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Event Analysis in Intelligent Aerial Surveillance Systems for Vehicle Detection and Tracking

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Abstract— *Vehicle* ***detection plays an important role in the traffic control at signalized intersections. One of the Advanced Event Assistance systems are being researched nowadays for Intelligent Vehicles has to deal with the detection and tracking of other vehicles. The present system to detect and track moving vehicles based on detectors and classifiers. In previous approach escapes some of the existing frameworks for detection vehicles in traffic monitoring systems. Moving vehicles detection based on the pixelwise classification in both detectors and classifiers using multilayer perceptrons and Dynamic bayesian network. 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. In the classification used dynamic Bayesian networks and in this network vehicle and non vehicle are identification purpose use a support vector machine. The classification of vehicles and non vehicles are identification purpose used a color histogram algorithm. In this framework used two detectors and two classifiers. Two detectors for local feature extraction are Harris corner detector and canny edge detector. Then, two classifiers of color feature extraction, SVM and multilayer perceptrons are introduced. Both of them have good performance on vehicle color classification but we choice SVM for color feature extraction in our system. Finally, the training process and classification process of dynamic Bayesian network are utilized. In experimental results are shown in different videos are taken at different cameras and different heights in surveillance systems.***

Index Terms— ***Aerial surveillance, Canny edge detection, Dynamic Bayesian Networks, Multilayer Perceptrons Soft Computing, 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 technological solutions. Most convincing applications are in vehicle tracking, and the crucial issue is initiating a track automatically. Traffic analysis then leads to reports of speed violations, traffic congestions, accidents, or illegal behavior of road users. Various approaches to these tasks were suggested by many scientists and researchers. Capabilities of the system include vehicle tracking and vehicle detected features of the system in dynamic object (vehicle) is detected is main important issue in now a days. Intelligent video surveillance systems deal with the real-time monitoring of persistent and transient objects within a specific environment. The objective of this system is to gather high-resolution still images of an area under surveillance that could later be examined by human or machine analysts to derive information of interest. Currently, there is growing interest in using video cameras for these tasks. Video captures dynamic events that cannot be understood from aerial still images. It enables feedback and triggering of actions based on dynamic events and provides crucial and timely intelligence and understanding that is not otherwise available. Video observations can be used to detect and geo-locate moving objects (vehicles) in real time and to control the camera.

In 2006, the U.S. Department of Transportation estimated that America loses $200 billion a year due to freight bottlenecks and delayed deliveries. In addition, consumers lose 3.7 billion hours and 2.3 billion gallons of fuel sitting in traffic jams. Intelligent Transportation Systems include sensor, communication, and traffic control technologies. These technologies are assisting states, cities, and towns nationwide meet the increasing demands on the surface transportation system.

Vehicle detection and surveillance technologies are an integral part of IT'S since they gather all or part of the data that is used in ITS.

The goals of IT'S include the following:

- Enhance public safety.
- Reduce congestion.
- Improved access to travel and transit information.
- Generate cost savings to motor carriers, transit operators, toll authorities, and government agencies.
- Reduce detrimental environmental impacts.

It is estimated that an investment in ITS will allow for fewer miles of road to be built, thus reducing the cost of mitigating recurring congestion by approximately 35 percent nationwide. Vehicle detection and surveillance technologies are being improved to provide enhanced speed monitoring, traffic counting, presence detection, headway measurement, vehicle classification, and weigh-in-motion data. This summary document was developed to assist in the selection of vehicle detection and surveillance technologies that support traffic management and traveller information services. The information will also be useful to personnel involved in traffic data collection for planning, policy, and research purposes. Included are descriptions of common types of vehicle detection and surveillance technologies that include their theory of operation, installation methods, advantages and disadvantages, and summary information about performance in clear and inclement weather and relative cost.

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Following each technology description is vendor-provided information about specific sensor models, their functions and applications, users, and installation and maintenance costs.

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, but not satisfy the identification approaches. So in this pixelwise classification method provides better results in vehicle detection stages.

Aerial surveillance has a long history in the military for observing enemy activities and in the commercial world for monitoring resources such as forests and crops. Similar imaging techniques are used in aerial news gathering and search and rescue aerial surveillance has been performed primarily using film or electronic framing cameras.

The objective has been to gather high-resolution still images of an area under surveillance that could later be examined by human or machine analysts to derive information of interest. Currently, there is growing interest in using video cameras for these tasks. Video captures dynamic events that cannot be understood from aerial still images. It enables feedback and triggering of actions based on dynamic events and provides crucial and timely intelligence and understanding that is not otherwise available. Video observations can be used to detect and geo-locate moving objects in real time and to control the camera, for example, to follow detected vehicles or constantly monitor a site. However, video also brings new technical challenges.

One of the main topics in aerial image analysis is scene registration and alignment. Another very important topic in intelligent aerial surveillance is vehicle detection and tracking. The challenges of vehicle detection in aerial surveillance include camera motions such as panning, tilting, and rotation. In addition, airborne platforms at different heights result in different sizes of target objects.

In the rest of paper is organized as follows. Section II guesses the Literature survey, Section III relevant Techniques discussion; Section IV Results and Discussions and section V conclusion and feature work.

II. LITERATURE SURVEY

Airborne moving vehicle detection for urban traffic surveillance is proposed by Lin et al. in 2008[10]. This system proposed a method by subtracting background colors of each frame and then refined vehicle candidate regions by enforcing size constraints of vehicles. However, they assumed too many parameters such as the largest and smallest sizes of vehicles, and the height and the focus of the airborne camera.

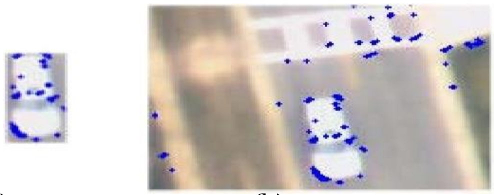
Vehicle detection from aerial images using local shapes proposed by Choi and Yang in 2009[12]. The proposed a vehicle detection algorithm using the symmetric property of car shapes. However, this cue is prone to false detections such as symmetrical details of buildings or road markings. Therefore, they applied a log-polar histogram shape descriptor to verify the shape of the candidates. Unfortunately, the shape descriptor is obtained from a fixed vehicle model, making the algorithm inflexible. Moreover, similar to the algorithm [13] in relied on mean-shift clustering algorithm for image color segmentation. The high computational complexity of mean-shift segmentation algorithm is another concern. Vehicle detection in aerial surveillance using dynamic bayesian networks proposed by Cheng et al. in 2012[1].The system proposed moving vehicle detection based on the pixelwise classification method. In this classification less amount of positive and negative sample need to collection for the training purpose and the detection stage moving vehicles are easy to detect [4] but this classification highly dependent on color segmentation algorithm. Different approaches are used to provide different techniques in vehicle detections. So some problem are there in this proposed system is solve the above problems and provides detection rates in less compared to previous frame works. The relevant techniques are used to develop a new framework in this system. The relevant techniques are explained in next section.

III. REVIEW OF RELEVANT TECHNIQUES

In this chapter, we introduce all the techniques that are used in our system. The following subsections including two detectors and two classifiers. Two detectors for local feature extraction are Harris corner detector and canny edge detector. Then, two classifiers of color feature extraction, SVM and multilayer perceptrons are introduced. Both of them have good performance on vehicle color classification but we choice SVM for color feature extraction in our system. Finally, the training process and classification process of dynamic Bayesian network.

3.1 Harris Corner Detection

Corner detection is an approach used within computer vision systems to extract certain kinds of features and infer the contents of an image. Corner detection is frequently used in motion detection, image registration, video tracking, image mosaicing, panorama stitching, 3D modeling and object recognition. Corner detection overlaps with the topic of interest point detection. The goals are what features are and why they are important and use the function corner Harris to detect corners using the Harris-Stephens method.



(a) (b)

Fig.1 : *Result of corner detection: (a), (b)*

In general, vehicles usually contain many corners even though they have different colors, orientations, sizes, or types. Therefore, corners can form a good feature for vehicle detection. In this paper, the Harris corner detector is used to extract various corners for the task of vehicle classification. Assume that I_x and I_y are the first derivatives of an image I in the x and y directions, respectively.

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Then, the detector operates on the matrix. Where Ne(x, y) is a local neighbourhood centered around (x, y) . If the two eigenvalues of M *are* large, then a small motion will cause significant changes of intensity at the point (x, y) . This indicates that the point is a corner. According to this observation, the corner response function CR is given by $CR = \det M - \kappa(traceM)^2$ where κ is a parameter set to 0.04. The local maxima of CR, which larger than a threshold will be regard as the corner's positions. Fig.1 shows the results of corner detection.

3.2 Canny Edge Detection

The Canny edge detector is an edge detection operator that uses a multi-stage algorithm to detect a wide range of edges in images. It was developed by John F. Canny in 1986. Canny also produced a computational theory of edge detection explaining why the technique works. Canny's aim was to discover the optimal edge detection algorithm. In this situation, an "optimal" edge detector means.

- *Good detection* – the algorithm should mark as many real edges in the image as possible.
- *Good localization* – edges marked should be as close as possible to the edge in the real image.

Input Vector Vehicle

Non-vehicle

- *Minimal response* – a given edge in the image should only be marked once, and where possible, image noise should not create false edges.

There are many ways to perform edge detection. However, the majority of different methods may be grouped into two categories:

- Gradient: The gradient method detects the edges by looking for the maximum and minimum in the first derivative of the image.
- Laplacian: The Laplacian method searches for zero crossings in the second derivative of the image to find edges. An edge has the one-dimensional shape of a ramp and calculating the derivative of the image can highlight its location.

Then it finds the gradient of image in highlight regions with high spatial derivatives. The algorithm will tracks along these regions and repress any pixel that is not at the maximum. Then remaining pixels that have not been repressed would be track. In traditional Canny edge detector two thresholds are selected and if the magnitude is below the lower threshold, it is set to zero (made a nonedge). If the magnitude is above the higher threshold, it is made an edge. And if the magnitude is between the two thresholds, then it is set to zero unless the pixel has connection to a pixel which gradient is above the high threshold. Following are the steps to implement the canny edge detector algorithm.

3.3 Multilayer Perceptrons (Mlps)

In addition to the SVM, we also try the multilayer perceptrons to classify vehicle pixels by colors. As shown in Fig. 2, the multilayer perceptrons we used including an input layer, one hidden layer with six neurons, and an output layer. Each neuron is with a sigmoid activation functions：

$$y_i = \frac{1}{1 + \exp(-v_i)}$$

where v_i is net internal activity level an y_i is the perceptrons, each node in one layer connects with a certain weight in the following layer. Learning occurs in the perceptron by changing connection weights after each piece of data is processed. It is a supervised learning, and is carried out through back propagation, a generalization of the least mean squares algorithm in the linear perceptron. The error in output node j in the nth data point by $e_j(n) = d_j(n) - y_j(n)$, where d is the target value and y is the value produced by the perceptron. Then we make corrections to the weights of the nodes based on those corrections which minimize the energy of error in the entire output, given by By the theory of differentials, the change in each weight. In programming applications, typically ranges from 0.2 to 0.8.

$$\varepsilon(n) = \frac{1}{2}\sum_j e_j^2(n)$$

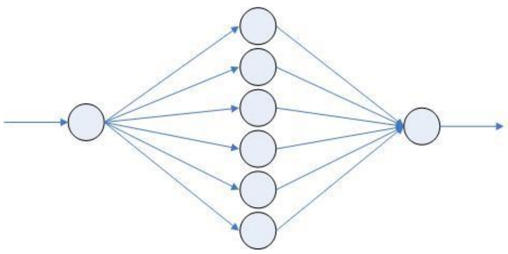

Fig 2: Structure of multilayer perceptrons

Nodes, which represent the output note that this depends on the change in weights of the k*th* layer. So to change the hidden layer weights, we must first change the output layer weights according to the derivative of the activation function, and so this algorithm represents a back propagation of the activation function.

III. PROPOSED SYSTEM FRAMEWORK

Intelligent video surveillance systems deal with the real-time monitoring of persistent and transient objects within a specific environment. The objective of this system is to gather high-resolution still images of an area under surveillance that could later be examined by human or machine analysts to derive information of interest. Currently, there is growing interest in using video cameras for these tasks. Video captures dynamic events that cannot be understood from aerial still images. It enables feedback and triggering of actions based on dynamic events and provides crucial and timely intelligence and understanding that is not otherwise available. Video observations can be used to detect and geo-locate moving objects (vehicles) in real time and to control the camera. The fig 1 shows the block diagram of proposed system.

3.1Background Color Subtraction

As the name suggests, background subtraction is the procedure of extricating the foreground objects from the background, in a sequence of video frames. Background subtraction is used in a lot of video functions, for example video surveillance, traffic monitoring, and motion recognition for human-machine interfaces, to name a few.

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Various systems are used for background subtraction, each one with different strengths and weaknesses in conditions of presentation and computational necessities. To consistently categorize parts of an image sequence as foreground or background is an important part of many computer vision systems, such as video surveillance, tracking and robotics. The scheme behind background calculation is to evaluate the present image with a reference image of the background, and from there choose on a pixel by pixel basis, what is foreground and what background is through examine the modification in the pixel series.

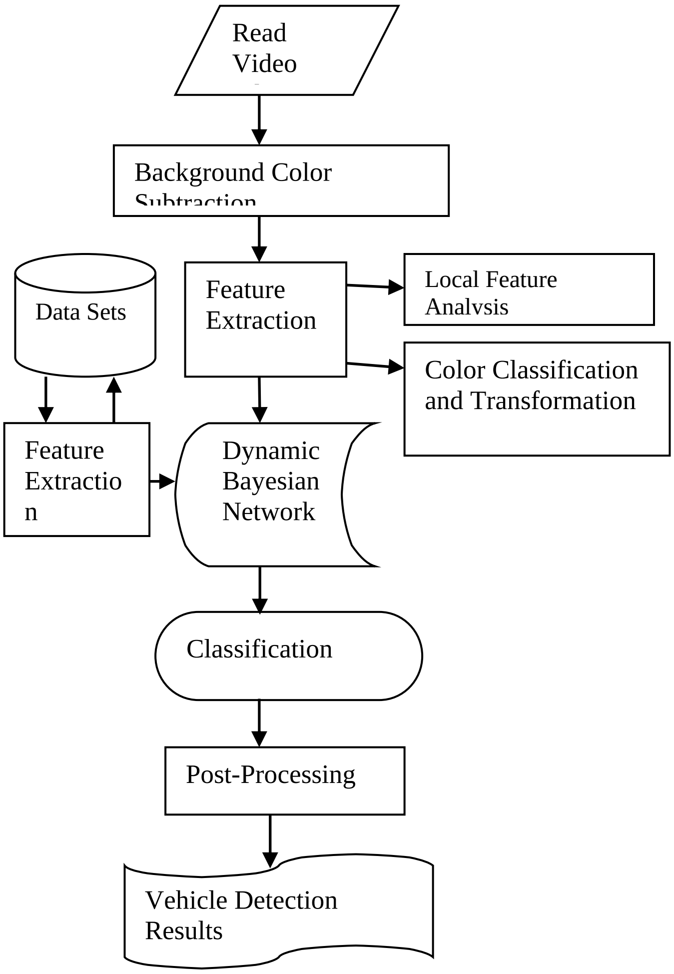

Fig. 3: Proposed system block diagram

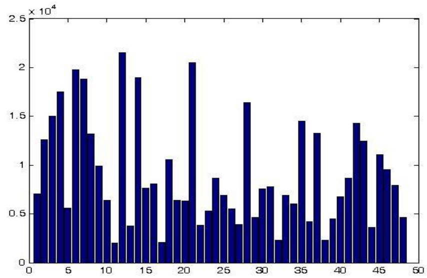

Fig. 4: Illustration of histogram bins of a frame

For real-time systems, frame-size and frame-rate reduction are commonly used to reduce the data processing rate. This method is applied in entire regions of the network in traffic control system and it will be used in color histogram algorithm.

Step 1: Read video file and extract RGB format pixel information from images.

Step 2: Create 48 bin normalized histogram of the RGB components.

Step 3: Three histograms associated in height of all bins.

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.

The background color subtraction to perform the pre-processing technique is important issue. In most computer vision systems, simple temporal and/or spatial smoothing is used in the early stage of processing to reduce camera noise. Smoothing can also be used to remove transient environmental noise such as rain and snow captured in outdoor camera.

For real-time systems, frame-size and frame-rate reduction are commonly used to reduce the data processing rate. If the camera is moving or multiple cameras are used at different locations, image registration between successive frames or among different cameras is needed before background modelling. Most of the algorithms handle luminance intensity, which is one scalar value per each pixel.

3.2.1 Shadow Detection

Shadows are caused by obstruction of light rays coming from a certain source. Shadows are characterized by two types of properties, photometric and geometric. Geometric properties depend on the type of obstruction and position of light source. Photometric properties determine relation of pixel intensity of background under illumination and under shadow. Geometric properties need a priori information such as object size or direction of light rays. Since our aim is to track object in outdoor environment we cannot rely on any a priori information. Since position of source of light (sun) would change during the day time. This would change both size and direction of shadows as the day progresses. We use two types of information for shadow detection they are mentioned below.

Spatial Information: Shadows are generally attached to the object. Shadows are attached to one side particular side of image blob. We can use this information to get rid of the false positive information.

Photometric properties: A pixel in image can be considered as background pixel, shadow pixel or foreground pixel (object). Studies have shown that illuminated background pixel and shadow pixel (background pixel under shadow) have approximately linear ratio.

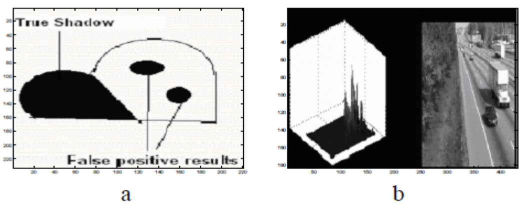

Fig.5: Background Generation.(a)Image Sequence 1.(b) Background for image sequence 1. The backgrounds are generated by performing median filtering on the input image sequences.

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3.3 Feature Extraction Process

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 extract the feature from the image frame. In this method do the following Edge Detection, Corner Detection, color Transformation and color classification methods.

3.3.1 Local Feature Analysis

The image contains more information in pixels but each pixel contains corners and edges, then use the harri's corner detector to detect corners in vehicles. Next use canny edge detector 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. Thresholding is based on low and high value of each image to be calculated. The canny edge detector, there are two importance thresholding. I.e. the lower threshold Tlow and the higher threshold is Thigh. As illumination in every aerial image differs to the desired threshold vary and adaptive thresholds are required in edge detection stages. Based on the vehicle moment to identify the automatically to calculate the threshold value.

The computational of Tsai's moment preserving method is deterministic without iteration for L-level with $L < 5$. Its derivation of threshold is described as follows. Let f be an image with n pixels and f(x, y) denotes the gray value (x, y). The ith moment mi of f is define as

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

Where nj is the total of pixels in image f with gray value zj and pj= $\frac{nj}{n}$, for bi-level threshold, 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 z0 and all the above threshold gray values be replaced by z1 and solve for p0 and p1 based on the moment-preserving principle. After obtaining p0 and p1, the desired threshold T is computed using p.

In order to detect edges 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 Thigh in the canny edge detector, then set the lower threshold as Tlow = 0.1 × (Gmax - Gmin) + Gmin, where Gmax and Gmin represents the maximum and minimum gradient magnitude in the images.

$$p = \frac{1}{n} \sum_1^T n_j \qquad (2)$$

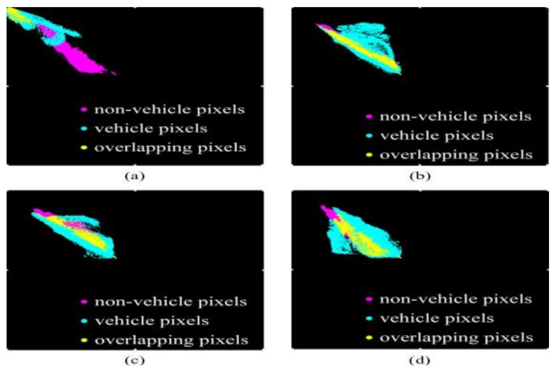

Fig. 6: Vehicle color and non vehicle colors in different color spaces (a) U-V,(b) R-G, (c) G-B, (d) B-R plane

3.3.2 Color Transform and Color Classification

In this paper proposed a new color transformation model is to separate vehicle colors and non-vehicle colors effectively. This system designs four different planes to combination of three colors. This color transforms (R, G, B) color components into the color domains (u, v). 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 are identified and the extraction process is five types is S, C, E, A, Z for a pixels.

$$U_p = \left(2Z_p - G_p - B_p\right) / Z_p \qquad (3)$$

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

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

$$S = \frac{\text{Nvehicle color}}{N^2} \qquad (5)$$

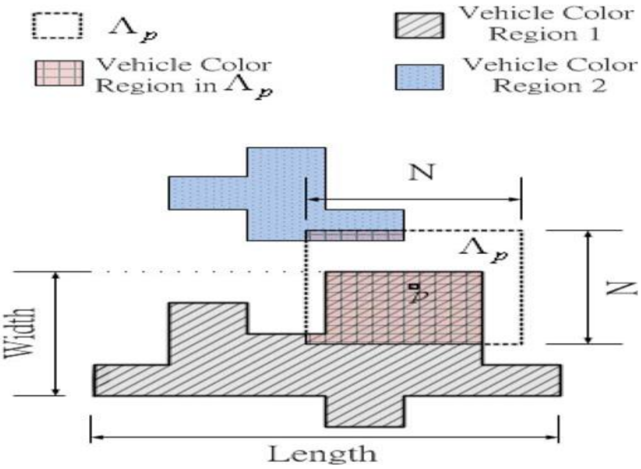

Fig. 7: Neighborhood regions for feature extraction

Feature C and E are defined, respectively as

$$C = \frac{\text{Ncorner}}{N^2} \qquad (6)$$

$$E = \frac{\text{Nedge}}{N^2} \qquad (7)$$

Similarly N_{corner} denotes to the number of pixels in Λ_p that are detected as corners by the Harris corner detector, 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.

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In this A=Length/Width, Z = count of pixels in "vehicle color region1" and Color classification is using Support vector Machine (SVM) machine.

3.4 DBN Classification

Bayesian networks provide a means of parsimoniously expressing joint probability distributions over many interrelated hypotheses. A Bayesian network consists of a directed acyclic graph (DAG) and a set of local distributions. Each node in the graph represents a random variable. A random variable denotes an attribute, feature, or hypothesis about which we may be uncertain. Each random variable has a set of mutually exclusive and collectively exhaustive possible values. That is, exactly one of the possible values is or will be the actual value, and we are uncertain about which one it is. The graph represents direct qualitative dependence relationships; the local distributions represent quantitative information about the strength of those dependencies. The graph and the local distributions together represent a joint distribution over the random variables denoted by the nodes of the graph.

In this approach perform pixelwise classification for vehicle detection using DBN. The DBN is performed in both training and detection phases. In the training stage 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. The design of the Dynamic Bayesian Network model is given fig: 3.3, a node Vt indicates if a pixel belongs to a vehicle at time slice t. In the state of Vt is dependent on the state of Vt-1. At each time slice t, state Vt has influences on the observation nodes St, Ct, Et, At, and Zt. The observations are not dependent in any others.

Discrete observations symbols are used in our system use k-means to cluster each observation into three cluster types that are the training stage 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.

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

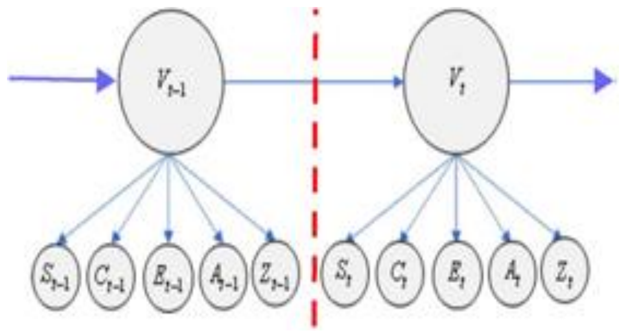

Fig. 8: DBN model for pixelwise classification

Joint probability P (V_t | 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|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(4.5)].Terms P(V_t|S_t) ,P(V_t|C_t) ,P(V_t|A_t)P(V_t|Z_t), and P(V_t|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 Bayesian Network, the structure of the BN is set as one time slice of the DBN model.

3.5 Post Processing

The post processing stage 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 the detection objects compare existing systems. If any vehicle is missing on the detection in starting stages will be detected in this stage. Post processing technique is important in this project because of the detection stage is useful.

In the detection stage identify the vehicles and non vehicles perform the post processing stage. But in this case detection rates are reduced and not identify the vehicles in previous systems. These frame work design a new morphological operations are used to improve of the identification of vehicles and detection in this system.

IV. RESULTS AND DISCUSSION

The experimental results are demonstrated here. To analyse 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 and 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. To obtain conditional probability tables of the DBN, to 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 and 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 and perform evolution every 100 frames. In the observation the neighborhood Λ_p with the size of 7×7 yields the best detection accuracy.

In this system designed to improve the performance compare to existing system. First click on detected vehicle button then detected the moving vehicles in fig. 9.

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The main system architecure and perform the different operations on this system . In this process first upload the video file. Click on browse button then chosee to where the video file is saved in system and to specify the path of video file in system to be select.

Fig. 9: Detected moving vehicles

The main system architecure and perform the different operations on this system . In this process first upload the video file. Click on browse button then chosee to where the video file is saved in system and to specify the path of video file in system to be select. Then next fig. 10 selects the play option then play video file and show the traffic monitoring system vehicles and non vehicles moving positions in this system.

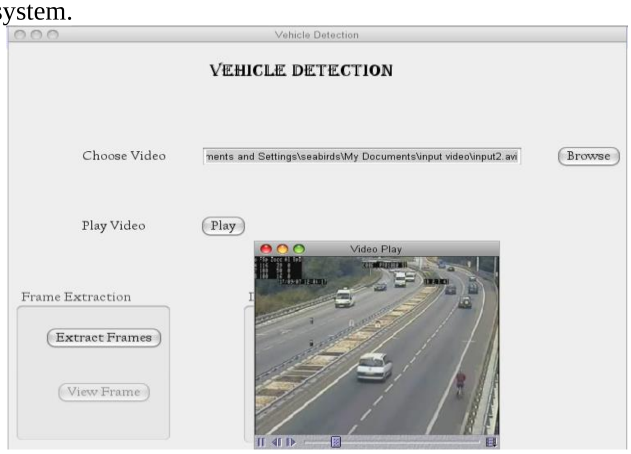

Fig 10: Play video file

Fig. 11 displays based on the video file size to be extracted the image frames in this stage. It shows the all image frames. Select any one of image frame then perform the detection operation. The selection of image frame is not a fixed, if select sequence or random order. Some of image frames are taken at night time the images are not shows the clarity that time also detect vehicles in this system easily by using background color subtraction and feature extraction process techniques.

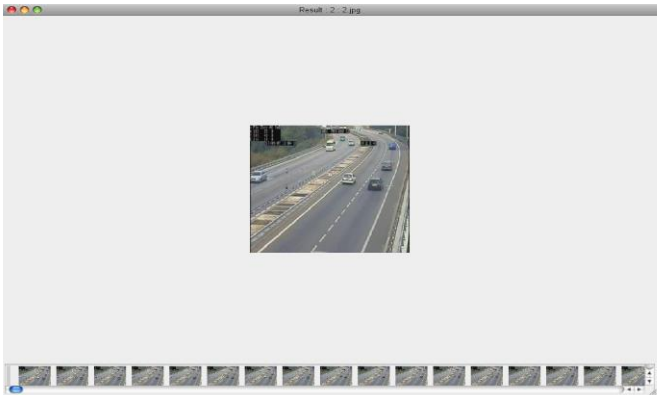

Fig. 11: View frames and select frame

Fig 12 shows the detect vehicles. In this system detected vehicles only not detected non vehicles (trees, man, buildings…etc). Moving vehicles are easy to detect in this system.

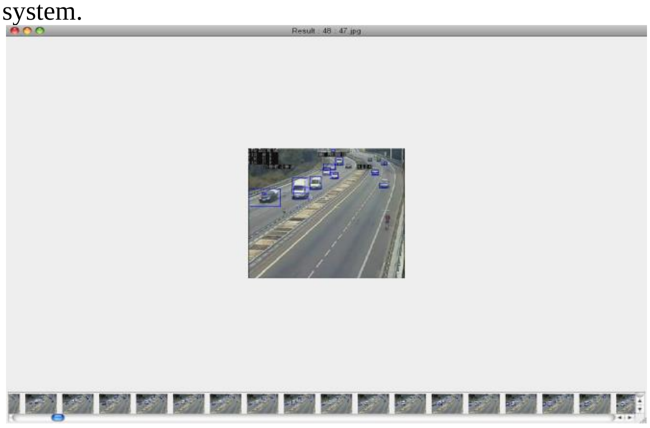

Fig. 12*:* Moving vehicles tracked and detected

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 color removal process and the enhanced edge detector, gather list of different scenes in table. This system observe the background color removal process is improved for reducing false positives and the enhanced edge detector is essential for increasing hit rates.

To be compare different vehicle detection methods in previous system table 1. 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.

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

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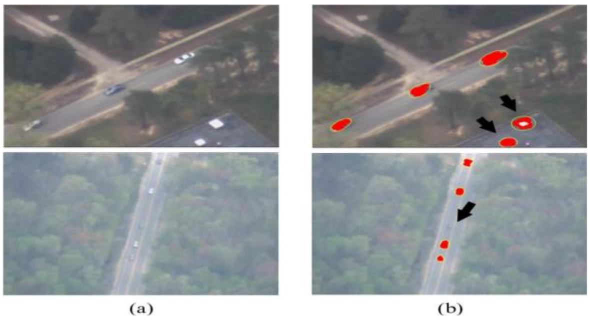

Fig 13: Vehicle detection error cases

Fig. 13 shows some detection error cases. Fig. `13(a) displays the original image frames, and fig. 13(b) displays the detection results. The back arrow in fig: 13(b) indicates the misdetection of false positive cases. In the first row fig: 13(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: 13(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.

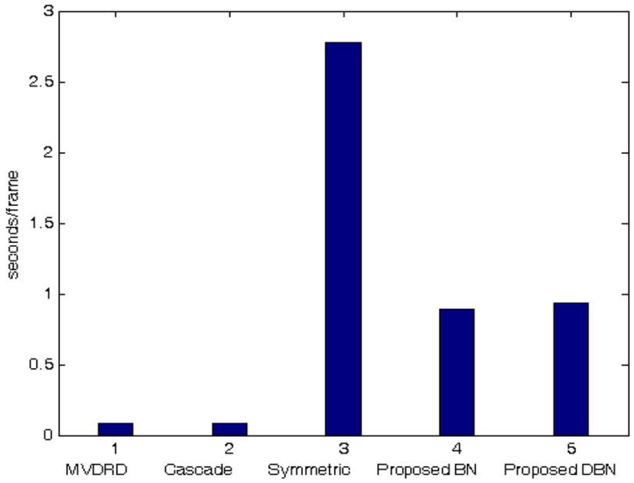

Fig 14: Pre-processing Speeds in Different methods.

In fig: 14 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.

V. CONCLUSION AND FUTURE WORK

The proposed framework 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 and detected 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 and tracking vehicles in very less amount of time is very important detection and tracking stages. To reduces the training local and feature extraction

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