A Project Report

on

Vehicle Detection and Counting

Submitted in partial fulfillment of the
requirement for the award of the degree of

Bachelor of Technology in Computer Science and Engineering

GALGOTIAS UNIVERSITY
(Established under Galgotias University Uttar Pradesh Act No. 14 of 2011)

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GALGOTIAS UNIVERSITY, GREATER NOIDA
INDIA
DECEMBER, 2021

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I/We hereby certify that the work which is being presented in the thesis/project/dissertation, entitled **"VEHICLE DETECTION AND COUNTING"** in partial fulfillment of the requirements for the award of the BACHELOR OF TECHNOLOGY IN COMPUTER SCIENCE AND ENGINEERING submitted in the School of Computing Science and Engineering of Galgotias University, Greater Noida, is an original work carried out during the period of month,JULY-2021 to DECEMBER-2021 under the supervision of Dr.Aanjey Mani Tripathi,Associate Professor, Department of Computer Science and Engineering/Computer Application and Information and Science, of School of Computing Science and Engineering , Galgotias University, Greater Noida

The matter presented in the thesis/project/dissertation has not been submitted by me/us for the award of any other degree of this or any other places.

———HARSH KUMAR,18SCSE1010559

This is to certify that the above statement made by the candidates is correct to the best of my knowledge.

Supervisor

(Dr.Aanjey Mani Tripathi)

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ABSTRACT

Moving vehicle detection, tracking, and counting are very critical for traffic flow monitoring, planning, and controlling. Traffic issues have become a bigger problem where city planners facing for years. The detection of moving vehicles more accurately, several computer vision techniques, vehicle counting is done by using a virtual detection zone.

Traffic analysis will calculate for the number of vehicles in an area per some arbitrary period of time and classify the vehicles. Video-based solution, comparing to other techniques, does not disturb traffic flow and is easily installed. By analyzing the traffic video sequence recorded from a video camera, this paper presents a video-based solution applied with adaptive subtracted background technology in combination with virtual detector.

Experimental results, implemented in Python code with OpenCV development kits, indicate that the proposed method can detect, track, and count moving vehicles accurately. we applied Open CV for real-time video applications.

Vehicles in Asia, such as in India, Nepal, and Bangladesh etc, have similar characteristics to the vehicles in our vehicle dataset, and the angle and height of the road surveillance cameras installed in these countries can also clearly capture the long-distance road surface. Therefore, the methodology and results of the vehicle detection and counting system provided in this analysis will become important references for Asian transport studies.

Intelligent transportation systems have received a lot of attention in the last decades. Vehicle detection is the key task in this area and vehicle counting and classification are two important applications. In this study, the authors proposed a vehicle detection method which selects vehicles using an active basis model and verifies them according to their reflection symmetry. Then, they count and classify them by extracting two features: vehicle length in the corresponding time-spatial image and the correlation

computed from the grey-level co-occurrence matrix of the vehicle image within its bounding box. A random forest is trained to classify vehicles into three categories: small (e.g. car), medium (e.g. van) and large (e.g. bus and truck). The proposed method is evaluated using a dataset including seven video streams which contain common highway challenges such as different lighting conditions, various weather conditions, camera vibration and image blurring. Experimental results show the good performance of the proposed method and its efficiency for use in traffic monitoring systems during the day (in the presence of shadows), night and all seasons of the year.

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CHAPTER-1
Introduction

Intelligent Transport System (ITS) is gaining very importance now a days, because everywhere we can find CCTV cameras which are used for security purpose and to keep track on the where abouts on that region. Traffic monitoring is also very important because of increasing traffic accidents. Therefore Vehicle detection and counting is very important in traffic congestion, keep tracking of vehicles and to control the traffic signal duration. The challenging part of the method is the estimation of the background because shadow, camera vibrations, change of illumination may occur and noise can get introduced. After detecting the moving vehicles it is counted by using the detection line drawn in video. The problems that can occur in counting is occlusion of two or more vehicles. Counting error can be reduced by taking care of camera angle or by taking the width of the moving objects. In this paper simple background subtraction method is taken to detect the moving vehicles. After detecting the moving objects only vehicles are considered and it is classified and counted for traffic monitoring. An important step in Vehicle detection is background estimation, region and feature based tracking algorithm with features to track correct objects continuously. After tracking objects their behavior and properties are recognized for analyzing traffic parameters.

Freeways, expressways and streets are getting packed with expanding of colossal number of vehicles. Wise transport frameworks are used to assemble and oversee data about transportation streams using different experts, they are trying to make traffic monitoring progressively proficient, solid, and more secure. To identify them and to tally the vehicle is getting indispensable for stream observing, arranging, and controlling of traffic. The identification of any vehicle is frequently customarily accomplished through sensor gear, for example, inductive circle finder, infrared identifier, radar indicator. These would be more cost effective so we came up with a video-based solution. Because the user cannot input any files in the senor equipment's such as video files. Comparing with other techniques using static cameras to capture the videos would be more suitable also it would fit in the outdoors like in rains, wind storms, etc..The user can reduce the cost by installing video cameras instead of sensor equipment. These video based solutions would be useful for the city engineers for road winding and the data would be stored securely for traffic learning. They have drawn huge consideration from specialists inside the previous decade. The essential issue is starting a track consequently. Here we portray two frameworks during which the issue is assaulted calm in an unexpected way. Initial one is virtual indicator built with a gathering of rectangular locales in each edge. Since the camera is fixed, the virtual identifier are frequently picked to traverse every path and along these lines the framework at that point screens and the virtual collector will do its job to find the vehicles .

The other is mass following. During this calculation, a foundation model is produced for the scene. For each information picture outline, totally the contrast between the information picture and subsequently the foundation picture is prepared to extricate closer view masses like the vehicles out and about. Both over two methodologies experience issues handling shadows, impediments, and huge sized vehicles. Few key methodologies of image processing have been applied in this project. Adaptive background subtraction with virtual detector is used to find the vehicles in a video frame. However it is time consuming and requires some automation to save lots of the time for image count and classification. The paper states about thanks to image process, sort of filter used and proposed technique are ready to detect, count and classify the image accurate

Vehicle detection and statistics in highway monitoring video scenes are of considerable significance to intelligent traffic management and control of the highway. With the popular installation of traffic surveillance cameras, a vast database of traffic video footage has been obtained for analysis. Generally, at a high viewing angle, a more-distant road surface can be considered. The object size of the vehicle changes greatly at this viewing angle, and the detection accuracy of a small object far away from the road is low. In the face of complex camera scenes, it is essential to effectively solve the above problems and further apply them. In this article, we focus on the above issues to propose a viable solution, and we apply the vehicle detection results to multi-object tracking and vehicle counting.

1.1 Related Work

The Jet Propulsion Laboratory used a computer vision method to detect vehicles for the first time in 1978 . Since then, various studies have been carried out to improve the performance of different parts of ITS . There are two main approaches in vehicle detection. The first one uses vehicle motion information and the second one uses the inherent features of vehicles to detect them in videos.

The basic idea behind the motion-based approach is that in a traffic scene, everything is static except for vehicles. So vehicle candidates can be identified by determining moving parts of the scene. Motion-based methods have some challenges which make them inappropriate in certain situations. As the basic idea is based on the motion of vehicles, they hardly detect static vehicles. Another challenge refers to the motion of other parts of the scene. It is common for a road to have moving things other than vehicles such as pedestrians, leaves of trees or birds. Even rain and snow may have similar effects. In addition, lighting changes during the day may result in moving shadows in the scene which come along with vehicles and may be determined as a part of them. Furthermore, at night, when a vehicle's headlights light up its front area, they actually create another moving region. Many researchers have proposed methods to overcome the above challenges. Some researchers have presented different background subtraction algorithms for improving moving object segmentation in a video. Others have proposed novel methods for background estimation . One researcher focused on heavy traffic and proposed an adaptive approach for vehicle detection in traffic jams and in complex weather . Another researcher suggested an approach using a full-search block matching method that detects the moving part and can prevent false motion using adaptive thresholding in a challenging environment . An improved version of the background subtraction method has also been suggested to alleviate the negative impacts from gradual changes. Then, a level set method has been used to determine blobs and finally a Kalman filter and support vector machine are utilised to improve the accuracy of vehicle classification.

The basic idea behind the inherent features-based approach is that vehicles have special features which can be used to differentiate them from other objects in traffic scenes. The methods use various features such as colour, texture, edge information and shape symmetry to find vehicle candidates. These methods can be applied to both traffic videos and images and do not have the challenges of the motion-based approach, but some are time consuming. Using the inherent features of vehicles, researchers also proposed a novel colour-based method to detect vehicles from images. They presented a statistic linear model of colour change space to compact vehicle colours and thus narrow down the search areas of possible vehicles . Other researchers proposed a generative model based on edges and constructed a Markov chain Monte Carlo method to detect and segment vehicles in static images. Some researchers presented night time vehicle detection algorithms for traffic surveillance by locating and analysing some features of vehicle lights . In another work, vehicle detection in videos is carried out by performing matching between a vehicle model based on the mixture of deformable part models to the features collected by sliding windows of a histogram of oriented gradients. Recently, some researchers constructed a multi-scale model to detect vehicles with various distances from the camera in traffic images . They also constructed a special and-or graph, hybrid image template and a part-based model to represent and detect vehicles in images with a congested traffic condition .In another research, a deformable model, the ABM, is constructed from a set of training images to detect vehicles in new traffic images by template matching. To improve the performance in vehicle recognition, the edge and colour symmetry features of the vehicle are used.

There are other studies which combined both inherent features like colour and edge and the motion information

Vehicle counting methods usually specify an area and check if any vehicle enters this area .Those investigations including vehicle classification extract shape-based features like length, width and area and then use a classifier such as the *k* nearest neighbour method or a neural network to categorise the vehicles.

1.2 Tool and Technology Used

- OpenCV
- Numpy
- Visual Studio
- Programming Language : PYTHON

CHAPTER-2
Literature Survey

Due to more traffic congestion Intelligent vehicle counting system has been developed with different methods. Blob analysis, background, image enhancement, object detection and counting the pedestrians using neural networks, by using night vision. Pedestrian detection cameras have been using in many countries. We have designed a software by taking input as a video file to count the number of vehicles.

By taking the video frame and perform Image segmentation, vehicle tracking, vehicle detection and blob analysis for traffic surveillance. A different approach to count the vehicles is by convolution neural network it would give real time results with high accuracy. By using virtual coils and CNN could be possible for high accuracy results. The above researches have approached high accuracy in counting the number of vehicles. We would use background subtraction with virtual collector and morphological operations track and count the vehicles on roads and highways.

2.1 VEHICLE DATASET

Surveillance cameras in roads have been widely installed worldwide but traffic images are rarely released publicly due to copyright, privacy, and security issues. From the image acquisition point of view, the traffic image dataset can be divided into three categories: images taken by the car camera, images taken by the surveillance camera, and images taken by non-monitoring cameras . The KITTI benchmark dataset contains images of highway scenes and ordinary road scenes used for automatic vehicle driving and can solve problems such as 3D object detection and tracking. The Tsinghua-Tencent Traffic-Sign Dataset has 100,000 images from car cameras covering various lighting conditions and weather conditions, although no vehicles are marked. The Stanford Car Dataset is a vehicle dataset taken by non-monitoring cameras with a bright vehicle appearance. This dataset includes 19,618 categories of vehicles covering the brands, models, and production years of the vehicles. The Comprehensive Cars Dataset is similar to the Stanford Car Dataset but contains many pictures. The 27,618 images include the vehicle's maximum speed, number of doors, number of seats, displacement, and car type. The 136,727 images include the overall appearance of the vehicle. The datasets are taken by surveillance cameras; an example is the BIT-Vehicle Dataset , which contains 9,850 images. This dataset divides the vehicle into six types: SUV, sedan, minivan, truck, bus, and micro-bus; however, the shooting angle is positive, and the vehicle object is too small for each image, which is difficult to generalize for CNN training. The Traffic and Congestions (TRANCOS) dataset contains pictures of vehicles on highways captured by surveillance cameras and contains a total of 1,244 images. Most of the images have some occlusion. This dataset has a small number of pictures, and no vehicle type is provided, which makes it less applicable. Therefore, few datasets have useful annotations, and few images are available in traffic scenes.

This section introduces the vehicle dataset from the perspective of the highway surveillance video we produced. The dataset has been published in: The dataset picture is from the highway monitoring video of Hangzhou, China (Fig. 1). The highway monitoring camera was installed on the roadside and erected at 12 meters; it had an adjustable field of view and no preset position. The images from this perspective cover the far distance of the highway and contains vehicles with dramatic changes in scale. The dataset images were captured from 23 surveillance cameras for different scenes, different times, and different lighting conditions. This dataset divides the vehicles into three categories: cars, buses, and trucks (Fig. 2). The label file is stored in a text document that contains the numeric code of the object category and the normalized coordinate value of the bounding box. As shown in Table 1, this dataset has a total of 11,129 images and 57,290 annotation boxes.. The images have an RGB format and 1920*1080 resolution. Note that we annotated the smaller objects in the proximal road area, and the dataset thus contains vehicle objects with massive scale changes. An annotated instance near the camera has more features, and an instance far from the camera has few features. Annotated instances of different sizes are beneficial to the improvement of the detection accuracy of small vehicle objects. This dataset is divided into two parts: a training set and a test set. In our dataset, cars accounted for 42.17%, buses accounted for 7.74%, and trucks accounted for 50.09%. There are 5.15 annotated instances in each image on average. Figure 3 compares the difference between the number of annotated instances in our dataset and the PASCAL VOC, ImageNet, and COCO datasets. Our dataset is a universal dataset for vehicle targets that can be used in a variety of areas, such as Europe. Compared with the existing vehicle datasets, our dataset has a large number of high definition images, sufficient lighting conditions, and complete annotations.

Fig. 1

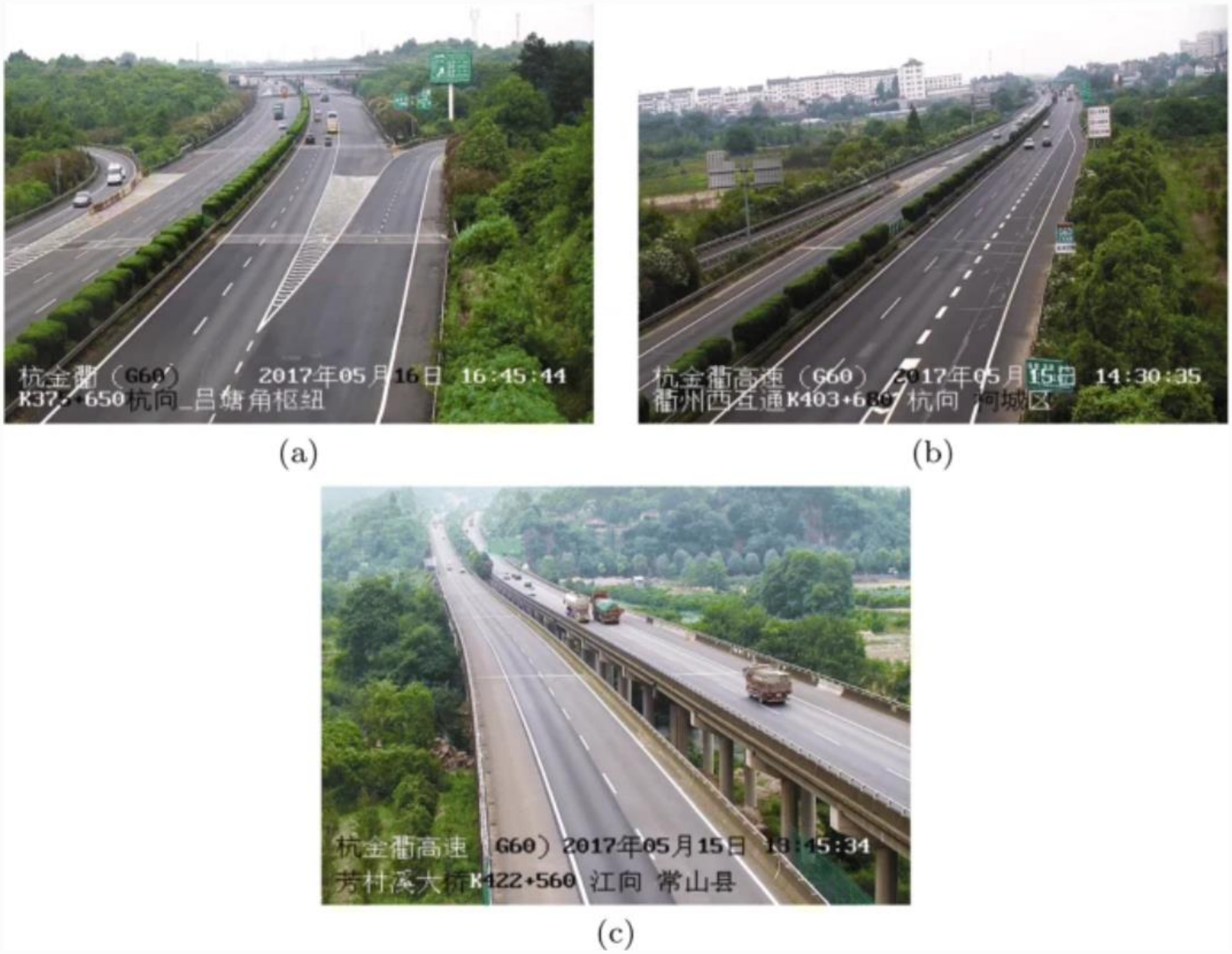
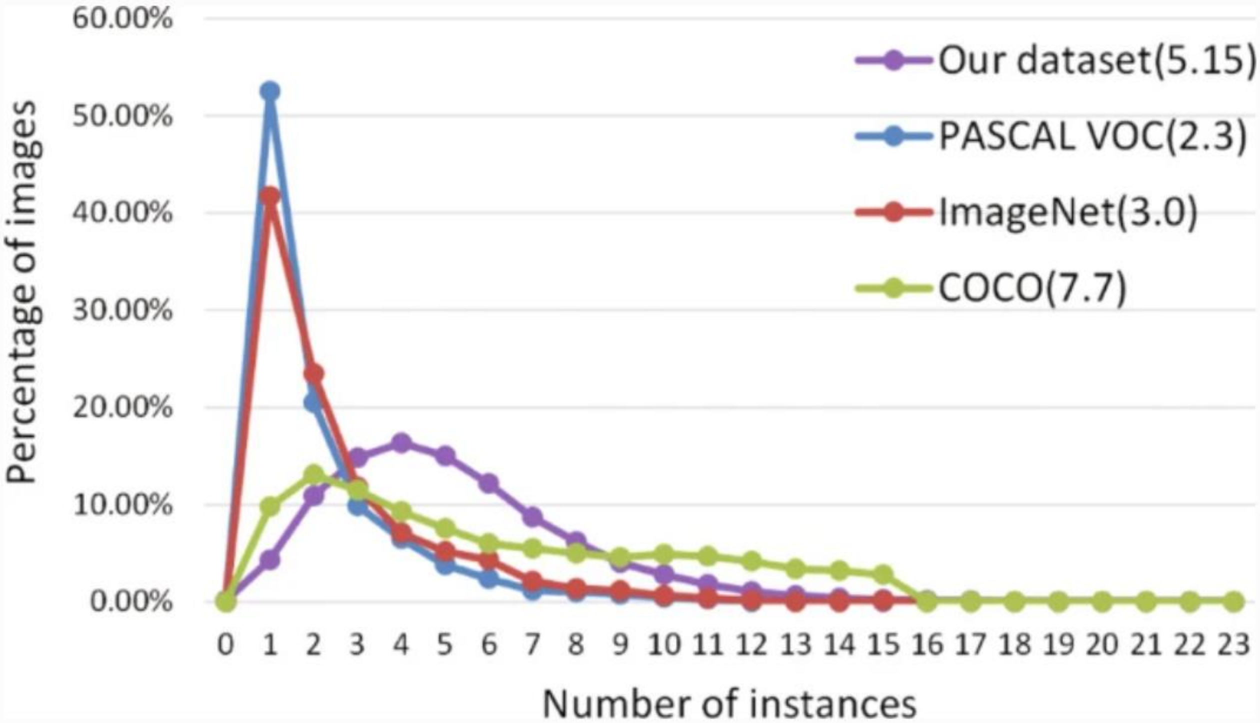


Fig. 2

Vehicle labelling category of the dataset

Fig. 3



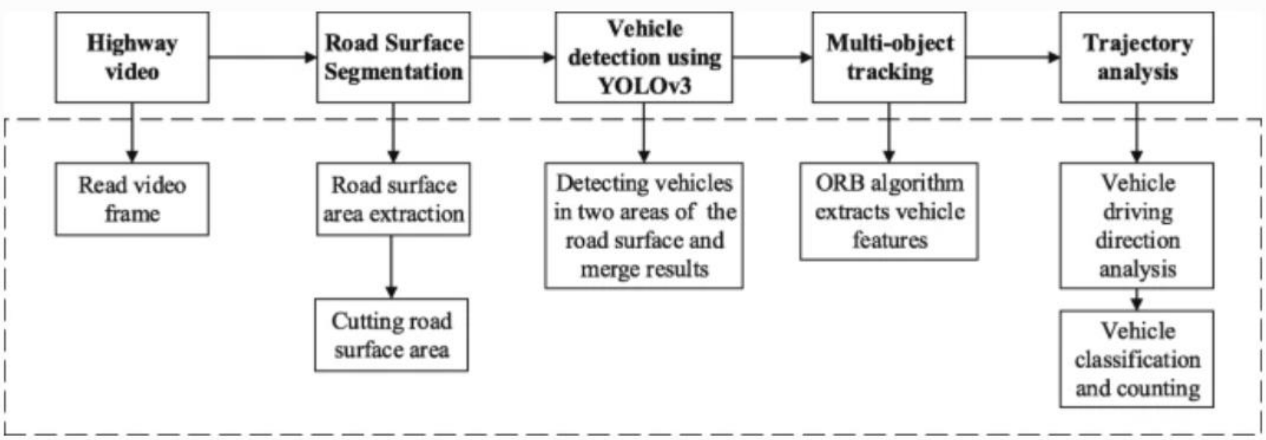
Annotated instances per image (average numbers of annotated instances are shown in parentheses)

2.2 System Structure

This section describes the main structure of the vehicle detection and counting system. First, the video data of the traffic scene are entered. Then, the road surface area is extracted and divided. The YOLOv3 deep learning object detection method is used to detect the vehicle object in the highway traffic scene. Finally, ORB feature extraction is performed on the detected vehicle box to complete multi-object tracking and obtain vehicle traffic information.

According to Fig. 4, the road surface segmentation method is used to extract the road area of the highway. The road area is divided into two parts based on the position where the camera is erected, a remote area and a proximal area. Then, the vehicles in the two road areas are detected using the YOLOv3 object detection algorithm. This algorithm can improve the small object detection effect and solve the problem that the object is difficult to detect due to the This system improves the accuracy of object detection from the highway surveillance video perspective and constructs a detection tracking and traffic information acquisition plan within the full field of the camera view.

Fig. 4



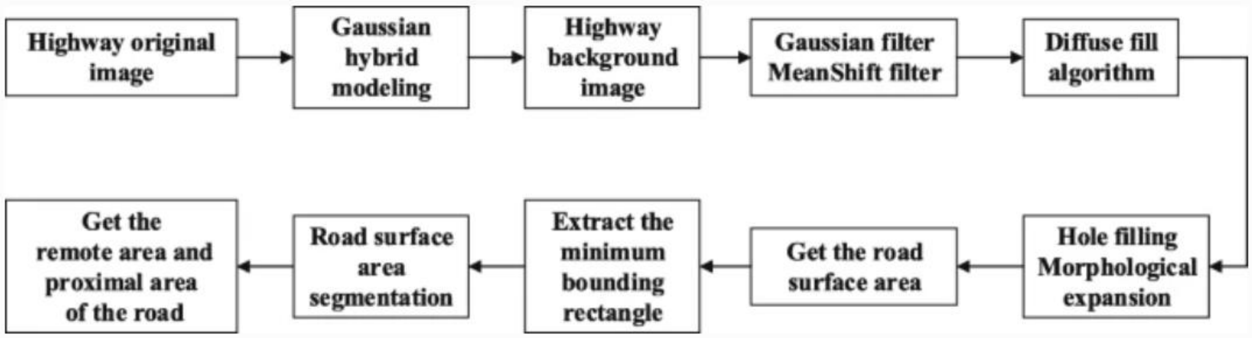
Overall flow of the method

2.3 METHODS

Road surface segmentation

This section describes the method of highway road surface extraction and segmentation. We implemented surface extraction and segmentation using image processing methods, such as Gaussian mixture modelling, which enables better vehicle detection results when using the deep learning object detection method. The highway surveillance video image has a large field of view. The vehicle is the focus of attention in this study, and the region of interest in the image is thus the highway road surface area. At the same time, according to the camera's shooting angle, the road surface area is concentrated in a specific range of the image. With this feature, we could extract the highway road surface areas in the video. The process of road surface extraction is shown in Fig. 5.

Fig. 5

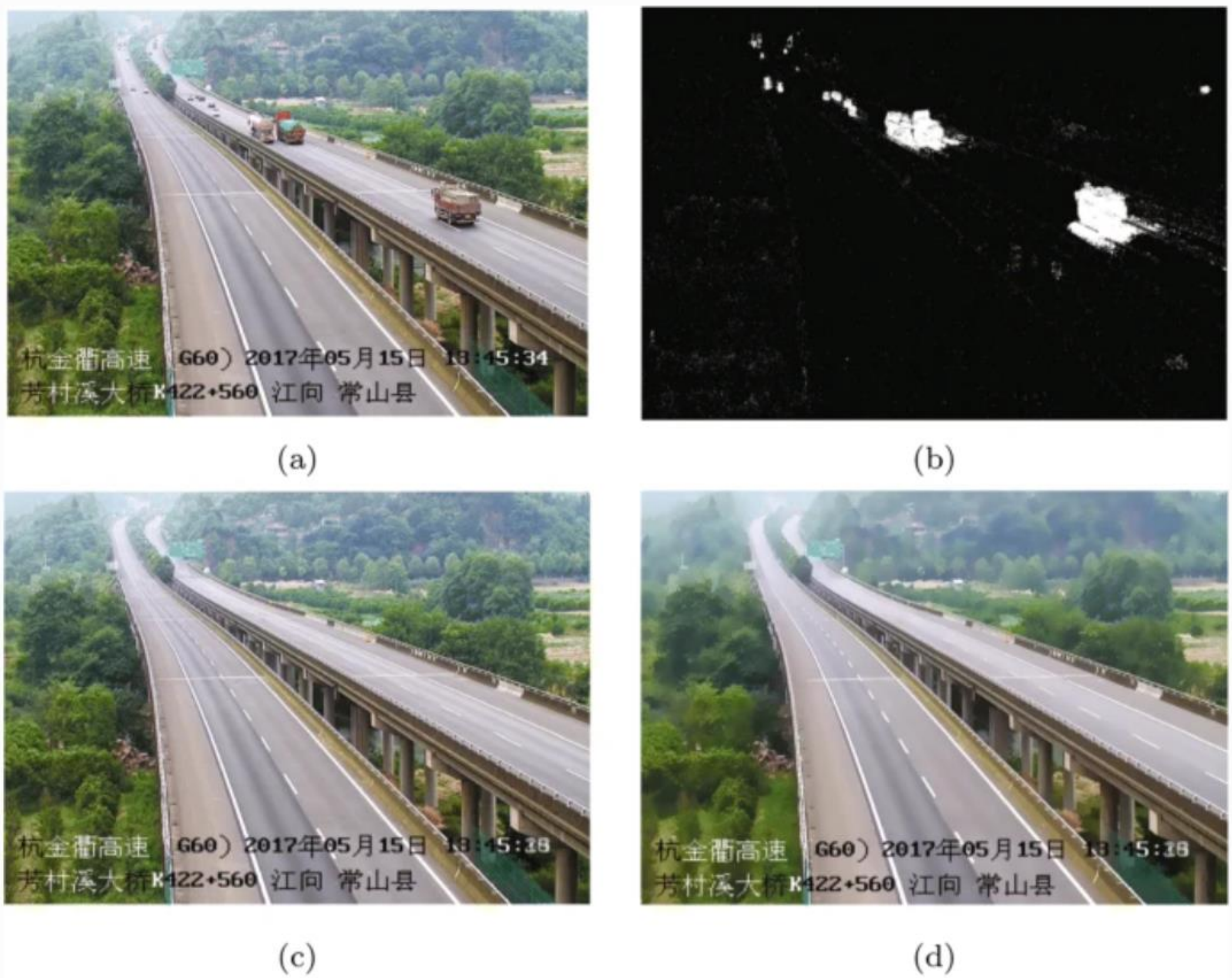


Overall flow of road surface extraction

As shown in Fig. 5, to eliminate the influence of vehicles on the road area segmentation, we used the Gaussian mixture modeling method to extract the background in the first 500 frames of the video. The value of the pixel in the image is Gaussian around a certain central value in a certain time range, and each pixel in each frame of the image is counted. If the pixel is far from the centre, the pixel belongs to the foreground. If the value of the pixel point deviates from the centre value within a certain variance, the pixel point is considered to belong to the background. The mixed Gaussian model is especially useful in images where background pixels have multi-peak characteristics such as the highway surveillance images used in this study.

After extraction, the background image is smoothed by a Gaussian filter with a 3*3 kernel. The MeanShift algorithm is used to smooth the colour of the input image, neutralize the colour with a similar colour distribution, and erode the colour area with a smaller area. On this basis, the flooding filling algorithm is used to separate the road surface area. The flooding filling algorithm selects a point in the road surface area as a seed point and fills the adjacent continuous road surface areas with the pixel value of the seed point. The pixel value of the adjacent continuous road surface areas is close to the seed point pixel value. Finally, the hole filling and morphological expansion operations are performed to more completely extract the road surface. We extracted the road surfaces of different highway scenes (Fig. 6), and the results are shown in Fig. 7.

Fig. 6

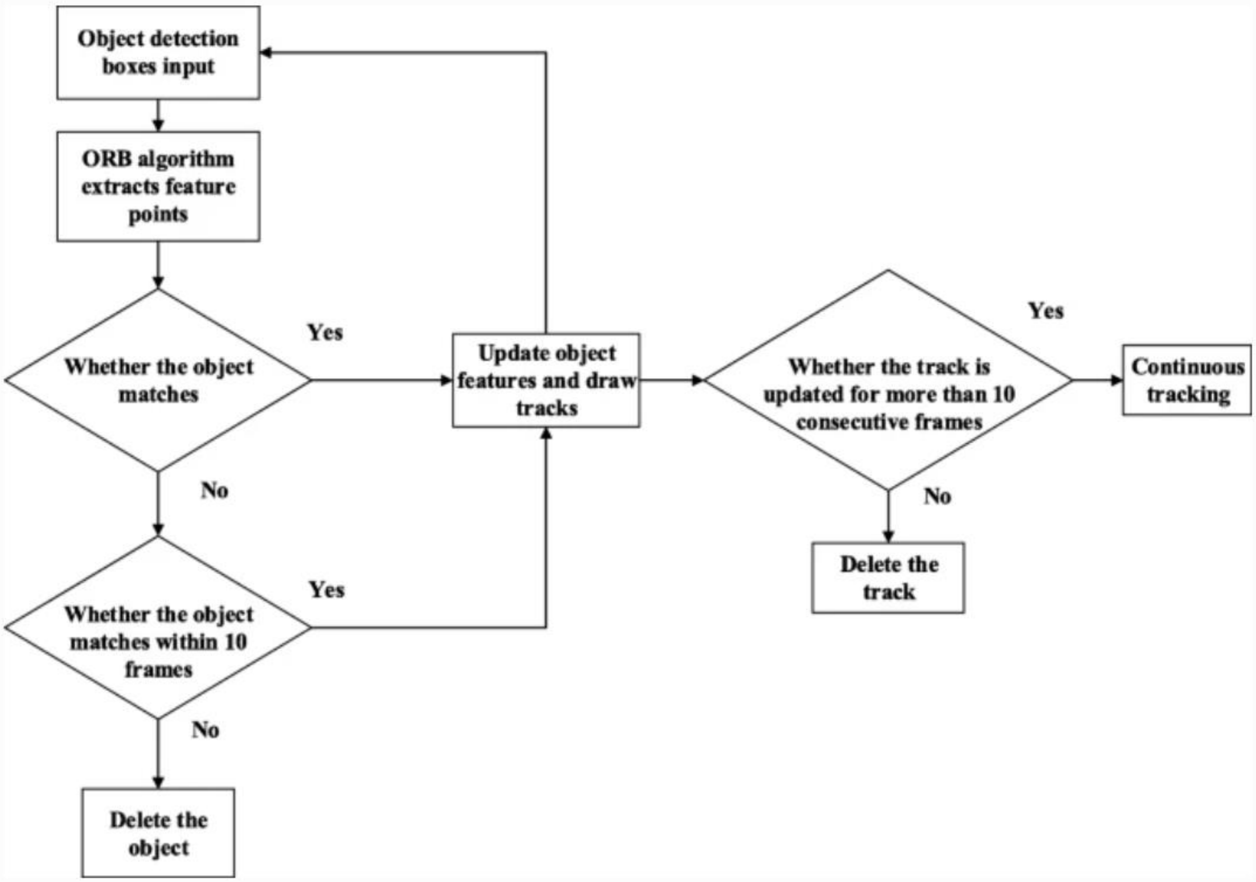


Process of road surface area extraction. **a** Original image; **b** image foreground; **c** image background; **d** Gaussian filter and MeanShift filter; **e** diffuse filling; **f** road surface area mask

Chapter 3
Multi-object tracking

This section describes how multiple objects are tracked based on the object box detected in "Vehicle detection using volo v3" section. In this study, the ORB algorithm was used to extract the features of the detected vehicles, and good results were obtained. The ORB algorithm shows superior performance in terms of computational performance and matching costs. This algorithm is an excellent alternative to the SIFT and SURF image description algorithms. The ORB algorithm uses the Features From Accelerated Segment Test (FAST) to detect feature points and then uses the Harris operator to perform corner detection. After obtaining the feature points, the descriptor is calculated using the BRIEF algorithm. The coordinate system is established by taking the feature point as the centre of the circle and using the centroid of the point region as the x-axis of the coordinate system. Therefore, when the image is rotated, the coordinate system can be rotated according to the rotation of the image, and the feature point descriptor thus has rotation consistency. When the picture angle is changed, a consistent point can also be proposed. After obtaining the binary feature point descriptor, the XOR operation is used to match the feature points, which improves the matching efficiency.

The tracking process is shown in Fig. 10. When the number of matching points obtained is greater than the set threshold, the point is considered to be successfully matched and the matching box of the object is drawn. The source of the prediction box is as follows: feature point purification is performed using the RANSAC algorithm, which can exclude the incorrect noise points of the matching errors, and the homography matrix is estimated. According to the estimated homography matrix and the position of the original object detection box, a perspective transformation is performed to obtain a corresponding prediction box.



Process of multi-object tracking

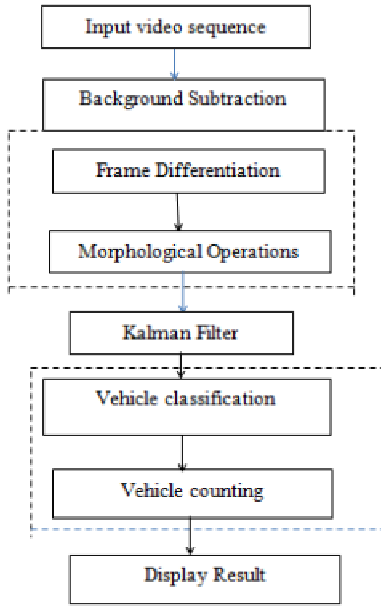
3.1 Trajectory analysis

This section describes the analysis of the trajectories of moving objects and the counting of multiple-object traffic information. Most of the highways are driven in two directions, and the roads are separated by isolation barriers. According to the direction of the vehicle tracking trajectory, we distinguish the direction of the vehicle in the world coordinate system and mark it as going to the camera (direction A) and driving away from the camera (direction B). A straight line is placed in the traffic scene image as a detection line for vehicle classification statistics. The detection line is placed at the 1/2 position on the high side of the traffic image (Fig. 12). The road traffic flow in both directions is simultaneously counted. When the trajectory of the object intersects the detection line, the information of the object is recorded. Finally, the number of objects in different directions and different categories in a certain period can be obtained.

3.2 ARCHITECTURE OF THE SYSTEM

This would describe an approach for inventing a system to count the vehicles and to detect from a video frame. Let us go through the flow chart of the system and know about each component and methods that we are using in the gngddfh jjkbkjqq jhvuyf76fv. A. Overall View Of The System First, video files are taken from the static cameras installed in highways, roads in cities, etc., The captured video file is firstly differentiated in frames by using frame differentiation technique.. Fore ground extraction is done on the video frame that can be seen in figure 3.

The background subtraction is applied on the video frames with virtual detector to find the foreground objects. Find contour method is used to draw the shapes like square (0, 0, 225) for cars and rectangles (0, 225, 0) for trucks according to their size. Due to wind, rain and illumination difficulties in the outdoor we would use morphological operations in our system to get high accuracy results during extreme weather conditions.[8] blob analysis is done on the video frames. Kalman filter is applied to the system to track the vehicles easily. Feature extraction is done the area of each car and truck passed through red and blue lines.



3.3 Background Subtractions

Background subtraction is an approach used to find the moving objects in video sequence to change it to foreground image. The foreground image would be formed after the background subtraction as shown in figure (b). Many researchers have developed methods background subtraction like kernel density estimation find out the density of the vehicle. Gaussian mixture model and etc. but in the real time applications there were not good enough. C.

3.4 Foreground extraction

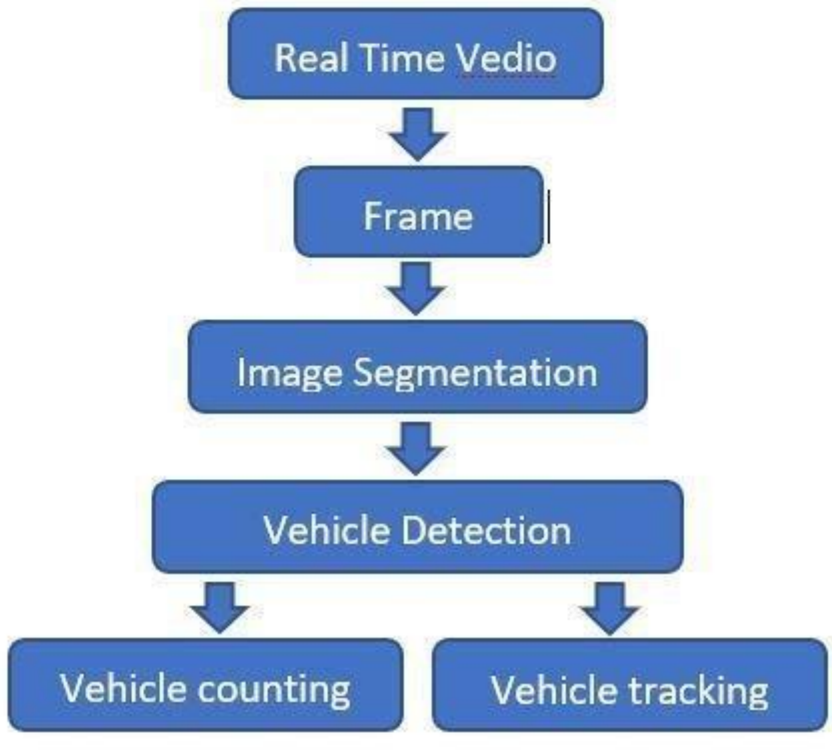
A particular image in figure (b) which has no vehicle on the road after the background subtraction on the video frame converted from color to gray scale image. For every pixel in the video frame the grey scale intensity of background image will be subtracted as shown in figure (b) by using hole editing, binary image and adaptive background subtraction. The total result will be stored in another image that image is called as difference image.

Chapter 4

4.1 VEHICLE DETECTION

To achieve vehicle detection we have used virtual detector to detect the vehicles and threshold operations are applied on the difference image to separate the fore ground image and background image. Fore ground mask is used mask the difference image as shown in figure (a). The morphological operations are applied on the images. They are erosion and dilations as show in figure (b) and (c).morphology is used to draw shapes and boundaries. Firstly, each frame of the output image is compared with the corresponding image with the input image. Dilation would add boundaries to the objects of the image and dilation add the extra boundaries in the image. We are using morphological operations so that we could get high accuracy results during extreme weather conditions or any illuminative issues like wind, rain, etc. By using contours the size of square sand rectangle sizes are fixed to calculate are of each vehicle. The size of cars would be set to 5 x 5 and trucks have been set 11 x 11. The values we got from the difference image are more than the value would be set to 1. If we got less value from the difference image then the value would be set to 0. We can use dilation and erosion to remove small objects from the images to make the borders smooth. Further the next step would be to count the number of vehicle

Flow Diagram



Block Diagram

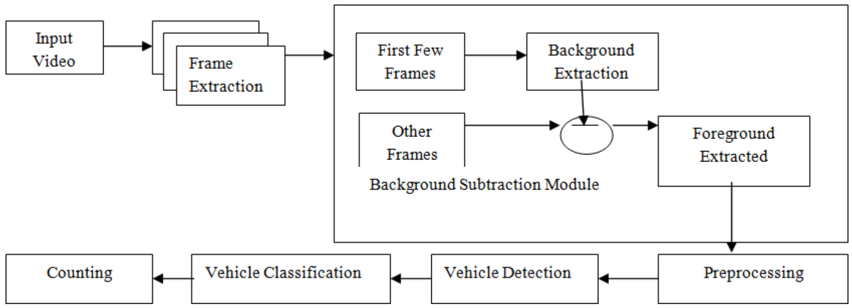


Figure 1: Block Diagram of Vehicle Detection and Counting

Figure shows the block diagram for Vehicle detection and counting. From the input sequence of images, first the segmentation of moving objects from background has to be done. Image subtraction from the input sequence and background is done, which gives the changes in two frames. This method can be used only for moving objects in the input sequence, not for the objects which are idle for some time in the video.

In this work, the background subtraction method is used to segment the moving object in the scene. Background is estimated based on first few input video frames. Thresholding is used to segment the moving object from difference between the background estimated image to the current image. Morphological operations are done after the segmentation to reduce noise this is called preprocessing. After detecting the moving vehicles the bounding boxes are drawn around the vehicle. These detected vehicles are classified into car, bike or heavy vehicle. The number of vehicles is counted.

4.2 Counting

First the line is drawn as region of interest. After detecting the moving vehicle its position and centroid is detected. Whenever this centroid crosses the region of interest that is the line drawn the counter is incremented means the vehicle count is noted. After all these steps the features of the vehicle can be extracted and classified into categories of vehicles such as car, bus, motorbike, non vehicle etc., Feature extraction can be done by Histogram Oriented Gradients , Principal Component Analysis (PCA). Classification can be done by using the Support Vector Machines (SVM), Latent Support Vector Machines, Neural Networks. Vehicle detection, classification and counting the vehicles with respect to their classes can be used in many areas for surveillance.

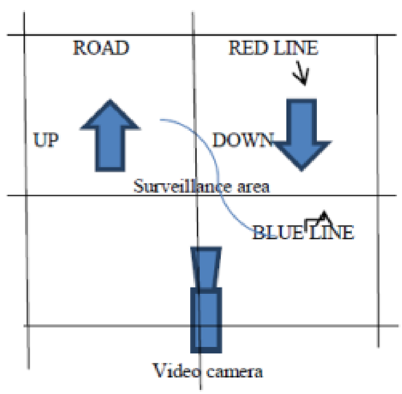
Once find contour methods are applied as shown in figure (c), next the area would be calculated for each vehicle and displays a value 1 if the vehicle is counted. And this count would be increased as the numbers of vehicles are detected. If no vehicle is detected then the value would be set to 0, and continue to detect the other frames. As shown in figure (a) the area size would be displayed in the output screen once the vehicle is counted as 1. As shown in figure (b) the red and blue are used as region of interest and centroid to calculate the area of each vehicle once the vehicle has crossed the red line frame differentiation is done to count the vehicles. After crossing the blue line the vehicle would be counted. It would work on bi-directional ways and also in single direction ways .If any vehicle has not detected then binary image would be stored as 0

Considering the original approach for vehicle counting is based on virtual test lines , which is to set up virtual test lines on the road, we design an algorithm that can be applied to multi-vehicle counting, which simultaneously counts different categories of vehicles.

Based on the local linearity of the expressway, we set up a vehicle counting area according to the shooting range of the camera (Figure 7(a)). The driving direction of vehicles can be divided into the forward direction and the backward direction. Since the multi-vehicle tracking algorithm we designed, it is not necessary to design multiple detection lines to determine whether there is a vehicle passing through. We divide the counting area into four regions, *A*, *B*, *C*, and *D*, and establish a coordinate system for the counting area (Figure 7(b)). Moreover, the center of the counting region is set to the origin of the coordinate system, and the four regions *A*, *B*, *C*, and *D* correspond to the four quadrants of the coordinate system, respectively. Suppose that the coordinates (coordinates of the center points of the detection bounding box) of the starting and ending points of the vehicle trajectory points in the counting area are expressed as and . It is necessary to calculate the angle between the start point of the trajectory and the *x*-axis and the angle between the end point of the trajectory and the *x*-axis, respectively. The calculation formula is as follows:

$$\begin{cases} \tan\theta_1 = \dfrac{-y}{x} \\ \tan\theta_2 = \dfrac{y}{x} \\ \tan\theta_3 = \dfrac{y}{-x} \\ \tan\theta_4 = \dfrac{-y}{-x} \end{cases} \xrightarrow{\text{solution}} \begin{matrix} \theta_1 = -\arctan\left|\dfrac{-y}{x}\right| \\ \theta_2 = \arctan\left|\dfrac{y}{x}\right| \\ \theta_3 = -\arctan\left|\dfrac{y}{-x}\right| \\ \theta_4 = \arctan\left|\dfrac{-y}{-x}\right| \end{matrix}.$$

(a)



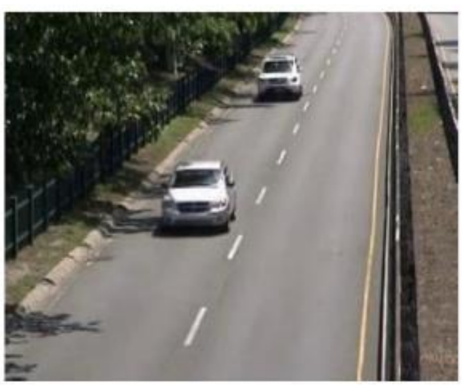
4.3 Vehicle classification

In the classification step, we classify vehicles into three classes: small (e.g. car), medium (e.g. van) and large (e.g. bus and trunk). To reach this goal, we extract two features to differentiate between different vehicle types. First, we compute a length-based feature that is very useful for classifying vehicles according to their size. However, this feature is sensitive to noise and the vehicle velocity changes. As a result, we add a texture-based feature to improve the classification accuracy. Then, a RF is used to classify vehicles. The details of these steps are described in the following sections.

EXPERIMENTAL RESULTS

The experiments are conducted in Microsoft Visual Studio 2010 Python with openCV libraries.

Fig 2.shows snapshot of a video which is taken as input and is converted into grayscale for further processing.



2a

2b

Fig 3 shows the results of vehicle detection. The detected vehicle is represented by a bounding box.

Figure3: Results of Vehicle Detection

CONCLUSION AND FUTURE WORK

Conclusion:

- The various techniques that are used in traffic video surveillance. It focuses on various techniques of vehicle detection and tracking to make an efficient traffic management system by the use of video surveillance.

- By using contour methods to identify the vehicles and counting the number of vehicles in the video sequence captured from static cameras. Once the vehicle has reached the region of interest count. Experimental results have showed an average of 97.25% accuracy in the proposed method.

- A solution for Vehicle Detection, Classification and Counting which can be used in traffic monitoring, parking area allocation is proposed. A technique that can distinguish whether the object is vehicles or other. The experiment is carried out in Microsoft Visual Studio 2010 Python with openCV libraries. The implemented method is easy to implement at very low expenses. Experiments give the good accuracy

- This paper has clearly explained about the vehicle counting detection system to identify and counting the number of vehicles from the video sequence captured from static cameras. Firstly, by using adaptive background subtraction with virtual detector, secondly foreground masking, find contour method, motion analysis and edge detection techniques have been used. By kalman filter and region of interest are used to calculate the area and to detect the vehicle. Open computer vision techniques like threshold calculation and blob analysis, hole filling, morphological operations, are applied to remove objects and to remove noises from the video frames for smoother boundaries. Thirdly, by using contour methods to identify the vehicles and counting the number of vehicles in the video sequence captured from static cameras. Once the vehicle has reached the region of interest count would begin as mentioned in the above methods. Experimental results have showed an average of 97.25% accuracy in the proposed method.

- This study established a high-definition vehicle object dataset from the perspective of surveillance cameras and proposed an object detection and tracking method for highway surveillance video scenes. A more effective ROI area was obtained by the extraction of the road surface area of the highway. The YOLOv3 object detection algorithm obtained the end-to-end highway vehicle detection model based on the annotated highway vehicle object dataset. To address the problem of the small object detection and the multi-scale variation of the object, the road surface area was defined as a remote area and a proximal area.

- The two road areas of each frame were sequentially detected to obtain good vehicle detection results in the monitoring field. The position of the object in the image was predicted by the ORB feature extraction algorithm based on the object detection result. Then, the vehicle trajectory could be obtained by tracking the ORB features of multiple objects. Finally, the vehicle trajectories were analyzed to collect the data under the current highway traffic scene, such as driving direction, vehicle type, and vehicle number. The experimental results verified that the proposed vehicle detection and tracking method for highway surveillance video scenes has good performance and practicability. Compared with the traditional method of monitoring vehicle traffic by hardware, the method of this paper is low in cost and high in stability and does not require large-scale construction or installation work on existing monitoring equipment. According to the research reported in this paper, the surveillance camera can be further calibrated to obtain the internal and external parameters of the camera. The position information of the vehicle trajectory is thereby converted from the image coordinate system to the world coordinate system. The vehicle speed can be calculated based on the calibration result of the camera. Combined with the presented vehicle detection and tracking methods, abnormal parking events and traffic jam events can be detected to obtain more abundant traffic information.

Future Work:

Vehicles in Asia, such as in India, Nepal, and Bangladesh etc, have similar characteristics to the vehicles in our vehicle dataset, and the angle and height of the road surveillance cameras installed in these countries can also clearly capture the long-distance road surface. Therefore, the methodology and results of the vehicle detection and counting system provided in this analysis will become important references for Asian transport studies.

REFERENCES

- https://s3-us-west-2.amazonaws.com/ieeeshutpages/xplore/xplore-shut-page.html

- https://www.ncbi.nlm.nih.gov/pmc/articles/PMC6111533/

- **Ravula Arun kumar, D. Sai Tharun Kumar, K. Kalyan, B. Rohan Ram**
- **Reddy**

- https://www.researchgate.net/publication/327554338_A_Video_based_Vehicle_Detection_Counting_and_Classification_System

- **. Dariu M.G. "Sensor-Based Pedestrian Protection", IEEE transaction on Intelligent Transportation Systems, November/December 2001 [**

- **Kaweepap Kongkittisan, "Object Speed Detection from a Video Scene", Mahidol University, Bangkok Thailand, May 2003.**

- **Liang Z. Charlea E.T. "Stereo- and Neural Network-Based Pedestrian Detection", IEEE Transactions on Intelligent transaction system, Vol. 1, No 3, September 2000.**

- **Sama M. and Nikolaos P.P. "A Novel Method for Tracking and Counting Pedestrians in Real-Time Using a Single Camera", IEEE Transactions on Vehicular Technology, Vol. 50, No. 5, September 2001.**

- **Finagling X., Xia L. and Kikuo F., "Pedestrian Detection and Tracking with Night Vision" , IEEE Transactions on Intelligent Transaction System, Vol. 6, No.1, March 2005.**

- **Massimo B., Alberto B., Alessandra F., Thorsten G, and MarcMichael M., "Pedestrian Detection for Driver Assistance Using Multiresolution Infrared Vision", IEEE Transaction on Vehicular Technology, Vol. 53, No 6, November 2004.**

- **Chia-Jung P., Hsiao-Rong T., Yu-ming L., Hong-Yuan M.L. and SeiWang C., "Pedestrian detection and tracking at crossroads", Pattern Recognition, Vol.37, Issue 5, May 2004.**

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