IJCRT.ORG ISSN : 2320-2882

INTERNATIONAL JOURNAL OF CREATIVE RESEARCH THOUGHTS (IJCRT)

An International Open Access, Peer-reviewed, Refereed Journal

VEHICLE DETECTION AND COUNTING SYSTEM

[1]Khushi Patel, [2]Diksha Bhatia, [3]Bijal Dalwadi

[1]B.Tech, [2]B.Tech, [3]Assistant Professor,

[1]Department of IT

Birla Vishvakarma Mahavidyalaya Engineering College, Anand, Gujarat, India

Abstract: In today's world, there are numerous vehicles moving on the road and traffic is unavoidable. By using the number of vehicles moving on the road as data we can evaluate the traffic. Vehicle detection and counting plays a very important role in traffic management. However, classification of the vehicles is a huge challenge. This paper mainly focuses on the methods used in vehicle detection and counting such as OpenCV techniques, and Haar cascade method for the classification of vehicles. The experiment is carried out by testing the video input in various conditions.

Keywords: Background learning, foreground extraction, Haar-cascade, vehicle counting

I. Introduction

Transportation is a very essential means in today's world. However, with the increase in need of transport, the number of vehicles on the road is also increasingly rapidly. Taking into consideration about the number of vehicles and the streets, highway, etc, we see a huge irregularity between the two quantities. This leads to the issue of traffic congestion. With the continuous movement of vehicles and managing them is very hectic for only human involvement and requires technical help. Vehicle detection and counting system helps to regulate and control traffic. For this it is necessary to detect vehicles on streets, highways, narrow roads, etc. and count them with accuracy as well.

In recent years, video surveillance and monitoring system has been widely used in traffic management, mainly for traffic density estimation and vehicle classification. In recent years, many algorithms have been proposed to detect, recognize, and track vehicles in front of them based on the corresponding relationship between regions and vehicles established by moving vehicles through image sequences. In the past decade, vision-based vehicle detection technology for road safety improvement has attracted more and more attention [1].

II. Literature Survey

At present, the detection and recognition of vehicles in front of us are mainly based on monocular vision, infrared sensors, lidar, and so on. Wang et al. [2] studied the digital signal processing technology of visual perception, ultrasonic sensor, and radar technology. Ahmed et al. [3] use real-time velocity data collected from AVI to check the identification of highway locations with high collision potential. Sivaraman and Trivedi [4] introduced the progress of vehicle detection in detail and discussed the application of monocular. The research involved the use of space-time measurement, trajectory, and various features to characterize road behaviour. Cheng et al. [5] designed an automatic vehicle detection system for aerial surveillance based on pixel classification, which retains the relationship between adjacent pixels in the region during feature extraction. Vehicle color and nonvehicle color are effectively separated by color transformation. The threshold of canny edge detector is adjusted automatically for edge detection. The results show that the method has flexibility and good generalization ability. Tian et al. [6] proposed a vehicle recognition method using multiple sensor nodes. Yong Tang et al. [7] used Haar-like feature for describing the object appearance and features, Heat maps to detect objects, AdaBoost algorithm to build an enormous classifier from multiple weaker classifiers, For vehicle recognition: Gabor's wavelet transformation Histogramic sequencing and Principal component analysis. Priyanka P. et al. [8] used various techniques as Hough transformation and segmentation which are major turning points. Further after being segmented, the image is smoothened and text from the segmented image is extracted into a group of single characters. Saran K. et al. [9] model proposal involves background subtraction using Gaussians and vehicle detection be done through ANN re-modelling. Re-modelling here refers to tweaking the routine features of ANN for vehicle detection to achieve better outputs. They proposed a trio of new features which are: HOG (Histograms of oriented gradients) and Geometric factors of vehicles such as dimensions/size of vehicle, angle portrayed in the image and contrast feature. Unzueta et al.[10] published a study where their approach relies on a multi-cue background subtraction procedure in which the segmentation thresholds adapt robustly to illumination changes. Even if the results are very promising, the datasets used in the evaluation phase are very limited. Alain Crouzil et al.[11] proposed a method as a solution of the method proposed by Unzueta et al.[10] The approach is threefold. (1) they propose an approach for background subtraction, derived from improved Gaussian mixture models (GMMs), in which the update of the background is achieved recursively. This approach is combined with a motion detection procedure, which can adapt robustly to illumination changes, maintaining a high sensitivity to new incoming foreground objects. (2) They also propose an algorithm able to deal with strong, moving casted shadows. One of the evaluation datasets is specifically shadow-oriented. (3) Finally, a new algorithm able to tackle the problems raised by severe occlusions among cars, and between cars and trucks was proposed.

III. Flowchart of The System

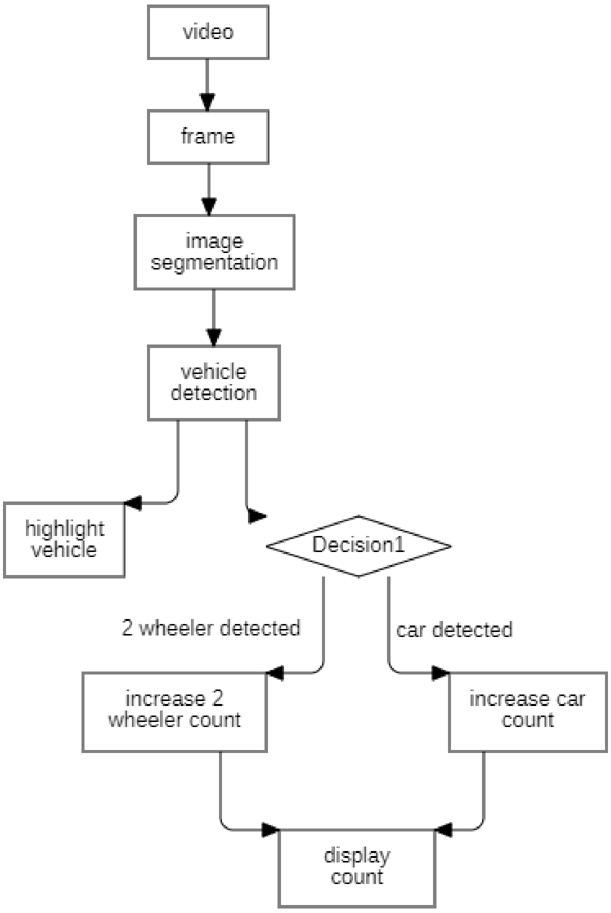


Fig 1. Flowchart

IV. Methodology

This paper aims to achieve vehicle detection and counting. The methods like background subtraction, foreground extraction, morphological activities are used to detect moving vehicles, eliminate noise in a video.

4.1 Background Learning

This module extracts the frame from the video input and learns about the background. The moving objects and static background are identified from the first few frames extracted from the input video. The Gaussian blur method is used for this purpose. The Gaussian blur is a type of image-blurring filter that uses a Gaussian function for calculating the transformation to apply to each pixel in the image. The formula of a Gaussian function in one dimension is

$$G(x) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{x^2}{2\sigma^2}} \quad (1)$$

In two dimensions, it is the product of two such Gaussian functions, one in each dimension:

$$G(x,y) = \frac{1}{2\pi\sigma^2} e^{-\frac{x^2+y^2}{2\sigma^2}} \quad (2)$$

where x is the distance from the origin in the horizontal axis, y is the distance from the origin in the vertical axis, and σ is the standard deviation of the Gaussian distribution.

4.2 Foreground Extraction

This module consists of three steps, background subtraction, image enhancement and foreground extraction. Background is subtracted so that foreground objects are visible. This is done usually by static pixels of static objects to binary 0. After background subtraction image enhancement techniques such as noise filtering, dilation and erosion are used to get proper contours of the foreground objects. The result obtained from this module is the foreground.

4.3 Classification

The classification is done using cascade classifier. The cascade classifier contains a list of stages. A window is passed over a frame. Initially, the algorithm needs a lot of positive images and negative images to train the classifier. Then we need to extract features from it. For this, Haar features shown in the below image are used. They are just like our convolutional kernel. Each feature is a single value obtained by subtracting sum of pixels under the white rectangle from sum of pixels under the black rectangle.

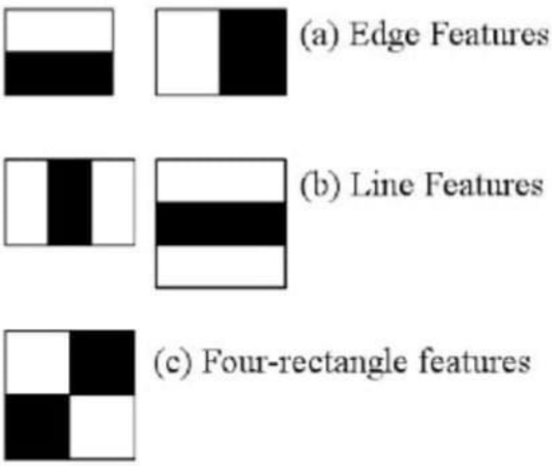


Fig 2. Haar features

For each feature calculation, we need to find the sum of the pixels under white and black rectangles. But among all these features we calculated, most of them are irrelevant. We select the features with minimum error rate. Each image is given an equal weight in the beginning. After each classification, weights of misclassified images are increased. Then the same process is done. New error rates are calculated. Also new weights. The process is continued until the required accuracy or error rate is achieved or the required number of features are found. The final classifier is a weighted sum of these weak classifiers. It is called weak because it alone can't classify the image, but together with others forms a strong classifier.

Cascade of Classifiers

Instead of applying all 6000 features on a window, the features are grouped into different stages of classifiers and applied one-by-one. (Normally the first few stages will contain very many fewer features). If a window fails the first stage, discard it. We don't consider the remaining features on it. If it passes, apply the second stage of features and continue the process. The window which passes all stages is a car or two-wheeler region.

4.4 Vehicle counting module

A line is drawn as the region of interest and after detecting moving vehicles its position and centroid is also detected. When the centroid of the moving vehicle crosses the line drawn, the vehicle is counted. No vehicle before the region of interest is counted. For e.g., if 2 two wheelers and a car are moving and are detected by the system then the system marks them with a rectangle frame and a centroid point. When this centroid point intersects with the line of interest, the counter of two-wheeler increases by 2 and that of car increases by 1.

However, while working on this method, it was found that these methods won't be able to achieve high accuracy in terms of classification of vehicles. Also using this type of specific techniques would require continuous monitoring, adjusting the angle of the surveillance camera. Therefore, to achieve high accuracy and proper classification of the vehicle we used Haar-cascade techniques.

V. EXPERIMENTAL RESULTS

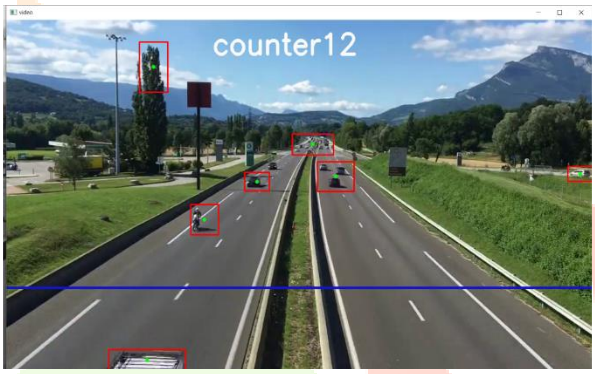
The experiment was carried out using two methods, one is using the method of background learning and the other is the Haar-cascade method.

a) input video

b) Grayscale conversion of input video

After the grayscale conversion of the input video, background subtraction and foreground extraction are applied. The output of this is shown below:

c) image after background subtraction and foreground extraction



d) Detection and counting of all vehicles

e) Detection, classification and counting of vehicles separately

VI. Conclusion

Vehicle Detection and Counting system is a very essential system in today's world. Using the methods of Gaussian blur for background learning, foreground extraction we achieved vehicle detection and counting accurately. However, the experimental results show that Gaussian blur method doesn't give much accuracy for classification. Therefore, we trained the dataset of the vehicles using the Haar-cascade method and we achieved better accuracy for the classification as compared to Gaussian blur method. The differences of these two methods are carried out

REFERENCES

[1] X. Cheng, L. Yang, and X. Shen, "D2D for intelligent transportation systems: a feasibility study," IEEE Transactions on Intelligent Transportation Systems, vol. 16, no. 4, pp. 1784–1793, 2015.

[2] W. Wang, Y. Song, J. Zhang, and H. Deng, "Automatic parking of vehicles: a review of literatures," International Journal of Automotive Technology, vol. 15, no. 6, pp. 967–978, 2014.

[3] M. M. Ahmed and M. A. Abdel-Aty, "The viability of using automatic vehicle identification data for real-time crash prediction," IEEE Transactions on Intelligent Transportation Systems, vol. 13, no. 2, pp. 459–468, 2012.

[4] S. Sivaraman and M. M. Trivedi, "Looking at vehicles on the road: a survey of vision-based vehicle detection, tracking, and behavior analysis," IEEE Transactions on Intelligent Transportation Systems, vol. 14, no. 4, pp. 1773–1795, 2013.

[5] H. Y. Cheng, C. C. Weng, and Y. Y. Chen, "Vehicle detection in aerial surveillance using dynamic Bayesian networks," IEEE Transactions on Image Processing, vol. 21, no. 4, pp. 2152– 2159, 2012.

[6] Y. Tian, H. Dong, L. Jia, and S. Y. Li, "A vehicle reidentification algorithm based on multi-sensor correlation," Journal of Zhejiang University SCIENCE C, vol. 15, no. 5,

[7] Tang, Y., Zhang, C., Gu, R. *et al.* Vehicle detection and recognition for intelligent traffic surveillance system. *Multimed Tools Appl* **76**, 5817–5832 (2017).

[8] P. Prabhakar, P. Anupama and S. R. Resmi, "Automatic vehicle number plate detection and recognition," 2014 International Conference on Control, Instrumentation, Communication and Computational Technologies (ICCICCT), Kanyakumari, India, 2014, pp. 185-190, doi: 10.1109/ICCICCT.2014.6992954.

[9] Saran K B and Sreelekha G, "Traffic video surveillance: Vehicle detection and classification," 2015 International Conference on Control Communication & Computing India (ICCC), Trivandrum, India, 2015, pp. 516-521, doi: 10.1109/ICCC.2015.7432948.

[10] L. Unzueta et al., "Adaptive multicue background subtraction for robust vehicle counting and classification," IEEE Trans. Intell. Transp. Syst. 13, 527–540 (2012).

[11] Alain Crouzi, Louahdi Khoudour, Paul Valiere, and Dung Nghy Truong Cong "Automatic vehicle counting system for traffic monitoring," *Journal of Electronic Imaging* 25(5), 051207 (1 June 2016). https://doi.org/10.1117/1.JEI.25.5.051207