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A Survey on Counting and Classification of Highway Vehicles

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***Abstract:** Vehicle tracking system is used for the observing vehicles on the move and supplying a timely ordered sequence of respective location data to model. Tracking vehicles on highways is a complex task since the count of vehicles increase day by day. The process of counting traffic along a particular road, either done electronically or by people counting by the side of the road is called vehicle counting sometimes referred as traffic counting. Local councils use vehicle count to identify which routes are used most, and to either improve that road or provide an alternative if there is an excessive amount of traffic. Some of the geography fieldwork involves a traffic count. They are useful for comparing two or more roads, and can also be used alongside other methods to find out where the Central Business District (CBD) of a settlement is located. Traffic counts that include speeds are used in speed limit enforcement efforts, highlighting peak speeding periods to optimize speed camera use and educational efforts. Many algorithms and methods have been proposed in this paper to detect, track, classify and count vehicles on highways.*

***Keywords:** vehicle tracking, vehicle counting.*

I. INTRODUCTION

Video sequences are captured by the camera, which is kept on the pole or other tall structure. Vehicle congestions, accidents and car robberies are occurred due to the increase in vehicles which leads to serious issues. To focus on vehicle classification and detection ITS (Intelligent Transportation System)is coped up with these issues[1].The vehicles are categorized as small vehicles, which contains small Cars or vehicles with the load but not more than 1 ton, medium vehicles contains Suzuki/van or vehicles with the load larger than 1 ton but less than 7 tons, whereas large vehicles contains truck/buses or vehicles with the load greater than 7 tons. A vision-based traffic analysis system consist of some components namely, foreground segmentation, feature extraction, shadow removal and tracking [2].The vehicles are also classified based on axles, in which wireless accelerometers sensors is used to detect vehicle axles and magnetometer sensors is to estimate the vehicles arrivals, departures and speed by WIM stations[3]. In Background Subtraction, the variation of the intensity values of background pixel are done with the following methods, such as Unimodal distributions[4],[5],non-parametric Kernel Density Estimation[6], Mixture of Gaussians[7],[8],and Adaptive multi-cue Background Subtraction[5] is efficient when comparing to all the above methods. Vehicle tracking algorithm contains some object tracking methods such as Feature based method, Model based method, Active contour based method, Region based method in[9] and vehicles are also tracked using kalman filter in[10]. To extract the foreground segments, here we use thresholds and morphological operations such as erosion and dilation. By using several classification techniques, namely Automatic Traffic Surveillance System, Neural Network-Based Classification, Eigenface Classification, Hough line Feature Classification, the vehicles are classified as shown in[11].Regression analysis is efficient in classifying vehicles. Here, Gaussian Process Regression, Bayesian Poisson regression and Standard Poisson Regression are discussed in the below sections and gives a conclusion.

II. PRE-PROCESSING TECHNIQUES

2.1 Background Subtraction:

In Background Subtraction, the variation of the intensity values of background pixel are done with the following methods, such as Unimodal distributions[4],[5],non-parametric Kernel Density Estimation[6], Mixture of Gaussians[7],[8],and Adaptive multi-cue Background Subtraction in[7]. In Background Subtraction algorithm, the foreground vehicles are segregated from the background and form a foreground mask. Background Subtraction is used in target tracking, object tracking, video appliances and traffic analysis and also used to detect foreground object by comparing the different frames. If the threshold value is less than the difference image, then it is taken as a moving object or otherwise a background image. The video sequences are observed in which, I is made of a static background B, that observes every moving object is made of a color and here the Background Subtraction summarize the formula such as ;

$$X_t(s) = 1 \text{if } d(\mathrm{I}_s, t, \mathrm{B}_s) > t, \text{ otherwise } 0$$

Where t is a Threshold, X_t is the motion label field at time t, d is the distance between I_s, t,the color at time t and pixel s and B_s,the background model at pixel s. This technique is based on computing the error between the background frame and current frame. Some background techniques are:

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2.1.1 Gaussian Mixture Model (GMM)

Each pixel is assumed to have a mixture of Gaussian distribution in the mixture of Gaussian model. The Gaussian Mixture Modelare sampled and estimated as spherical, tied, diagonal and full covariance matrices supported from data. It provides the number of components appropriately. From a mixture of a finite number of Gaussian distributions with unknown parameters, the probabilistic model, which assumes all the data points, where Gaussian mixture model is a probabilistic model. It generates k-means clustering to incorporate the covariance structure of data and centres of latent gaussians. For learning mixture models, Gaussian Mixture Modelis the fastest algorithm. If it has many points per mixture, which is insufficient, so estimating the covariance matrices becomes difficult. In the absence of cues, only the data theoretical criterion decides how many components are to be used.

2.1.2Adaptive Multi-cue Background Subtraction

In Adaptive multi-cue background subtraction, this technique is to obtain accurate background subtraction results by using different cues. This technique has been proven to be the best approach. There are two serious issues, which arise at this point are: (i) in which way cues are fused, and (ii) which cues are to be used. Pixel intensity (gray-level), pixel color, (gray-level) and edges are theuseful cues, which have been used in some works such as [12], [13]. In the measurement of traffic data, these approaches provide the interesting conclusions namely, vehicle counting and classification. From processing periods, the real applications training periods are not seperated. Here, the background should be continuously trained when the system observes the scene, which is adapted to global changes, and it affects the standard deviation values and background mean. Image processing methods that is related to the resolution and frame rate requires the computation power. Here, new multi-cue segmentation architecture is used to fuse different image cues, it combines both the bottom-up and top-down strategies to solve global and local illumination changes and obtain a background model. The bottom-up strategy, which includes a higher sensitivity and a color model to scene changes using conical RGB models and cylindrical RGB models in [14], [13] and gradient cues, which reinforce segmentation masks efficiently. According to its luminance and chromaticity characteristics, different segmented regions are easily defined, whereas the top-down strategies, without the need of extra sensors, the scene information are taking from shadows. In sunny days and also in dense traffic situations, the improved background model is used and ignores some moving objects such as raindrops, flies, etc. Here, the proposed background subtraction method describes to perform well, to obtain the position and volume for estimating the vehicles 2D/3D strategy heavily relies on it. Real-time performance can be achieved by implementing this algorithm.

2.2Foreground extraction

The difference image, which is obtained from the background subtraction, is used for extracting the foreground features. Here, the image is converted into a threshold and vehicle-related events are observed by the binary image on highways. In binary images, the values of '0' or '1' are represented as 'black' or 'white'. For extracting the foregrounds, in the threshold images, the noise levels are eliminated and there are some Morphological operations are used such as Erosion and Dilation. Erosion, from a binary image the irrelevant details are eliminated. Dilation, which increases the size of the object and size of the holes are reduced and present it in the form of white blob.

2.3Foreground Segmentation:

Warping method is used for detecting the foreground segments. To detect the unclassified vehicles, image warping is not applied directly. Here, we estimate a nonlinear mesh grid using warping algorithm. After warping, vehicle shape is distorted when the vehicle height is large. Projective transformation is applied to reduce the distortions. For modeling the distortions of large vehicles, 2D Projective transformation is noted.

III. VEHICLETRACKING

Tracking of vehicle is the process of monitoring the location of a car, truck or any moving vehicle using the GPS system. Widely deployed to keep track of truck fleets, vehicle tracking ensures that the vehicles are being used properly and that they can be recovered in the event they are stolen. There are some object tracking methods in vehicle tracking[17]**.**InFeature based method, instead of tracking the whole object, only the significant features of the object is tracked. In Model based method, the detailed geometric model of different objects are relied.Active contour based method, in which bounding contour is used to represent the detected object. Region based method for initializing; the background subtraction technique is employed. Using region tracking techniques such as Kalman filter, the detected objects has been traced. They are considered with 2D image objects and using the camera calibration, 3D volumes and positions are inferred. Based on 2D tracking, results are taken from the rectified images by using Kalman Filter. In 2D, there is a lack of accuracy in classifying, this problem is tackled with a large angle and looking down on to the road. Due to this problem, the effect is reduced and length and width are measured in lower error.Several potential road viewing angles are considered for flexible approaches. The problem affects the 2D approach, which provides the maximum accuracy, in such situations only 3D methods can estimate the vehicle measurements.Expensive high definition cameras are used for tracking vehicles. Based on the state space techniques, Kalman filter is a predictive method. The state of a dynamic system is estimated in two steps: a) To predicting the object state, the predict step uses dynamic model, b) using the measured or observed model, it corrected the prediction using the correction step. In predicting the position of a target, Kalman filter plays an important role in it. Bounding boxes are added to each of the detected object, when vehicles cross the intersection and enters into the detection zone. When tracked vehicles are closest to the camera, here we segmenting the tracked vehicles, so vehicle's color and structures are clear and visible. Kalman filter provides almost 96% accuracy in tracking of vehicles as shown in [18].

IV. VEHICLE DETECTION

For implementing any detection algorithm, there are several key considerations that may vary depending on the task. First, the count of each of the vehicle is done only once, when counting vehicles. The vehicles are counted only when the vehicles pass over the reference line. Secondly, the vehicles which are measured using the line are known to be the longitudinal line. The vehicle detection algorithm descriptions are divided into two sections: vehicle count and length classification.

4.1 Vehicle Count:

In the field of traffic prediction and controlling, can be beneficial in tracking of vehicle counts and count register contains the information of the registered object. Centroid of the vehicle is required to implement the vehicle counts for predetermining the point on the pixel-plane. The vehicle count is incremented by one, when each of the vehicles crosses. The input image is formed by the tracked binary images for counting. The image should be scanned from top to bottom for the purpose of detecting the object. Check whether a object is already registered in a buffer, if a new vehicle is encountered, if not then that object is assumed as a new object and increment the count. This concept is applied for the entire image and achieves a good accuracy counts. The images of RGB values of each pixel on a registration line and each pixel in the same locations are compared in the background image. The pixels are considered similar, when the absolute difference of all RGB values is lower than the threshold, if it exceeds the pixels are considered different. The smaller vehicle does not entirely cover the registration line. A vehicle is counted only if no vehicle was present in the previous frame, in order to prevent over-counting vehicles. Whenever a vehicle is present on the line, each of the registration line changes from green to red. The total count of each detector, the total number of unique vehicles detected in the current frame, and the sum count of all vehicles detected, these are the outputs provided by the vehicle count algorithm.

4.2 Length Classification:

In this Length Classification algorithm, truck or long vehicle is considered to be a vehicle with the length exceeding 40ft. The bimodal vehicle length distribution is to break into short and long vehicles, which is considered as a reasonable value. The Washington State Department of Transportation (WSDOT) implemented the loop detection system and by using those values, there is a boundary between short vehicles and long vehicles. Wang and Nihan [19] demonstrated that vehicle lengths follow a bimodal distribution. This algorithm runs only when there is a detection of vehicles and at least one longitudinal line is turned on. Length Classification is performed only on a lane. Corresponding to the longitudinal line, when a vehicle exits the registration line, then this algorithm is run to measure the length of the vehicle in pixels. In a lane, the lengths of all the vehicles are measured at the same starting point. The actual length of the vehicle is not represented, a relative length is noted. The longitudinal line counts the number of different pixels. To begin the counting, atleast five consecutive pixels must be different from their background values; this is enough to prevent noise. When the pixels of vehicles length are obtained, then it is stored in an array for later comparison with other vehicles. Before the array is get to fill, Fifteen vehicles must be measured. When the arrays are filled, then the length of array is sorted in ascending order. This Length Classification is used to count only long vehicles, which are already detected. If the vehicle length range is greater than 75%, then they are considered as trucks. The length of array is checked and trucks are recorded, then the array is cleared for next fifteen vehicles. The output of this algorithm is the total count of all trucks (long vehicles) detected.

4.3 Program Features:

To fit in different locations and situations, the registration and longitudinal lines of each of the detector is adjusted. For controlling the rapid lighting changes, and global light changes, which is bounded as a white box, an automatic gain control (AGC) area is used. In order to work accurately, AGC is placed in areas where the background remains the same. For filtering out the lighting effects and for detecting the vehicle accurately, the average lighting affect is used. To improve the light filter and to avoid vehicle occlusion, some improvements are to be made from those errors. In lane merge situations, loop detection system performance is not better in it. In classifying trucks, there are three errors. In lane two, among the 15-vehicles, seven large trucks are included. In processing the vehicles, the mean vehicle length was driven high enough and recognizes only the four longest trucks. Each detector is to keep a memory of distribution of vehicle length is allowed rather than starting from every fifteen vehicles, for solving the above problem. The method which is used in this section is clearly defined that for truck detection through relative length comparison and there is a accuracy of 92% in truck classification as such in [28].

V. FEATURE EXTRACTION

In low quality image frames, extracting features is difficult in detecting and tracking features reliably. Here, low level features are used for the vehicle count. Low level features include segment length and width along the road directions but they are not sensitive, segment area, in segment boundary, the number of pixels are associated with segment perimeter, texture coarseness, and distinguish multiple small vehicles and large vehicles, which they have segment length and segment area in the segment of horizontal edge length. Texture coarseness, which consists of measuring the homogeneity, entropy and energy in [15], [16].Different vehicle classes are estimated by using texture coarseness.

VI. VEHICLE CLASSIFICATION

According to the size of the vehicles, vehicles are classified into three categories, namely small, medium and large vehicles. For each of the new vehicle which enters into the line on the region of interest is to finding the length of vectors is easy and according to the defined sizes, the length has been taken as a parameter to classify the vehicles. The goal is to determine the vehicles, which is passing continuously and keeping track of vehicles that have passed through the detection zone. Here, the passed object is taken as a input by the classifier, that is represented by the object descriptor. First, analyze the object descriptor to check whether the positions of the objects are in a consistent manner or otherwise, the objects are labeled as noise and discarded. The vehicles are categorized as per the videos are 1) small-cars 2) vans/Suzuki 3) heavy trucks. These categories are based on the vehicle types. In different fields, Automatic vehicle classifications are applicable such as traffic surveillance, avoidance of traffic congestion, car robbery avoidance, etc. For automatic vehicle detection and vehicle classification, several techniques are available to detect the different types of vehicles. For detecting the vehicles, these techniques are more effective and efficient.

6.1 Automatic Traffic Surveillance System

This Automatic Traffic Surveillance technique is used to classify vehicles based on the size and linearity features of vehicles[20].Due to shadow, vehicle occlusions are occurred in order to remove it, an algorithm is designed by this system. To recognize different types of vehicles, the size classification technique is used and to recognize the difference between truck and buses, linearity feature is used. In this technique, firstly taking the input as videos and that are converted into frames, and then vehicles are detected by updating the background and image differencing. Secondly calculate the vehicle histogram and lane dividing the line detection. Lanes are divided into lines and width. Again vehicles are detected by updating the background and image differencing. Then, based on Horizontal and Vertical line, shadows are eliminated. Finally, by applying Kalman Filter, Vehicle Tracking and Vehicle Classification is done to identify the vehicles. The accuracy of this system is 82% with shadow elimination but 69% without elimination.

6.2 Neural Network-Based Classification

This technique is used to classify the vehicles automatically. From different angles, the videos of vehicles are captured to extract the features, and then images are normalized. System used classifier which is based on new training method that is DSM (Direct Solution Method). By adding more neurons, the original DSM is modified. But it doesn't handle shadow problem and natural weather conditions. Back Propagation, Direct Solution Method and Direct Solution Method is added with neurons are compared and the percentage of classification rate for all three methods are shown in[21].Here input is taken as video and converted into frames and features are extracted and selected based on shape, then Multi-Layer Preceptron (MLP) classifier is used to classify the vehicles such as car,truck,bus,etc. The accuracy of this neural network is 62% of test-set while 100% on training set.

6.3 Eigenface Classification

Eigenface technique consists of two parts: Training and Classification [22]. In training, to get the outline of vehicle the background model is used and based on outline, it determine right, left and bottom border of vehicle and Training data is loaded. Real world conditions (such as rain and fog etc.) are not handled. This technique is to build the vehicle feature library is used in classification step. Using Eigenvector method, features of vehicles are extracted and comparing the vehicles with recorded data for Classification. Here, 100% for training set but not implemented in test set is performed accurately.

6.4 Hough line Feature Classification

Hough line Feature Classification technique is related to recognize vehicles and peoples[23].In this technique, first capture the videos of vehicles, then extract the Region of Interest but ,when part of moving object enters into region of interest wrong results are obtained. Apply the Gaussian model for Background Subtraction, and using canny operator, Edges are detected. Lines of edges are detected using Hough line transform and finally, vehicles and peoples are classified. In video set, there is a 97% of accuracy but it is varying between 91% to 94%.

6.5 Partial Gabor Filter-Based Classification

In this technique, for supporting vision based classification different digital cameras are utilized. Due to optimal localization capability in spatial analysis and frequency domain, Gabor Filter is applied in the area of pattern recognition and also Gabor Filter becomes inefficient due to high memory requirement and computational burden, so partial Gabor filter is used. No occlusion, shadow, rain problems are handled. Some vehicles are identified at the top side of vehicle the ratio of noise is greater. Sedan, van, bus and truck are easily classified by using this algorithm [24]. Here, Vehicles are segmented upto 68% top side, then extracting Gabor feature from gray image of vehicle and edge image of vehicle, but edge image produces better result than grey-image of vehicles and vehicles are classified. The accuracy of this classification system is 89.57% for vehicle grey-images while 95.17 % for edge images of vehicles.

6.6 Hybrid Dynamic Bayesian Classification (HDBC)

This Hybrid Dynamic Bayesian Classification technique, uses rear view of vehicles, which is less investigated and a front license plate is not required by all the countries [25].Firstly, the different type of vehicles videos are captured namely, sedan, SUV's and categorize other vehicles as unknown vehicles and secondly, based on rear view features are extracted

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using tail-lights and license plates and features are selected and finally vehicles are classified. The accuracy of HDFC is 97.63% for Correct Classification Rate With approximately 2 % of False Alarm Rate.

6.7 Regression Analysis

When comparing to all the above techniques, Regression Analysis is efficient to count and classify the vehicles. There are different vehicle classes such as small, medium and large vehicles. Here, vehicle counts and classes are combined to estimate emissions on highways. Difficulties in detecting many different classes, when cameras capture low quality videos and which are inaccurate. The different classes of vehicles are heavy-duty trucks (trucks with three or more axles), medium-duty trucks (i.e., trucks with two axles and six tires), and light-duty trucks are used in [26]. Based on the criteria of number of axles and tires, it would be difficult to categorize. Features are less affected by the counts of small and medium vehicles for large vehicles. The count estimation is treated as a feature and they are concatenated to the original feature vector. Then that feature vector is taken as input to estimate the count for medium vehicles. The above estimated counts are concatenated to estimate the count of small vehicles. The linear regression is the simplest regression, which the input variables are in a linear combination. Here, nonlinear functions of the input variables are also used namely, spline functions, polynomial functions, and logistic sigmoid functions. Therefore, firstly Gaussian process is evaluated to specify nonlinear regression, by using this Gaussian process, the output could be negative. Secondly, to count data Poisson regression is evaluated. Finally, for comparison Bayesian Poisson regression is evaluated in[27].

VII. CONCLUSION

In this paper, video sequences which are captured by the camera is converted into frames. By using Adaptive multi-cue segmentation, the background subtraction technique is obtained to detect the foreground pixels. Vehicle counting and vehicle classification are done by using this Regression model. For vision based systems our Regression algorithm is more suitable. For estimating the traffic density and vehicle emissions, regression method is applied. The different classes of vehicles such as, small vehicle, medium vehicle and large vehicles are taken to count and classify the vehicles based on our proposed regression analysis.

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