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3D Model Based Vehicle Detection and Tracking

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ABSTRACT

Vehicle detection and tracking plays an important role for military applications such as in highway traffic surveillance control, management and urban traffic planning. In this paper a novel method is proposed for vehicle detection and tracking. This consists of four phases: 1) background subtraction 2) Boundary extraction and 3) feature extraction based vehicle detection and tracking. Two-way supervision dot based MOG subtraction method is used for background subtraction and an Enhanced Global Mass Differential Equation method is applied for boundary extraction. The proposed method gives a promising result when compared with other methods.

INTRODUCTION

One of the significant applications of video-based systems is the traffic surveillance. So, for many years of researches have investigated in the Vision-Based Intelligent Transportation System (ITS), transportation processing and traffic engineering applications to extract useful and precise traffic information for traffic image analysis and traffic flow control like vehicle count, vehicle tracking, vehicle flow, traffic density, vehicle velocity, traffic lane changes, license plate recognition, etc. In the past, the vehicle detection and tracking systems used to determine the charge for various kinds of vehicles for automation toll levy system. Recently, vehicle recognition system is used to detect (the vehicles) or detect the traffic lanes or check the type of vehicle class on highway roads like cars color, model. However, the traditional vehicle systems may be declines and not recognized due to the vehicles are occluded by other vehicles or by background obstacles such as road signals, trees, weather conditions, traffic problems etc., and the performance of these systems depend on a good traffic image analysis approaches to detect, track the vehicles.

Current vision-based question identification frameworks frequently depend on channel based component extraction by method for Gabor, Haar-like, or Gaussian subordinate channels. Appearance-based strategies are best in class in question recognition and large relevant to protest discovery issues. These strategies take in the attributes of question appearance from an arrangement of preparing pictures which catch the changeability in the vehicle class. Diverse blends of highlight extraction strategies and learning calculations are proposed to shape an appearance based protest recognition framework. Lately, the Viola and Jones quick protest identification approach turned out to be exceptionally prevalent. The framework is computationally proficient because of quick calculation of the Haar-like elements by method for the fundamental picture and the fell structure of the classifier. The approach utilizes a sliding window strategy which requires a quick calculation of the elements.

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The expansion in the quantity of vehicles on the roadway organize has constrained the vehicle administration organizations to rely on upon propelled advancements to take better choices. In this viewpoint airborne reconnaissance has better place these days. Airborne observation gives observing outcomes if there should arise an occurrence of quick moving targets since spatial territory scope is more prominent. One of the fundamental subjects in clever aeronautical reconnaissance is vehicle recognition and following. Elevated observation has a long history in the military for watching adversary exercises and in the business world for checking assets.

II. Related Work:

In [1] the author has presented a strategy for the airborne video enlistment and movement stream parameter estimation which concentrate on airborne video for estimation activity parameters. The airborne video is taken from an advanced camcorder connected to the slip of the helicopter. Move, pitch, a yaw of the helicopter makes the video hard to see, shaky and the inferred parameters less precise. The upsides of the framework incorporate intemperate dependence on sensor information, insufficient adjustment and accessibility of height maps.

In [2] considered various pieces of information and utilized a blend of specialists to combine the hints for vehicle recognition in elevated pictures. The framework comprises of shading division by means of mean-move calculation and movement examination by means of progress identification. The principle fault of this technique is that there is a great deal of miss preparing and miss identification.

In [3] have proposed a vehicle identification calculation utilizing the symmetric property of auto shapes. But this is inclined to false location, for example, symmetric points of interest of structures or street checking. With a specific end goal to dodge this, a log-polar histogram shape depiction is utilized to confirm the state of the applicants. The shape portrayal is acquired from the settled vehicle display, making the calculation resolute. Likewise the high computational unpredictability of mean-move division calculation is another worry.

In [4] the author proposed a vehicle following and characterization strategy to evaluate imperative activity parameters from video succession utilizing one camera. The framework can arrange vehicles into more particular classes by presenting once again linearity highlight in vehicle portrayal. Additionally this framework can without much of a stretch handle the issue of vehicle impediment brought about by shadows. This issue is understood by shadow calculation that uses an arrangement of lines to dispose of every undesirable shadow. Foundation subtraction is a procedure which intends to portion moving frontal area objects from a moderately stationary foundation. The favorable position incorporates its great exactness and drawback incorporate high computational cost and high execution time.

In [5] the author proposed an approach which lessens the calculation time and memory data transfer capacity. Here, a Bayesian approach is figured to choose the required number of Gaussian modes for every pixel in the scene. Advantage incorporate quick contrasted with GMM, proficient and precise. Detriment incorporates decrease calculation time**.**

Dhanya, *et al.*, 2014, proposed an effective traffic surveillance system to detect and track vehicles in night traffic. The vehicle headlights and taillights are used vehicle detection and tracking system Because at night only the features available for the vehicle is headlight and taillights.

(Chung-Cheng Chiu, *et al*., 2010) propose a real time traffic surveillance system for detection, tracking multiple vehicles in a image sequences. All the moving vehicle sequence is tracked in a sequence according to the frames in the video. The frame sequence and boundary extraction indicated the flow of vehicles in multiples.

III. 3D Based Automated vehicle Detection and tracking system:

In this paper, a novel framework is proposed preserves the advantage of the existing works and avoid there drawbacks. The framework shown in fig1 can be divided into the training phase and the detection phase. . In this paper a novel method is proposed for vehicle detection. This consists of four phases: one is background subtraction phase ,edge/corner detection ,feature extraction and vehicle detection and tracking .In the first phase the background color will be subtracted from the video. In the second phase the edges/corners of the object will be detected and places the color transform. In the third phase the feature extraction is processed by extracting the features from the image frame .In fourth phase the vehicle detection and tracking i.e., vehicle will be tracked from the video. Such design is more effective and efficient than region-based or multi scale sliding window detection methods

A. Background Subtraction:

In this paper, the background has been subtracted by applying the Two-way supervision dot based MOG subtraction method is used because of the following reason.

- The proposed method analyzes the illumination changes and shadow of the vehicle in the moving or multi-model background (sand and grassy) with efficient manner.
- The method consumes the same database for foreground and background analysis of the particular vehicle.

- In addition the proposed method analysis the video frames in terms of past to present and future to present concept which provides the efficient background modeling video frame. This leads to eliminate the several challenges like, shadow, illumination changes, multiple backgrounds.
- The proposed method uses the accepted delay (0.33) for analyzing the video frames of the moving objects in the real applications.

To carry out the background subtraction process the background has to be modeled first then the frame differencing concept has to be carried out among various frames sequentially. The background subtraction is done with the help of three frames. They are current frame, previous frame and next frame. The comparisons between these frames give the subtracted background.

The shadow is also a prominent task for this process because there are chances of misdetection of shadow as an object. Therefore the shadow has to be removed. The shadow is of two types. They are cast shadow and self shadow.

The Self shadow is one which falls on the object that is vehicle. So this cannot be eliminated. The cast shadow which falls on the ground has to be removed to obtain a better background subtracted object.

Algorithm: Background modeling:

```
Load input
For each frame at time t
1. Learning Stage (Process this stage every C frames)
 For each pixel (u,v) in ROI template
If I(u,v) > TROIthen
Process pixel (u,v) in current frame
- Update mean for each channel (Red, Green and Blue)
mean(u,v) = (1-LR)*mean(u,v)+LR*I(u,v)
- Calculate variance (σ^2) for each channel
var(u,v) = (1-LR*LR)*var(u,v)+ (LR*(I(u,v)-mean(u,v)))^2
If var(u,v) < min_var then
var(u,v) = min_var
```

2. Classification Stage:

```
For each pixel (u,v) in ROI template
If I(u,v) > TROIthen
Process pixel (u,v) in current frame
- If for each channel
I(u,v)-mean(u,v)<T*(var(u,v))^0.5
then
FGt(u,v) = 0 %Background
else
FGt(u,v) = 1 %Foreground
else
FGt(u,v) = 0 %Background
```

3. Post-processing Stage:

```
For each pixel (u,v) in detected foreground
Look into M×M neighborhood and count number of foreground pixels k.
If k<Tneig
then
FGt(u,v) = 0 %Background
Do connected component analysis and create a list of blobs %foreground objects
For each blob j
If Area(blob(j))<min_Area
Assign blob j to background %remove it from
%foreground
%object list
```

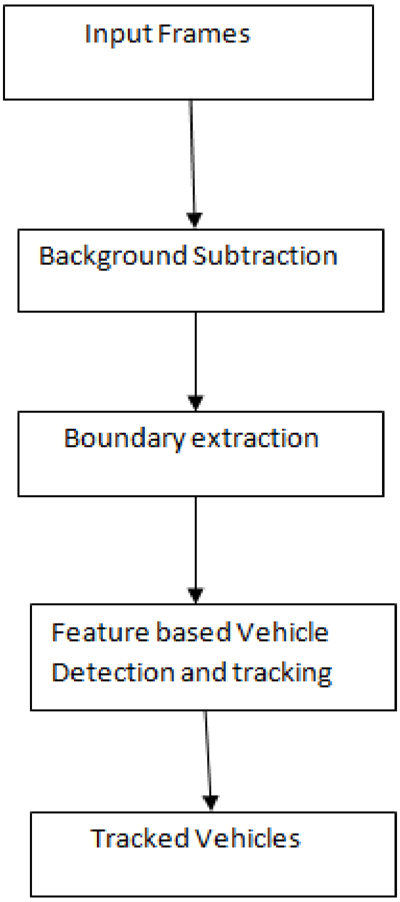

Fig. 1: Vehicle Detection and Tracking System

The method analyze the captured the video frames, pixel by pixel which analyze the illumination changes and the moving object background simultaneously. The method fixed the accepted delay value while analyzing the video frame which leads to produce the future N frame. From the n frame the background has been analyzed. During the background analysis process, the pixel is evaluated for analyzing the illumination changes and the same pixel is evaluated based on the future frame, for analyzing the background of the video frame. In the moving object the background and foreground is estimated and modeling by applying the MOG method. The MOG method investigates that the probability value of the each pixel, which is compared to the three different components. If the pixel having the darker value which is considered as the shadow that has been removed. From the remaining components, the largest variance considered as the vehicle and other one is treated as the road which needs to be removed. This process is repeated for all moving objects to remove the illumination changes, shadow and multiple backgrounds from the video frame. This modeled background models are fed into the next phase for extracting the meaningful edges and boundaries with efficient manner.

The shadow is also a prominent task for this process because there are chances of misdetection of shadow as an object. Therefore the shadow has to be removed. The shadow is of two types. They are cast shadow and self shadow.

The Self shadow is one which falls on the object that is vehicle. So this cannot be eliminated. The cast shadow which falls on the ground has to be removed to obtain a better background subtracted object.

Algorithm: Shadow removal:

Inputs: BK, fr_shadow
Output: fr_shadowless
Steps:
1. Compute the difference between fr_shadow and BK
and convert the result to black & white image
Diff=abs(BK- fr_shadow)

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Diff=im2bw(Diff)
2. Normalize the frame
fr_shadow= fr_shadow / BK
3. Apply Gamma Decoding to the normalized frame
fr_shadow=A * fr_shadow γ
4. Convert fr_shadow from RGB image to grayscale image
fr_shadow= RGBtoGrayscale(fr_shadow)
5. Compute the suitable threshold using Otsu's method
Thresh= Otsu's method (fr_shadow)
6. Thresholding fr_shadow
For i=1 to fr_height
For j=1 to fr_width
If Diff(i,j) > 0 then
If fr_shadow(i,j) > Thresh then
fr_shadowless(i,j)= fr_shadow(i,j)
else
fr_shadowless(i,j)= 0
end if
end if
end for
end for

B. Boundary Extraction:

The 2 way dot supervision models the background from each frame to frame to extract the foreground, where it initialize the probability p(a) of background model at the first frame and updated for subsequent frame to extract the foreground. The distance between the frames gives the background values.

In this paper, the edges and boundary value of the video frames are segmented by utilizing the Enhanced Global Mass Differential Equation method. The proposed work uses this method because of the following reason.

- The method analyzes the edges and boundary present in the dynamic video frame.
- Sensitive edges contour and structure of the vehicle has been extracted very effective.
- Analyze the images with different direction which reduces the error rate also eliminate the false video frames.

The method analyzes the image curves and edges by solving the numerical scheme which is easily reconstruct the vehicle structures by using the extracted edges. During the edges analyzing process the glowworm swarm optimization method is used because the method estimates the edges in the concept of optimized sigmoid function value. The calculated value which has maximum value that considered as the contour or edge value. In addition the Global mass method analyzes the video frame edge in the dynamic manner using the parametric method and level set method. The extracted edges and boundary values are used to extract the meaningful feature.

Algorithm: Boundary extraction:

Require: input image, threshold th.
1: imORIG $\longleftarrow$ input image
2: if imORIG is grayscale then
3: im $\longleftarrow$ imORIG
4: else
5: im $\longleftarrow$ (6968imORIG;R+ 23434imORIG;G+ 2366imORIG;B)=32768 {Grayscale conversion, assuming RGB image.}
6: end if
7: Define operator x and operator y {Roberts, Prewitt or Sobel.}
8: g x $\longleftarrow$ convolution(im,operatorx)
9: gy $\longleftarrow$ convolution(im,operatory)
10: maxM $\longleftarrow$ 0
11: for all pixel i in image do
12: M [i] $\longleftarrow$ $\sqrt{g_x^2 + g_y^2}$ {Gradient magnitude.}
13: if M [i] > maxM then
14: maxM $\longleftarrow$ M [i]

```
end if
end for
for all pixel i in image do
if M [i] >= th * maxM then
imOUT[i] ← 255
else
imOUT[i] ← 0
end if
end for
return output image imOUT
```

C. Feature Extraction Based Vehicle Detection and tracking:

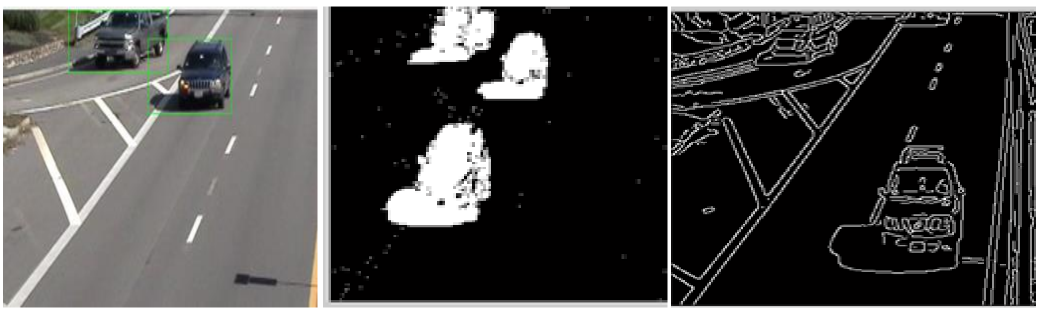
Feature subset selection or attribute selection is a data pre-processing technique used to reduce the number of features in high-dimensional datasets, crucial in identifying the behaviour and performance of the system. Feature selection finds applications in the areas of image processing, forecasting, document classification, object recognition, anomaly detection and bioinformatics. The benefits of using feature subset selection include improvements in the data mining algorithm’s accuracy, efficiency and scalability.

Feature selection methods are divided into two : filter and wrapper, based on the classifier’s evaluation strategy. The filter methods ranks the importance of features based on the relevance score, which is calculated by using distance, information, correlation and consistency measures. Filter methods (Anwar Ali Yahya et al. 2011) are scalable to high-dimensional datasets, computationally simple and fast, and is also independent of the classification algorithm. Feature selection needs to be performed only once, after which the feature subset can be evaluated by the classifier. Features chosen by this method are univariate and feature dependency is largely ignored, culminating in a worse classification performance. Wrapper methods are classifier-dependent feature selection methods (Huan Liu & Lei Yu 2005), Which interact between feature subset searches and model selection. They also have the ability to take into account feature dependencies. The setback of this method is the higher risk of over fitting and the fact that it is computationally intensive, especially if building the classifier involves high computational costs. The embedded method selects features based on the filter method and evaluates it with the classifier within the model, based on the wrapper method. Embedded methods are less computationally intensive than wrapper methods, but specific to a learning classifier.

Various shape color and GLCM features are taken to carry out tracking process. There are several features are obtained and the feature are reduced to make the matching process simple and easy. When there is a minimum number of feature match then the vehicle are matched. There is fixed a stopping range, upto this stopping range the features are matched and the vehicles are tracked

IV. Experimental Results:

The performance of the proposed system tested on a video containing a sequence of 5000 frames containing 100 vehicles. The system was able to detect and track the most of vehicles correctly under various conditions.



a b c

Fig. 2 a: Tracked vehicle, b. Background subtraction c. Boundary extraction

A. Performance Metrics:

$$True\ Positive\ (TP) = \frac{Numbers\ of\ vehicles\ detected \times 100}{Number\ of\ vehicles\ appearing\ in\ the\ video\ frames} \quad (1)$$

$$False\ Positive\ (FP) = \frac{Number\ of\ false\ detections \times 100}{Number\ of\ vehicles\ detected + Number\ of\ false\ detection} \quad (22)$$

$$False\ Negative\ (FN) = \frac{Number\ of\ Vehicles\ missed \times 100}{Number\ of\ vehicles\ appearing\ in\ the\ video\ frames} \quad (2)$$

$$Precision = \frac{TP}{TP+FP} \quad (3)$$

$$Recall = \frac{TP}{TP+FN} \quad (4)$$

The average velocity of a vehicle is defined as the total displacement over time and is denoted by

$$Average\ velocity = \frac{\overline{\Delta \vec{d}}}{\Delta t} \quad (5)$$

B. Discussion:

The False Negative cases are caused mainly due to vehicle occlusions. The occlusions are caused when a vehicle is partially covers with some other vehicle. The False Positives are caused mainly by the foreground detection incorrectly. Figure 3 shows the ROC curve of the proposed automated vehicle surveillance system, where it provides confident True positive rate by controlling the false positive rate.

Conclusion:

This paper presents an effective method for background subtraction, Boundary extraction, Vehicle detection and tracking based on Feature extraction process. The proposed method gives a promising result when compared with other methods. The proposed method can able to detect and track vehicle in any various conditions. This method can able to detect and track multiple vehicles.

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