicle Detection and Tracking by SVM Improving Surveillance System Efficiency

Sonal S. Chaudhari and Mr. Manoj D. Bagde

M.E. Student Digital electronics, Dept. of Electronics and Telecommunication, G. H. Raisoni institute of engineering & Management, Jalgaon, India

Ass. Prof. Dept. of Electronics and Telecommunication, G. H. Raisoni Institute of Engineering & Management, Jalgaon, India

ABSTRACT

In this an era of intelligence one of the challenging term is intelligent transportation system (ITS). Intelligent transportation system (ITS) has much attention on computer vision techniques, are mainly used to collect traffic parameters and analyze traffic behaviors for its surveillance. Traffic surveillance is important topic in intelligent transportation systems. This paper proposes vehicle detection and tracking method based on multiple vehicle salient parts using a stationary camera and also presents an effective traffic surveillance system for detecting and tracking of moving vehicles under various weather conditions traffic scenes using SVM classifier. It shows that spatial modeling of these vehicle parts is crucial for overall performance. First, the vehicle is treated as an object composed of multiple salient parts, including the license plate and rear lamps. In this model (MRF) we identify the detected vehicle part as graph nodes. After that, the marginal posterior of each part is inferred using loopy belief propagation to get final vehicle detection. Holes fill term employed to fill the background and get object clearly. Finally, the vehicles' trajectories are estimated using a Kalman filter and a tracking-based detection technique is realized. Two class classifier SVM is used for further modification in 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. It can be shown that this method adapts to partial occlusion and various lighting conditions Experiments also show that this method can achieve real-time performance.

Keywords —Kalman filter (KF), Markov random field (MRF), part-based object detection, tracking, vehicle detection, SVM classifier.

1. INTRODUCTION

Intelligent Transportation System (ITS) are used to reduce traffic jamming and to enhance shipment data. Traffic surveillance is an important topic in intelligent transportation systems. Robust vehicle detection and tracking is one challenging problem for complex urban traffic surveillance. Detection and tracking is one of the challenging technologies to detect the vehicle parts which are normally done in tracking. It is mainly focus on the vehicle detection and tracking. Computer vision techniques are mainly used to collect traffic parameters and analyze traffic behaviors for traffic surveillance. Various recent studies on vehicle detection and tracking has proposed systems that are very beneficial for traffic surveillance. In parallel control and management for intelligent transportation system has proposed overview of background concepts, basic methods, major issues and current applications of parallel transportation management system Video processing results can provide valuable information derived from the actual traffic world for PTMSs Various vehicle appearances and poses make it difficult to train a unified detection model. Reliable and robust vehicle detection is a fundamental component for traffic surveillance. Complex urban environments, bad weather, illumination changes, and poor/strong lighting conditions will degrade the detection performance dramatically. In particular, for traffic congestion, vehicles are occluded by each other so that separate vehicles will easily merge into a single vehicle. The parameter learning

 COPYRIGHT © 2018 IJREST, ALL RIGHT RESERVED

for the vehicle detection is also a critical issue. A detection method with complex parameters is usually not practical. The advances of machine learning techniques can be used to learn the parameters. In a weakly supervised approach for object detection was proposed. This method does not need manual collection and labeling of training samples. A boosting algorithm was extended to train samples with probabilistic labels.

In this paper, we aim to develop vehicle detection and tracking system particularly for urban traffic surveillance under various environments. The system utilizes a rear-view stationary camera to capture the image sequence. Rear-view vehicle detection and tracking method based on a high resolution camera. In practical traffic scenarios, occlusion between vehicles often occurs; therefore, it is unreasonable to treat the vehicle as a whole. Much research has detected the object by detecting its parts first and measuring their spatial relationships; this is called a part-based model. First, novel methods are propose to localize vehicle parts including the license plate and rear lamps, roof, corners, color features using their distinctive features. Second, MRF is used to propose a part based vehicle detection model and combined detected vehicle parts into vehicle. Detected object parts are combined into a vehicle using an MRF model in which parts are treated as graph nodes. 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 detection of vehicle first and then tracks the vehicle clearly and applied to the different video for the good result. Basically, this method implies two steps, first training i.e. data creation and second is testing i.e. created data then compared with evaluated data. After vehicle detection, vehicle tracking is implemented using KF. Vehicle classification is done using Support vector machine. It is realized that a detection-by-tracking technique in which the prediction locations of KF were added into the MRF model as graph nodes. That is detected vehicles are tracked by employing a Kalman filter (KF) to obtain vehicle trajectories. A detection-by-tracking strategy is realized to improve vehicle detection performance. This method can adapt to partial occlusion and various lighting conditions. The details of the system will be discussed in later sections.

2. LITERATURE SURVEY

Recent studies on vehicle detection and tracking by its salient parts in surveillance system has overcome various difficulties, such as occlusion, weather conditions, bad lightening conditions etc. Advanced researches have been made in intelligent transformation system in order to develop technique of object detection and tracking, such that will improve surveillance system efficiency. For vehicle detection and tracking it is necessary that method could detect object accurately, in different conditions. Rear-view vehicle detection and tracking by combining multiple parts of vehicle [1] method adapts to partial occlusions and various lightening conditions and achieve real-time performance. In parallel control and management of intelligent transformation system [2] overview of the background, concepts, basic methods, major issues, and current applications of parallel transportation management systems (PTMSs) was proposed. In [3], a weakly supervised approach for object detection was proposed. This method does not need manual collection and labelling of training samples. Video processing results can provide variety of information derived from the actual traffic world for PTMSs. Various kind of detecting and tracking algorithms have been developed. In good and stable lighting conditions, moving object detection methods are widely used for vehicle detection in ITSs. These methods can be classified into background modeling, frame differencing, and optical flow [4]. They can handle illumination change and apply to multimode and slight background change. However, there are some drawbacks in that they are unable to detect a stationary vehicle and the detected moving object is not necessarily a vehicle. Therefore, much research utilizes the visual features of the vehicle to detect it in a still image [5]. Features such as Gabor, color, edge, and corner are usually used to represent the vehicle. Then, they are fed into a deterministic classifier and a generative model to identify vehicles. In addition, researchers usually employ a two step method, including hypothesis generation and hypothesis verification [6], to locate the vehicle. This method works well during the sunny daytime but may fail during poor lighting conditions such as nighttime.

 COPYRIGHT © 2018 IJREST, ALL RIGHT RESERVED

Real time vehicle detection algorithms for vision based sensor have been developed.

Traffic surveillance during night time is one of the challenging task for ITS. Many recent studies on part-based models have been developed to recognize vehicles. According to a human cognitive study [7], a vehicle is considered to be composed of a window, a roof, wheels, and other parts. These parts are usually learned and detected by using their appearance, edge, and shape features. After part detection, the spatial relationship, motion cues, and multiple models are usually used to detect vehicles. The approach toward target representation and localization, the central component in visual tracking of non rigid objects, proposed [8]. The feature histogram based target representations are regularized by spatial masking with an isotropic kernel. The kernel-based tracking technique, when Effective nighttime vehicle detection, tracking, and identification approaches have been proposed for traffic surveillance by locating and analyzing the spatial and temporal features of vehicle lights using the SVM classifier[9].

The feature histogram based target representations are regularized by spatial masking with an isotropic kernel. The kernel-based tracking technique, when combined with prior task-specific information, could achieve reliable performance [8],[10]. Tracking of multiple, partially occluded humans based on static body part detection system were proposed that detects the body parts in single frames which makes the method insensitive to camera motions. The responses of the body part detectors and a combined human detector provide the “observations” used for tracking. It can work under both partial scene and inter-object occlusion conditions reasonably well [10]. After part detection, the spatial relationship, motion cues, and multiple models are usually used to detect vehicles. Winn *et al.* [11] decomposed an object into several local regions to detect them. The relationships between them were used to improve detection performance by a layout conditional random field model.[12] further expanded this method by using 3-D models to mark the learning samples. In addition, vehicle parts can be selected and learned automatically in a deformable part-based model [13]. Niknejad *et al.* [14] employed this model composed of five components, including the front, back, side, front truncated, and back truncated. Each component contained a root filter and six part filters, which were learned using a latent support vector machine and a histogram of oriented gradients features.

To use the part-based model in parameter transfer learning, Xu and Sun [15] proposed a basic learning framework named part-based transfer learning (PBTL). All the complex tasks are regarded as a collection of constituent parts, and each task can be divided into several parts, respectively. Transfer learning between two complex tasks can be accomplished by sub-transfer learning tasks between their parts. To avoid negative transfer and improve the effectiveness of transfer learning, Sun *et al.* [16] extended PBTL into an effective learning framework named multisource PBTL. By this, it is possible to focus on the parts that contribute more to the target task. The inference method is critical for a probabilistic graph model. In [17], Sun gave a comprehensive introduction of loopy belief propagation (LBP). The pros and cons of LBP were listed, and the improved methods were analyzed in detail with a sufficient survey of the literatures.

Vehicle detection at night-time is a dramatic challenge for traffic surveillance. Generally, vehicle headlights and taillights are used to represent the vehicle [18]. Robert [18] detected bright blobs as candidate headlights. To filter out false detection, they assumed that two headlights were aligned horizontally. Inspired by [18], Wang *et al.* [19] proposed a two-layer nighttime detection method. In the first layer, the headlight detection process was the same as in [18]. In the second layer, Haar features based on the AdaBoost cascade method were employed to recognize vehicle frontal views. Zhang *et al.* [20] modeled the reflection intensity map, the reflection suppressed map, and image intensity into an MRF model to distinguish light pixels from reflection pixels. For taillight detection, its color information is mostly utilized. O’Malley *et al.* [21] proposed a system to detect and track vehicle taillight pairs. Taillight candidates were extracted with a hue–saturation–value (HSV) color threshold and paired by their symmetry features. To detect nighttime brake lights, Chen *et al.* [22] modeled taillights using the Nakagami distribution. Vehicle tracking is used to obtain trajectories of moving vehicles, enabling higher level tasks such as traffic incident detection and behavior understanding. A detailed survey about object tracking is shown in [23]. Vehicle tracking can be classified into four categories: model-based tracking, region-based tracking, deformable template-based tracking,

 COPYRIGHT © 2018 IJREST, ALL RIGHT RESERVED

and feature based tracking. Various filtering algorithms are used in tracking tasks, such as the Bayesian filter, the KF, and the particle filter [14], [18]. Object tracking based on the mean-shift algorithm is an appearance-based tracking method and performs well tracking moving objects even in dense traffic [24]. However, this method needs manual initialization of a target model. In [25], kinematic variables including position, speed, and size of the vehicle were estimated with a projective KF to initialize the mean-shift tracker.

Different from the aforementioned methods, we treat the vehicle as an object composed of multiple salient parts, including the license plate and rear lamps. For classification purpose two-stage classifier used to obtain better results in proposed work. With the advance of the MRF model, the visual features and structure of the parts are modeled into probability distributions. Another important thing is use of inference method will help good experimental results from proposed system. Hence, the method proposed in this paper can adapt to partial occlusions and various lighting conditions.

3. VEHICLE DETECTION

Vehicle detection form the first step in video based analysis for different ITS applications. Accuracy and robustness of vehicle detection have a great importance in vehicle recognition, tracking, and higher level processing. The research effort in this field was divided into; motion based and appearance based techniques. Motion segmentation techniques use the motion cues to distinguish moving vehicles from stationary background. On the other hand, appearance based techniques employ appearance features of the vehicle like color, shape and texture to isolate the vehicle from the surrounding background scene. Some basic steps for vehicle detection are given in below secti*on.*

3.1 Part-Based Vehicle Detection

3.1.1 Outline of Vehicle Detection

Reliable and robust vehicle detection is one of the challenging issues in traffic surveillance. In practical traffic scenarios sometimes it is difficult treat the vehicle as whole due to occlusion between vehicles, so that it is unreasonable. In proposed system the vehicle is treated as an object consist of multiple salient parts, including rear lamps, number plate, side mirror, etc., which usually exist on each vehicle. These parts are localized using their distinctive color, texture, and region features. Then, an MRF model is constructed to model the spatial relationships among these parts to infer and localize the vehicle. In proposed system feature based vehicle tracking and identification process is applied to analyze the spatial and temporal information of these vehicle features from the consecutive frames using SVM. Thus, actual vehicles and their types can be efficiently detected and verified from SVM classifier to obtain accurate traffic flow information. Even if some parts are occluded, vehicles can be correctly detected. Meanwhile, this method can cope with several weather and lighting conditions.

An illustration of the system model for vehicle detection and tracking pipeline is shown in Fig. 1.

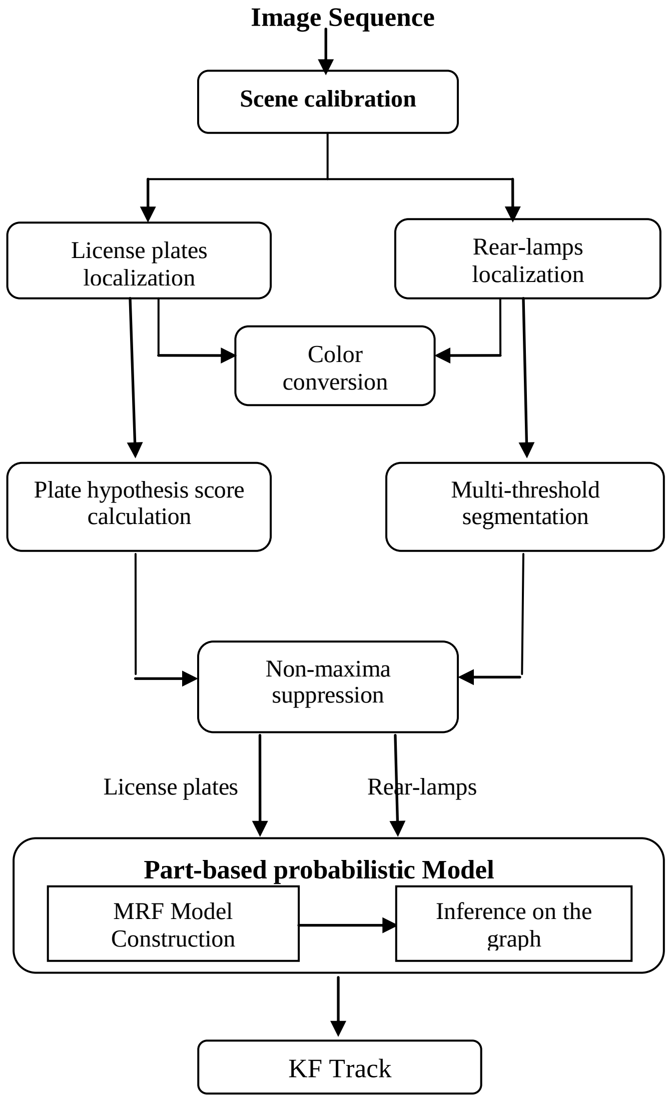


Fig 1.System model for vehicle detection and tracking

3.1.2 Number Plate Localization

Number plate detection is a vital technology in ITS. The Number plate includes a blue background/White character plate, a yellow background/black character plate, a white

COPYRIGHT © 2018 IJREST, ALL RIGHT RESERVED

background/black and -red character plate, and a black background and white character plate. In this section, we localize the number plates with a coarse to- fine strategy. It has its unique texture features that are distinguished from the other vehicle parts. The number plates generally include white background with black characters, in some other countries there may be different kind of plates include a blue background/white character plate, a yellow background/black character plate, a white background/black and- red character plate, and a black background and white character plate, etc.

Our license plate localization process is shown in Fig. 1. Here, we use plate with white background and black character plate. To get the width of the plate for each image coordinate,

3.1.2.1 Deriving Plate Color Converting Model:

We mainly utilized the color difference between plate characters and plate background. The vast majority of plate characters are white or black, whose values are not certain in HSV space. Consequently, we chose the red–green–blue (RGB) color space. A database of 50 license plate images was created for the blue–white pair. The color distributions of plate pixels are shown in Fig. 2. As observed, the plate background and plate characters have some unique characteristics [1]. For the plate background pixel, its value of the blue channel is far greater than those of the other two channels. Moreover, the values of the green and red channels are both relatively small. For the plate character pixel, the values of all three channels are relatively large. The characteristics were analyzed to find the appropriate color conversion for the plate. According to these observations, we converted the image into a specific color space as in

$Cx, y = Bx, y - \min\{Rx, y, Gx, y\}$ (1)

where Cx, y is the converted color of pixel (x, y), and Rx, y, Gx, y, Bx, y are the red, green, and blue channel values. The converted color image is shown in Fig. 3(b), which is also called the plate color image. The conversion can enhance the difference between the plate background and characters.

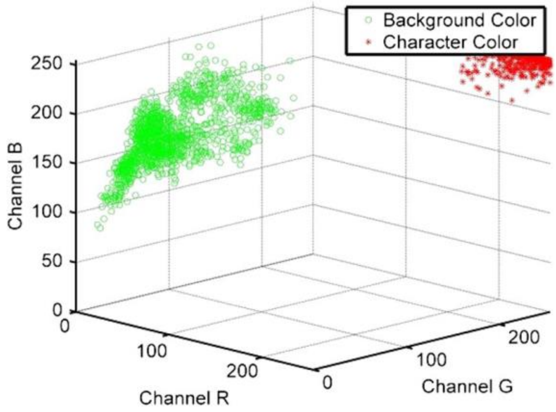
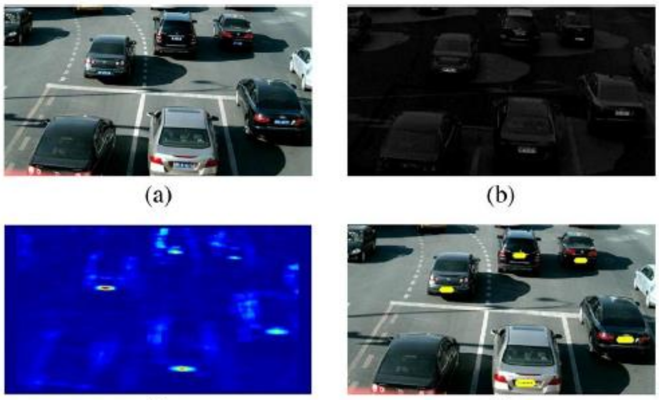


Fig. 2. RGB scatter plot of pixels from a database of license plate images for a blue background/white character plate.



(a) (b)

(c) (d)

Fig. 3. Example of the license plate location process. (a) Input image.(b) Converted license plate color image. (c) Score image obtained by gradient statistics. (d) License plate localization results.

3.2 Plate Hypothesis Score Calculation:

After color conversion, the image gradient was calculated for the plate color image. We calculated the image gradient by computing the difference between the maximum and minimum of the neighboring pixels, as calculated in

$\text{Grad}x, y = \max \{\text{Nb}x, y\} - \min\{\text{Nb}x, y\}$.................(2)

3.2.1 Rear Lamp Detection

Rear lamp detection is mainly focus on Multi threshold segmentation and connected component analysis. Original image is converted into R-G-B color image which satisfies some properties. The value of Red channel is large. The blue and green values are small. These values are identifying the color conversion for the rear lamp. The R-G-B color image is converted into gray scale image. For Multi-threshold segmentation is used to segment the rear lamp color image. For Connected component Analysis is to get the connected

 COPYRIGHT © 2018 IJREST, ALL RIGHT RESERVED

regions and select the rear lamp regions with areas. A vehicle rear lamp is an obvious feature of the vehicle. Usually the color of the vehicle rear lamp is red and falls within a specified range. We adopted the multi-threshold segmentation and connected component analysis to extract as many candidate rear lamps as possible. In this section, we focus on candidate rear-lamp localization without pairing them. The localization process is shown in Fig. 1.

3.2.2 Deriving the Color Converting Model:

Similar to license plate localization, we operated rear-lamp localization under the RGB color space. As observed, a rear-lamp pixel satisfies some unique properties. The value of the red channel is large. The values of the green and blue channels are small. The differences between the values of the green and blue channels are small. The characteristics were analyzed to find the appropriate color conversion for the rear lamp. The conversion can suppress the values of the non rear-lamp pixels. The RGB image was converted into a color gray-scale image, which is called the rear-lamp color image, as calculated in

$C_{x,y}=R_{x,y}-\max\{G_{x,y},B_{x,y}\}-2*\| G_{x,y}-B_{x,y} \|$ (3) where Cx, y is the converted color of pixel (x, y), whereas $R_{x,y}$, $G_{x,y}$, $B_{x,y}$ are the red, green, and blue channel values. The converted rear-lamp color image is shown in Fig. 4(b).

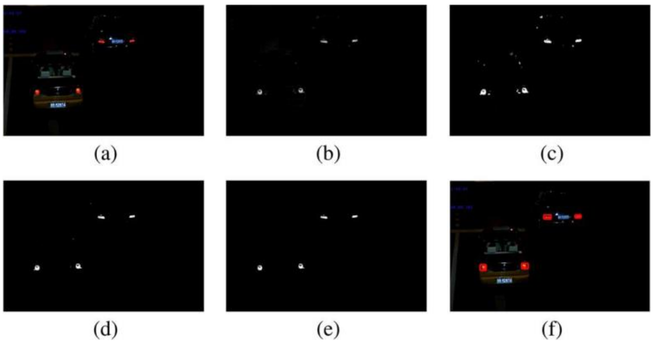


Fig. 4. Example of the rear-lamp localization process. (a) Input image.(b) Converted rear-lamp color image. (c)–(e) Binary images obtained by three thresholds ($\sigma 1 = 20$, $\sigma 2 = 40$, $\sigma 3 = 80$). (f) Rear-lamp localization results.

3.2.3 Rears-Lamp Candidate Generation by Multi-threshold Segmentation:

Motivated by the maximally stable extremal region detector , we adopted a multi-threshold segmentation method to segment the rear-lamp color image. To adapt to relatively dark and bright lamps, we used three thresholds to execute binarization. Three binary images were obtained, as shown in Fig. 4(c)–(e). Finally, a connected component analysis was used to extract candidate rear lamps on the binary images as follows.

Step 1) Get the connected regions by multi-threshold segmentation: $Q1$, $Q2$, $Q3$ ($Q_i \subset Q_{i+1}$).

Step 2) Select the rear-lamp regions with appropriate areas in the threshold ascending order, i.e., Area(Q_i) ∈ [γ_1, γ_2].

Step 3) Clear the remaining regions Q_k ($k < i$) and analyze the next connected region to Step 1. An NMS strategy was used to remove overlaid rear lamps. The final localization results are shown in Fig. 4(f).

4. Vehicle Detection Using MRF

Earlier, we localized the vehicle parts, including the license plate and rear lamps. Then, it became a challenge how to efficiently combine these parts into a vehicle. In this section, to make better use of the relationships among vehicle parts, we adopted an MRF model to localize the vehicle.

4.1 Probability Model Representation:

At first, we constructed an MRF graph model and defined its model parameters. Vehicle parts were treated as the graph nodes, and the relationships among them were the graph edges. First, we selected one detected license plate as a graph node in the current frame. Then, neighboring vehicle rear lamps were added into the graph if they were close enough to the license plate. In improved detection by tracking section, we will mention that tracking results are used to improve the detection results by adding predictions of vehicle location into the graph.

Graph G = {V, E} was constructed with one license plate and multiple rear-lamp candidates, where V ={v_1, v_2, . . . , v_n} are nodes denoting vehicle parts and E = {e_1, e_2, . . . , e_m} are edges denoting relationships among neighboring nodes. G is a complete graph and each pair of nodes is connected by an edge. Each node in G corresponds to a random variable F_i. Order f = {f_1,f_2... ,f_n} is a configuration of F. f_i belongs to Q = {1, 2, 3, 0}. In our MRF graph, there are four types of nodes:

- q = 1, license plate node;
- q = 2, left rear-lamp node;
- q = 3, right rear-lamp node;
- q = 0, false detection node.

This MRF model is a pair-wise model with the distribution in

 COPYRIGHT © 2018 IJREST, ALL RIGHT RESERVED

$$P(F) = \frac{1}{Z}\prod_{c\in C}\Psi_c(f_c) = \frac{1}{Z}\prod_{i\in V}\varphi(f_i)\prod_{(i,j)\epsilon E}\emptyset(f_i,f_j) \quad (4)$$

$$Z = \sum_F \prod_{i\in V}\varphi(f_i)\prod_{(i,j)\in E}\emptyset(f_i,f_j) \quad (5)$$

Where Z is a partition function. $\phi(f_i)$ is the node potential, representing detection confidence of each node. $\varphi(f_i, f_j)$ is the edge potential, representing the relationship between each pair of nodes. Then, we will determine the node potentials and edge potentials.

4.1.1 Node potentials:

The node potential $\phi(f_i = p)$ indicates the probability of node i to be part p without considering other nodes. It depends on the scores of part detectors S_i. To integrate the discriminative detectors into the MRF model, it is necessary to give a probabilistic meaning to the outputs. We introduce the sigmoid function to normalize the scores of the vehicle parts. The final node potential is

$$\varphi(f_i = p) = \begin{cases} \dfrac{1}{1+\exp\{A_P * S_i + B_p\}} & node\ i\ is\ detected\ as\ p \\ 1 - \dfrac{1}{1+\exp\{A_P * S_i + B_p\}} & p = 0 \\ \lambda & otherwise \end{cases}$$

4.1.2 Edge potentials:

The edge potential $\varphi(f_i=p,\ f_j=q)$ evaluates the compatibility between the neighboring nodes. It represents the relationship between the node pairs connected by an edge. A vehicle model is defined to model the edge potentials, as shown in Fig. 5. In the model, there are two main spatial relationships between vehicle parts, i.e., the relationship between the plate and a rear lamp, and the other one between both rear lamps as follows:

1) The distance between vehicle parts, i.e., $d(LP_i, LR_j)$ and $d(LR_j, RR_k)$;

2) The angle between vehicle parts, i.e., $\tan^{-1}(d_x(LP_i, LR_j)/d_y(LP_i, LR_j))$ and $\tan^{-1}(d_x(LR_j, RR_k)/d_y(LR_j, RR_k))$.

Since the poses of vehicles on the road vary greatly, we chose the Gaussian to model the spatial relationship between parts. In addition, since a variety of types of vehicles exists, the relationships between nodes might be multimodal.

5. Support Vector Machine

SVM is an efficient algorithm that was developed for recognizing 3D object in recent years and is new generation learning system based on recent advances in statistical learning theory. This supervised learning methods used for classification, regression, outlier detection. SVMs are developed based on the statistical learning theory of Vapnik. It is primarily a two-class classifier. The basic idea of the SVM is to map the training data of two object classes from the input space into a higher dimensional feature space. This is done via a mapping function, %. Then an optimal separating hyperplane with maximum margin is constructed in the feature space to separate the two classes.

The probability of the node to be false detection is obtained by computing the complementary probability of the detection. If node i is not detected as q, its probability is set to be a small constant λ (10^{-2} in this paper). The parameters A_p and B_p for each part were learned by the sigmoid fitting. For the rear lamps, there are no discriminative features, except their color. Therefore, its detection score was set to be a constant 0.8 by careful selection and cross validation. The corresponding sigmoid parameters were set to be $A_p = -1$ and $B_p = 0$.

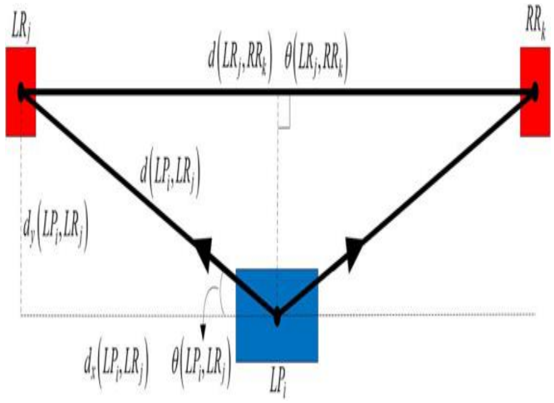


Fig. 5. Spatial relationship among vehicle parts.

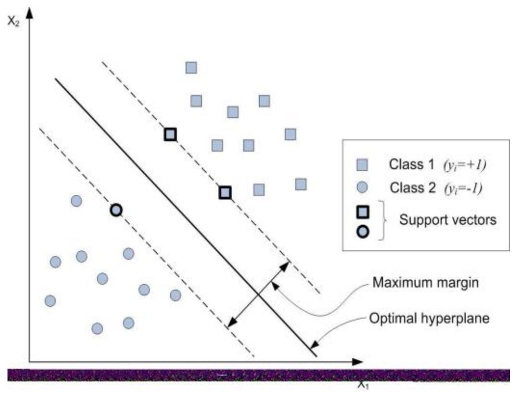


Figure 6: An example of the optimal separating hyperplane and margin for a two-dimensional feature space

 COPYRIGHT © 2018 IJREST, ALL RIGHT RESERVED

Given a set of l labeled training samples (input-output pairs):

(**xi**, y*i*), $i = 1, 2, ..., l$

where,

$x_i \in \mathbb{R}^N$ are the N dimensional input feature vectors and

$y_i \in \{-1, +1\}$ are the labels for Class 1 and Class 2

The decision function is defined as

$f(x) = \sum_{i=1}^{l} y_i \alpha_i k(x, x_i) + b$

The coefficients,α_i and bias, b are estimated from the training data. This is done by solving the constrained optimization problem with the aim of finding a separating hyperplane with maximum margin. Training data that are associated with a non-zero $\alpha_i$are the support vectors from Class 1 and Class 2. They are the data instances that sit on the boundary in the hyperspace. The optimization with the SVM resulted in a sparse representation of the input pattern since only a fraction of the training data are support vectors and used in the decision. k(**x**, **xi**) is the kernel function. The trick of using the kernel function is that we do not need to explicitly derive the mapping function, %, which in many cases is a non-trivial task. Instead, only the kernel function, which can be evaluated efficiently, is used in the training and classification.

The following are some commonly used kernel functions:

1. Linear
2. Radial Basis Function (RBF)
3. Polynomial

By using different kernel functions, SVMs have the flexibility of implementing different learning machines. In the thesis, the RBF kernel was chosen due to its high performance. It also requires a simpler parameter selection since there is only one parameter (γ) to be optimised. The correct choice of kernel parameters is critical for good classification results. In this experiment, we conducted an extensive search on the parameter space and used cross validation to find the parameters that give the best performance.

6. Vehicle Tracking

Vehicle detection has been described in the earlier sections. In this section, detected vehicles are tracked to obtain vehicle trajectories. A simple detection-by-tracking strategy was used to improve vehicle detection accuracy.

7. The Vehicle Tracking Module

After the vehicles are detected by the verification stage, they will be passed to the tracking function. The tracking function manages all detected vehicle in a tracking list and tracks their movement in subsequent video frame. By having tracking function monitor the detected vehicle, the relatively time consuming cueing and verification stages can be bypassed for certain video frame to improve overall speed of the system. This will not cause huge impact to the detection rate since a vehicle comes gradually into the scene overall several image frames. At every tracking cycle, the tracker updates the positions of the vehicle in the tracking list by trying to redetect the vehicle around the previous positions.

This is assisted by Kalman filter which predicts the trajectory and the most probable locations of the vehicle in the subsequent video frames. This will narrow down the search area for re-detecting a vehicle if a vehicle is detected in the search area, the tracking function will if it is near to any newly detected vehicle. Two nearby vehicles with size and aspect ratio close to each other will merge and the result updated to the tracking list. Ideally each tracked vehicle should be redetected if it does not leave the scene. However, due to occlusion and the variable contrast between vehicle and the road background, some vehicles are not redetected in every frame.

7.1 Outline of the Tracking Process

Vehicle tracking is used to predict vehicle positions in subsequent frames, match vehicles between adjacent frames, and ultimately obtain the trajectory of the vehicle. In our system, we used the KF to track vehicles. In statistics, the KF is a minimum variance estimation of linear movement. Each KF corresponds to a tracked object, which is called a tracker. It estimates the true values of observations with noise.

7.2 KF

In our system, we treated the center of the vehicle license plate and the speed of the vehicle as the state vector, which is shown as

$x = [p_x, p_y, s_x, s_y]^t$

Where px and py are x and y coordinates of the vehicle, respectively. sx and sy are the speeds of the x-axis and y-axis directions. KF is a recursive estimation method and can be split into two steps, i.e., prediction and update.

7.2.1 Prediction:

In the prediction step, we predicted state vector x and state error covariance matrix P at the current time k, as in

$$\hat{x} = F_{xk-1}$$

$$\widehat{p_k} = FP_{k-1}\,F^t + Q$$

Where, $x_k{-}1$ is the state of previous time $k - 1$; F is the state transition matrix; $\widehat{x_k}$ is the state of current time; $P_k{-}1$ and $\widehat{P_k}$ are error covariance matrices of the previous time k – 1 and current time k, respectively; and Q is the process noise covariance matrix.

7.2.2 *Improved Detection by Tracking*

The camera view is for rear-facing vehicles. When the vehicle enters the camera field of view, the vehicle parts can be seen without any occlusion. With the vehicle moving forward, the camera perspective is lower, which may cause severe occlusion of the license plate. Detection by tracking further improved by observing the inferences achieved in proposed system; such as repeated inferences were eliminate.

4. EXPERIMENTAL RESULTS

Final observation table from above results:

Video no.	Accuracy	Delay
Video 1	60 %	0.253 sec
Video 2	80 %	0.183sec
Video 3	90 %	0.166 sec
Video 4	90 %	0.167 sec

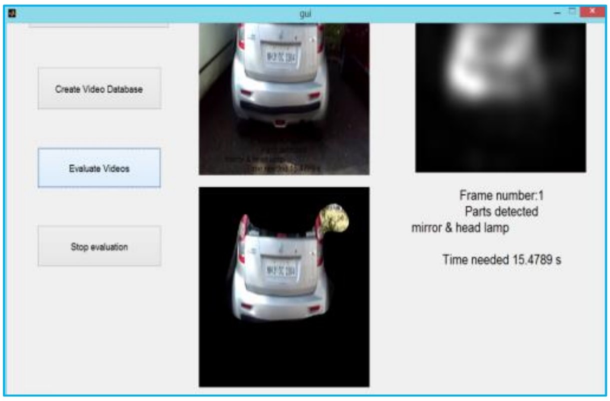


Fig.7: Evaluation result generated in GUI

5. CONCLUSIONS

Vehicle external features are particular to each model, allowing distinguishing one from others. In this system we proposed vehicle detection and tracking method based on a high-resolution camera. The input training dataset consist of number of frames in the form of video, which taken is from traffic area. Image pre-processing is carried, such that image denoising, enhancement, resizing, etc. in order to improve image quality in dataset. The object detection is carried out using part based model; saliency map of vehicle is proposed. Saliency map detection includes object features like gabor color, edges, rear images, rear lamps, etc., we combined these salient part for vehicle detection. Kalman filter is used to detect vehicle trajectory. The trained and tested data set features provided to train SVM classifier, which gives better classification results. Our method could adapt to partial occlusion and various weather conditions. The experiments showed that the proposed method could achieve real-time performance. In the output we can calculate time, accuracy of detection. However, the most recent approaches show that the evolution of computer vision techniques is increasing the ability to build a robust vehicle detection system based on its external features, allowing recognizing also the manufacturer and model. Proposed system is efficient for surveillance application, such as play an important role for civilian and military applications such as in highway traffic surveillance control, management and urban traffic planning. Vehicle detection process on-road are used for vehicle tracking, counts, average speed of each individual vehicle, traffic analysis and vehicle categorizing objectives and may be implemented under different environments changes. The SVMs may be more efficient and widely applicable than conventional methods, in classifying various complicated images with occlusion, shadow from other objects and noise problems, which factors are inevitable in real world images.

In future, we will work on detection of more salient parts of vehicle aiming to deal with different conditions such as severe occlusion, traffic congestion, posture, etc. The inference will also improve for better performances. In future the system will be integrated into embedded camera platform as a low cost implementation. Also, we look forward to minimize evaluation time for detection and to avoid percentage of false detection for better inference

 COPYRIGHT © 2018 IJREST, ALL RIGHT RESERVED

performance. This system could be a part of a wide variety of applications that include visual surveillance, traffic monitoring and access control, in special environments like motorways or parking lots.

6. REFERENCE

[1] Bin Tian, Ye Li, Bo Li, and Ding Wen, "Rear-view vehicle detection and Tracking by combining multiple parts for complex urban surveillance" IEEE Trans. on intelligent transportation systems, vol. 15, no. 2, april 2014

[2] F.-Y. Wang, "Parallel control and management for intelligent transportation systems: Concepts, architectures, and applications," IEEE Trans. Intell. Transp. Syst., vol. 11, no. 3, pp. 630–638, Sep. 2010.

[3] W. Wang, Y. Wang, F. Chen, and A. Sowmya, "A weakly supervised approach for object detection based on soft-label boosting," in Proc. IEEE Workshop Appl. Comput. Vis., 2013, pp. 331–338.

[4] C. Stauffer and W. E. L. Grimson, "Adaptive background mixture models for real-time tracking," in Proc. IEEE Conf. Comput. Vis. Pattern Recognit., 1999, vol. 2, pp. 246–252.

[5] Z. Sun, G. Bebis, and R. Miller, "On-road vehicle detection using gabor filters and support vector machines," in Proc. IEEE Conf. Digital Signal Process., 2002, vol. 2, pp. 1019–1022.

[6] H.-Y. Cheng, C.-C. Weng, and Y.-Y. Chen, "Vehicle detection in aerial surveillance using dynamic bayesian networks," IEEE Trans. Image Process., vol. 21, no. 4, pp. 2152–2159, Apr. 2012.

[7] W. W. L. Lam, C. C. C. Pang, and N. H. C. Yung, "Vehicle-component identification based on multistate textural couriers," IEEE Trans. Intell. Transp. Syst., vol. 8, no. 4, pp. 681–694, Dec. 2007.

[8] Dorin Comaniciu "Kernel-Based Object Tracking" IEEE Conference on Computer Vision and Pattern Recognition, IRI 99-87695, Vol.25,May 2003

[9] Dr. N.Raj kumar "Svm classifier for vehicle surveillance Under night time video scenes" IRACS-(IJCSITS), ISSN: 2249-9555, Vol. 2, No. 1, 2012T. vol. 42, no. 7, pp. 1297–1307, Jul. 2009.

[10] Bo Wu and Ram Nevatia "Tracking of Multiple, Partially Occluded Humans based on Static Body Part Detection" 2006 IEEE, Proc. IEEE Conf. Comput. Vis. Pattern Recognit., 2006

[11] J. Winn and J. Shotton, "The layout consistent random field for recognizing and segmenting partially occluded objects," in Proc. IEEE Conf. Comput. Vis. Pattern Recognit., 2006, vol. 1, pp. 37–44.

[12] D. Hoiem, C. Rother, and J. Winn, "3d layoutcrf for multi-view object class recognition and segmentation," in Proc. IEEE Conf. Comput. Vis. Pattern Recognit., 2007, pp. 1–8.

[13] P. F. Felzenszwalb, R. B. Girshick, D. McAllester, and D. Ramanan,"Object detection with discriminatively trained part-based models," IEEE Trans. Pattern Anal. Mach. Intell., vol. 32, no. 9, pp. 1627–1645,Sep. 2010.

[14] H. T. Niknejad, A. Takeuchi, S. Mita, and D. McAllester, "On-road multivehicle tracking using deformable object model and particle filter with improved likelihood estimation," IEEE Trans. Intell. Transp. Syst.,vol. 13, no. 2, pp. 748–758, Jun. 2012.

[15] Z. Xu and S. Sun, "Part-based transfer learning," in Proc. Int. Conf. Adv. Neural Netw., 2011, pp. 434–441, ser. ISNN'11.

[16] S. Sun, Z. Xu, and M. Yang, "Transfer learning with part-based ensembles," in Proc. Multiple Classifier Syst., 2013, pp. 271–282.

[17] S. Sun, "A review of deterministic approximate inference techniques for bayesian machine learning," Neur. Comput. Appl., pp. 1–12, 2013.

[18] K. Robert, "Night-time traffic surveillance: A robust framework for multivehicle detection, classification and tracking," in Proc. IEEE Conf. Adv. Video Signal Based Surv., 2009, pp. 1–6.

[19] W. Wang, C. Shen, J. Zhang, and S. Paisitkriangkrai, "A two-layer nighttime vehicle detector," in Proc. Digit. Image Comput., Tech. Appl., 2009, pp. 162–167.

[20] W. Zhang, Q. M. J. Wu, G. Wang, and X. You, "Tracking and pairing vehicle headlight in night scenes," IEEE Trans. Intell. Transp. Syst., vol. 13, no. 1, pp. 140–153, Mar. 2012.

 COPYRIGHT © 2018 IJREST, ALL RIGHT RESERVED

[21] R. O'Malley, E. Jones, and M. Glavin, "Rear-lamp vehicle detection and tracking in low-exposure color video for night conditions," IEEE Trans. Intell. Transp. Syst., vol. 11, no. 2, pp. 453–462, Jun. 2010.

[22] D.-Y. Chen, Y.-H. Lin, and Y.-J. Peng, "Nighttime brake-light detection by nakagami imaging," IEEE Trans. Intell. Transp. Syst., vol. 13, no. 4, pp. 1627–1637, Dec. 2012.

[23] A. Yilmaz, O. Javed, and M. Shah, "Object tracking: A survey," ACM Comput. Surv., vol. 38, no. 4, pp. 1–45, 2006.

[24] D. Comaniciu, V. Ramesh, and P. Meer, "Kernel-based object tracking," IEEE Trans. Pattern Anal. Mach. Intell., vol. 25, no. 5, pp. 564–577, May 2003.

[25] P. L. M. Bouttefroy, A. Bouzerdoum, S. L. Phung, and A. Beghdadi, "Vehicle tracking by non-drifting mean-shift using projective kalman filter," in Proc. Int. IEEE Conf. Intell. Transp. Syst., 2008, pp. 61–66.

[26] M. Cheon,W. Lee, C. Yoon, andM. Park, "Vision-based vehicle detection system with consideration of the detecting location," IEEE Trans. Intell. Transp. Syst., vol. 13, no. 3, pp. 1243–1252, Sep. 2012.

[27] J. Matas, O. Chum, M. Urban, and T. Pajdla, "Robust wide-baseline stereo from maximally stable extremal regions," Image Vis. Comput., vol. 22, no. 10, pp. 761–767, Sep. 2004

[28] Wen-Chang Cheng, Chih-Chuan Chen and Shan-Xiong Wei" Applying the Particle Filter and Classifier to Front Vehicle Detection and Tracking",IJETTCS Vol.1, ISSN 2278-6856 Sept.-Oct.20012.

 COPYRIGHT © 2018 IJREST, ALL RIGHT RESERVED