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Automatic Vehicle Detection Using Pixelwise Classification Approach

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Abstract : *We present a system to detect and track moving vehicles based on the pixelwise classification approach. In this approach escapes some of the existing frameworks for detection vehicles in traffic monitoring systems. So many researchers and intelligent minds are introduces so many technique but not provided the accurate results. Proposed technique uses designed pixel wise classification method, canny edge detection techniques and back ground color subtraction method that leads to accurate results in vehicle detection rate. Pixel wise classification provides not only region wise but also sliding window also detected the vehicles. The feature extraction performed in both training and detection stages. The classification purpose we use dynamic Bayesian networks and in this network vehicle and non vehicle are identify purpose used a support vector machine. The classification of vehicles and non vehicles are identification purpose used a color histogram algorithm. When we performed all the methods easily identify the vehicles and provides accuracy results to compare the previous approaches. In experimental results are shown in different videos are taken at different cameras and different heights in surveillance systems.*

Keywords – *Aerial surveillance, Canny edge detection, Dynamic Bayesian Networks, Soft Computing, and Vehicle Detection.*

I. INTRODUCTION

Traffic flow monitoring and traffic analysis based on computer vision techniques, and especially traffic analysis and monitoring in a real-time mode raise precious and complicated demands to computer algorithms and technical solutions of Traffic control departments are facing so many problems with the identification of vehicles in proper manner during the signal time which leads to over accidents and causes serious loss to living and non living things. In the previous so many of the researches applied approaches like sliding window, region based method, hierarchical method, multiple clues and etc [4],[5], but not satisfy the identifications approaches. So in this system pixelwise classification method provides better results in vehicle detection stages. In previous techniques are highly depends on vehicle sizes and colors, so that's only not provide accurate results. In present system do not depend any sizes and color of vehicles, it will be taken less amount of traing samples.

Identification of vehicles depends on the factors like size, shape, color, type, model and etc... As these factors changes from vehicle to vehicle identification becomes quiet complex and a challenging domain. This motivates the present result and a method is proposed referred as back ground color subtraction model based on pixelwise classification approach is mainly works in this way that is an aerial surveillance will be taken a video in different positions and angles. In this video is taken as input file and the input video file is extracted in based on the memory size of videos is extract the frames in some amount of pixels wise frames converted. The extercted frames will be selected any one frame and to perform the detected operation on the frame it will be detected the vehicles.

Videos are to be captured in the traffic monitoring system with the usage of digital cameras it is not possible and complex because streaming videos are takes lots of time. So to overcome the problems use digital cameras aerial surveillance video cameras are placed. The main functionality of this cameras are to record the video in the traffic without mankind help. To identify the vehicle a part of video is needed which can be taken from aerial video by providing parameters like time, area and etc.

Vehicles are identified for security purposes. At this end clarity plays a vital role. As the vehicles are mostly in movable positions their identification becomes complex for every second the pixel value changes. Sometimes the videos are large and at this point a compression algorithm is needed. With the usage of compression algorithms due to loss phenomenon existing with the compression technique there may be a chance of video loss which parallel reduces the identification of correct vehicle. Clarity of the camera, compression technique which is using during video compression plays a key role in the accurate identification of vehicle.

In the rest of paper is organized as follows. Section II guesses the proposed system framework and section III is desired vehicle results. Finally conclusion and feature recommended tasks are made in section IV.

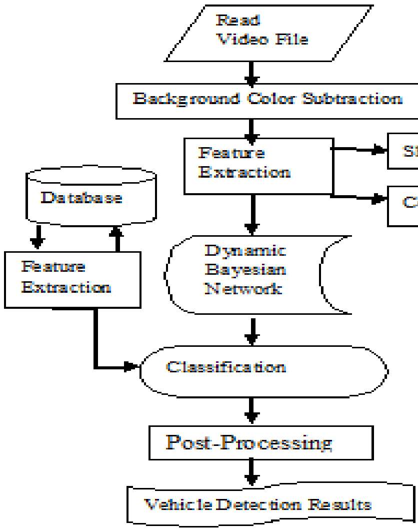

Fig 1: Proposed System Framework

II. PROPOSED SYSTEM FRAMEWORK

2.1Background Color Subtraction

Background Color subtraction is one of the classic techniques of the image processing. The back ground is removed in any images easy to identify objects in the real world. In this paper is a use to this technique provides better identification of vehicles in detection phases. This method is applied in entire regions of the network in traffic control systems and it will be used in color histogram algorithm. The algorithm is provides entire region of network provides color in bins wise. If you remove the color in frequently in subtraction of background you can easily identify vehicles and non vehicle regions in this process. Then we apply the canny edge detection and Harris corner detector is used to perform the reaming operation in vehicle detection process. It will increase the speed detection process when the completion of back ground color subtraction process.

2.1.1Color Histogram Algorithm

Step 1: Read video file database and extract RGB format pixel information from images.
Step 2: Create 48 bin normalized histograms for each of the RGB components of each image read from Database and each image will have 3 histograms associated with it.
Step 3: Color Histogram highest bins are frequently background color removed.
Step 4: Detected in pixels will not perform further subsequent detection process.
Step 5: Detection speed up increase and false alarm reduced.

2.2. Feature Extraction Techniques

Feature extraction is performed both training and detection phases. Feature extraction considers as local features and as well as color features in this system. In this method we extract the feature from the image frame. In this method we do the following Edge Detection, Corner Detection, color Transformation and color classification method is used to provide better results compared to existing approaches.

2.2.1 Local Feature Analysis

The image contains more information in pixels but each pixel contains corners and edges, so we use the Harris corner detector [8] is used to detect corners in vehicles. Next we use canny edge detector [6] is used to detect the edges in vehicles. In the edge detection based on the moment-preserving thresholding method will be calculating different scenes in aerial images of vehicles. In the canny edge detector, there are two importance thresholding. I.e. the lower threshold T_{low} and the higher threshold is T_{high}. As illumination in every aerial image differs to the desired threshold vary and adaptive thresholds are required in edge detection stages. The computational of Tsai's moment preserving method [10] is deterministic without iteration for L-level with $L < 5$. Its derivation of threshold is described as follows.

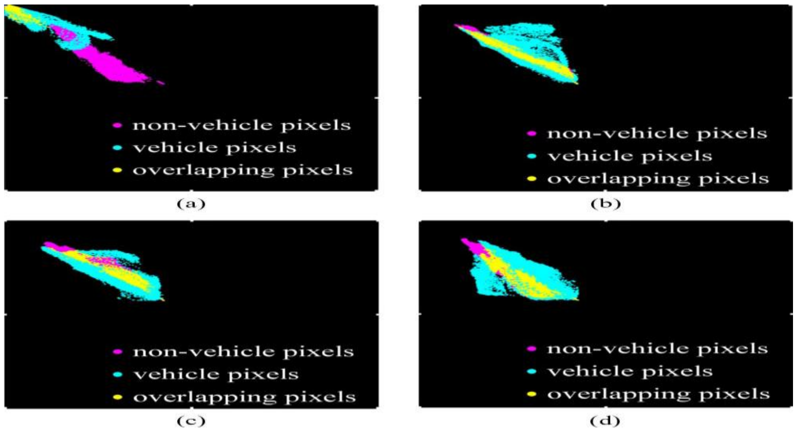

Fig 2: Vehicle color and non vehicle colors in Different Color Spaces (a) U-V, (b) R-G, (c) G-B, (d) B-R Planes.

Let f be an image with n pixels and f(x, y) denotes the gray value (x, y). The i^{th} moment m_i of f is defined as

$$M_i = (1/n) \sum_j n_j (z_j)^i = \sum_j p_j (z_j)^i, \quad i = 1,2,3,\ldots n \quad (1)$$

Where n_j is the total of pixels in image f with gray value z_j and $p_j = n_j/n$. For bi-level threshold, we would like to select threshold T such that the first three moments of image f are preserved in the resulting bi-level image g. let all the above threshold gray values in f be replaced by z_0 and all the above threshold gray values be replaced by z_1, we can solve for p_0 and p_1 based on the moment-preserving principle. After obtaining p_0 and p_1, the desired threshold T is computed using

$$P_{0 = (1/n)} \sum_1^T n_j. \quad (2)$$

In order to detect edges, we use the gradient magnitude G(x, y) of each pixel to replace the gray scale values f(x, y) in Tsai's method. Then the adaptive threshold found by (2) is used as the higher threshold T_{high} in the canny edge detector, we set the lower threshold as $T_{low} = 0.1 \times (G_{max} - G_{min}) + G_{min,}$ where G_{max} and G_{min} represents the maximum and minimum gradient magnitude in the images. Thresholds automatically and dynamically selected by our method give performance on the edge detections [9].

2.2.2 Color Transform and Classification

In this paper proposed new color transformation model is to separate vehicle colors [12] and non-vehicle colors from effectively. This color transforms (R, G, B) color components into the color domains (u, v), i.e.

$$U_p = (2Z_p - G_p - B_p) / Z_p \quad (3)$$

$$V_p = \max \{((B_p - G_p) / Z_p), ((R_p - B_p) / Z_p)\} \quad (4)$$

Where (R, G, B) is the R, G, and B color components of pixel p and $Z_p = (R_p + Gp + Bp)/3$. It has been shown in that all vehicle colors are concentrated in a much smaller areas on the u-v plane than in other color spaces and are therefore easier to be separated from non vehicle colors. SVM classification is used to non-vehicle color areas identified. The extraction process is five types is S, C, E, A, Z for a pixels. These features serve as observations to infer the unknown state of a DBN, which will be elaborated in the next sections.

S denotes the percentage of pixels in Λ_p that are classification as vehicle colors by SVM, as details in below

$$S = N_{vehicle\ color} / N^2 \quad (5)$$

Feature C and E are defined, respectively as

$$C = N_{corner} / N^2 \quad (6)$$

$$E = N_{edge} / N^2 \quad (7)$$

Similarly N_{corner} denotes to the number of pixels in Λ_p that are detected as corners by the Harris corner detector [8] ,and N_{edge} denotes the number of pixels in Λ_p that are detected as edge by the enhancement canny edge detector. The pixels that are classified as vehicle colors are labeled as connected vehicle color regions. A, Z are defined as the aspect ratio and the size of the connected vehicle color region where the pixel P resides. In this A=Length/Width, Z = count of pixels in "vehicle color region1" and Color classification is using SVM machine.

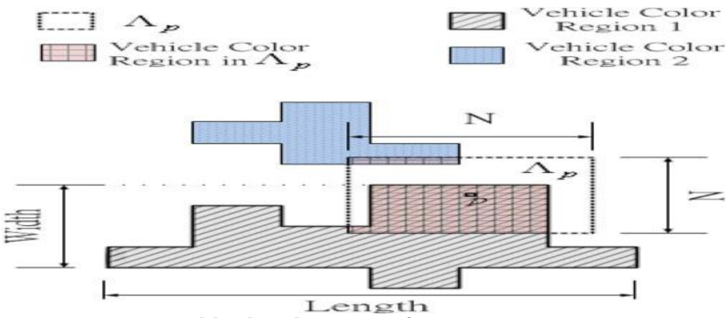

Fig 3: Neighborhood Regions for Feature Extractions

2.3. Classification

In this approach we perform pixel wise classification for vehicle detection using Dynamic Bayesian Networks (DBN). The DBN is performed in both training and detection phases. In the training stage, we obtain the conditional probability tables of the DBN model via expectation-maximization algorithm by providing the ground-truth labeling of each pixel and its corresponding observed features from several training videos. In the detection phase, the Bayesian rule is used to obtain the probability that a pixel belongs to a vehicle at particular time slice.

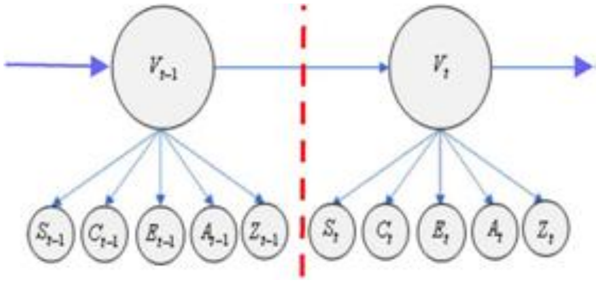

Fig 4: DBN model for Pixelwise Classification

The design of the DBN model is given fig: 4, a node V_t indicates if a pixel belongs to a vehicle at time slice t. In the state of V_t is dependent on the state of V_{t-1}. At each time slice t, state V_t has influences on the observation nodes S_t, C_t, E_t, A_t, and Z_t. The observations are not dependent in any others. Discrete observations symbols are used in our system. We use k-means to cluster each observation into three cluster types that are the training stage we obtains the conditional probability tables of the DBN model via exception maximization algorithm by providing the ground truth labeling of each pixel and its corresponding observed features from several training videos. In detection stage the Bayesian rule is used to obtain the probability that a pixel belongs to a vehicles. i.e.

$$P(V_t \mid S_t, C_t, E_t, A_t, Z_t, V_{t-1}) = P(V_t \mid S_t)\, P(V_t \mid C_t) \times P(V_t \mid E_t) P(V_t \mid A_t) P(V_t \mid Z_t) P(V_t \mid V_{t-1}) P(V_{t-1}) \qquad (8)$$

Joint probability $P(V_t \mid S_t, C_t, E_t, A_t, Z_t, V_{t-1})$ is the probability that a pixel belong to a vehicle pixel at time slice t given all the observations and the state of the previous time instance. Naive Bayesian rule of conditional probability the desired joint probability can be factorized since all the observations are assumed to be independent. $P(V_t \mid S_t)$ is defined as the probability that a pixel belong to vehicle at time slice given observation S_t as instance t[S is defined in eq (5)]. Terms $P(V_t \mid S_t)$,$P(V_t \mid C_t)$,$P(V_t \mid A_t)P(V_t \mid Z_t)$, and $P(V_t \mid V_{t-1})$ are similarly defined.

Proposed vehicle detection framework can also utilize a Bayesian Network (BN) to classify a pixel as a vehicle or non vehicle pixel. When performing vehicle detection using BN, the structure of the BN is set as one time slice of the DBN model.

2.4. Post processing

The post processing method we use morphological operations to enhance the detection mask and perform connected component labeling to get the vehicle objects. The size and the aspect ratio constraints are applied again after morphological operations in the post processing stage to eliminate objects that are impossible to be vehicles. However, the constraints used here are very loose. By using pre-processing technique reduced of the detection objects compare existing systems. If any vehicle is missing on the detection in starting stages will be detected in this stage.

III. DESIRED VEHICLE RESULTS

Research is a continuous process. If one imagine that research on a field is completed and then rephrase the sentence. Research continues beyond this point. In the literature, there are a lot of researches which are committed for predicting the precipitation to most accurate possible rate. Some of them used traditional methods of background color removed and edge detection techniques for prediction traffic control systems while other methods include recent developments like data mining, image processing etc.

Experimental results are demonstrated here. To analyze the performance of the proposed system, various video sequences with different scenes and different filming altitudes are used. The experimental videos are assuming any prior information of camera heights and target objects sizes for this challenging data set. When performing background color, we quantize the color histograms bins as16×16×16. Color corresponding to the first eight heights bins are regarded as background color and removed from the scenes. The input videos are extracted into frames by using pixelwise classification approach in fig 5.

To obtain conditional probability tables of the DBN, we select the training clips from the first six experimental videos displayed. The remaining four videos are not involved in the training process. Each training clips contains 30 frames, whose ground-truth vehicle positions are manually marked. The select size of the neighborhood area for feature extraction, we list the detection accuracy using is measured by the hit rate and the number of false positives per frame. There are a total of 224025 frames in the data set. When evolving the detection accuracy, we perform evolution every 100 frames. We can observe that the neighborhood Λ_p with the size of 7×7 yields the best detection accuracy. In this system vehicles are detected based on the input frame, the input frames are divided based on the video sizes.

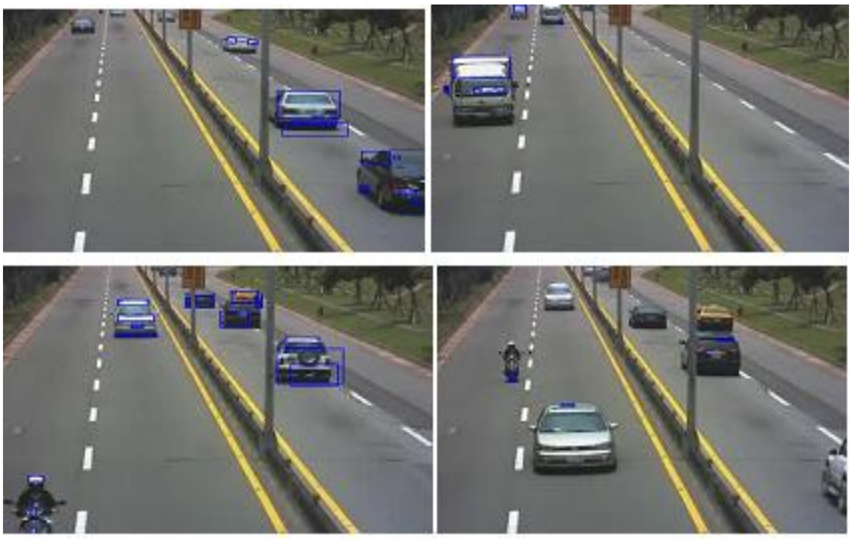

Fig5: input frames extracted from video file

. The videos are extracted so many frames then you select any one frame then automatically vehicles are detected based on frames. In this system don't depends any morphological operations and other aspect ratios. It will perform when the objects (vehicle) are moved are constant at any point of time, it will be detected. Mainly concentration on object size and number plate of object at any point of time in the traffic control system there in object it will be detected the vehicles results in fig 6.

The impacts of the enhancement canny edge detector on vehicle detection results can be observed. The results obtained results can be observed using the traditional canny edge detector with detector with moment preserving threshold selection. Non adaptive threshold can't adjust to different scenes and would therefore results in more majorities of the dynamic background removal process and the enhanced edge detector; we list different scenes in table. We can observe that the background removal process is improved for reducing false positives and the enhanced edge detector is essential for increasing hit rates.

Fig5: output of vehicle detection

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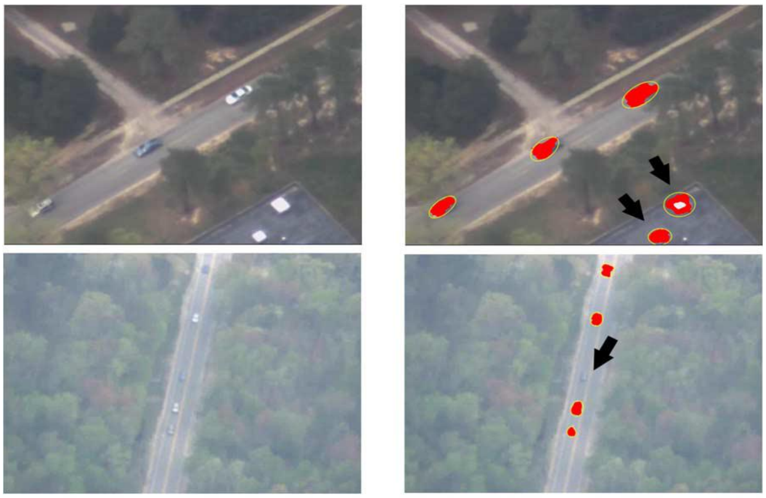
Table 1: Detection Accuracy Using Different Neighborhood Sizes

Size of Λp	Hit rate	Number of positives per frame
5×5	70.91	0.523
7×7	92.31	0.278
9×9	87.06	0.281
11×11	82.35	0.401
13×13	75.58	0.415

We compare different vehicle detection methods in fig. The moving vehicle detection with road detection method in requiring setting a lot of parameters to enforce the size constraints in order to reduce false alarms. However for the experimental data set, it is very difficult to select one dataset of parameters that suits all videos. The shape description used to verify the shape of the candidate is obtained from a fixed vehicle model and is therefore not flexible.



(a) (b)

Fig 6: Vehicle Detection Error Rate.

Table 2: Detection Accuracy of Four Different Scenarios

Scenarios	Hit rate	Number of false positives per frame
Without background removal and without enhanced edge detector	75.08	0.399
Without background removal and with enhanced edge detector	92.35	0.459
With background removal and without enhanced edge detector	74.96	0.297
With background removal and with enhanced edge detector	92.31	0.278

Fig: 6 show some detection error cases. In the fig: 6(a) displays the original image frames, and fig: 6(b) displays the detection results. The back arrow in fig: 6(b) indicates the misdetection of false positive cases. In the first row fig: 6 (a) the rectangle structures on the building are very similar to the vehicle. Sometime this rectangle structure would be detected as vehicle incorrectly. In the second row of fig: 6(b) the miss detection is caused by the low constraints and the small size of the vehicle .however, others vehicle are successfully detected in this challenging setting.

Fig: 7 show the average processing speeds of different vehicle detection methods. The proposed framework using BN and DBN cannot reach the frame rate of the surveillance videos, it is sufficient to perform vehicle detection every 50-100 frames. Tracking algorithm can be applied on the intermediate frames between two detection frames to track each individual vehicle. Therefore, high detection rate and low false alarm rate should be the primary considerations of designing detection methods given the condition that the execution time is reasonable.

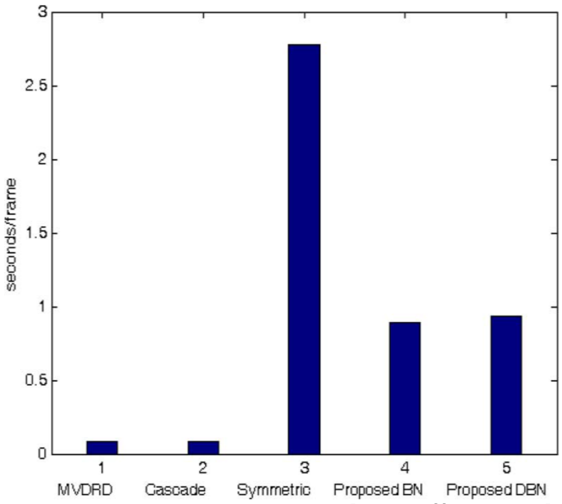


Fig 7: Pre-processing Speeds in Different methods.

IV. CONCLUSION AND FEATURE WORK

In this paper proposed an automatic vehicle detection system using pixelwise classification approach that does not assume any prior information of camera heights and vehicle sizes and aspect ratios. Instead of the region based classification, a pixelwise classification method is used in the vehicle detections using DBNs. The DBNs is used to easy to classification of regions. In this system regions are identified in two ways, these are vehicle regions and non-vehicle regions. These regions are using easy to detect the vehicles in this system in adjacent regions also. The extraction processes comprise not only pixel level information but also region level information. Vehicle color and non vehicle color identification to use SVM Classification method. More ever the number of frames required to train the DBN is very small. The Moment preserving threshold value is useful in the detection of vehicle corners and edges point of view. Detection purpose used enhance canny edge detector and corners is used to identify vehicles corners then increases the adaptability and accuracy for detection in various aerial images. In the proposed method any prior information of camera in different angles and different heights to taken. In this approach is provides better accuracy rates in vehicle detection and tracking. In this system is controlling the traffic monitoring system easily compare with existing systems.

For future work, will be performing vehicle tracking on the detected vehicle can further stabilize the detection results. Automatic vehicle detection and tracking is very important aspect of the intelligent aerial surveillance systems and also improve the morphological operations in pre- processing and post processing stages.

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