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Classification and Counting of Vehicles for Traffic Surveillance

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Abstract: Traffic surveillance is a system used to observe the traffic congestion of a specific area. The surveillance system involves detection of moving vehicles, counting the number of vehicles and the classification of the detected vehicles. Recognition of the moving vehicles is the initial step which can be carried out either in each and every frame based on background modeling with discrete cosine transform (DCT). The proposed method is an efficient approach for vehicle segmentation based on texture analysis, a 2D discrete cosine transform (DCT) which is utilized to extract texture features in each image block. By this method the foreground object is detected by eliminating the background, vehicles are recognized based on their size and highlighted by drawing a bounding box around them. The actual count of the vehicles is estimated by counting the number of bounding box present in the video. Further the detected vehicles present in the video can be classified into car, bike, truck etc. based on the SVM classifiers. Support vector machine (SVM) are supervised learning tools which is applied for data classification and regression, It maps the training samples that are the points in features space into different categories which are clearly separated with the widest gap in between them. The proposed system can be used to conduct a survey and allow the users to monitor the condition of traffic flow by counting the number of vehicles passing through a specific location.

Keywords: Surveillance, Detection, Counting, Vehicle classification, Traffic flow, bounding box

I. INTRODUCTION

Traffic congestion is an emerging problem in this generation due to the increasing number of vehicles. Detecting and counting vehicles can be used to analyze traffic patterns. The traffic congestion can be effectively estimated by the surveillance of a specific area. For most traffic surveillance systems, major stages are used to estimate the desired traffic parameters, i.e., vehicle detection, counting and classification. Detection is also a first step prior to performing more sophisticated tasks such as tracking or categorization of vehicles by their type. The vehicles are detected by subtraction of background which is also known as foreground detection, is a technique in the fields of image processing and computer vision. Estimating the bounding box of the connected components corresponding to a moving vehicle further filters the detected foreground by thresholding pixels of the blob. The number of bounding boxes corresponds to the number of vehicles found in the video frame. We display the number of found vehicles in the upper left corner of the processed video frame. The detected vehicles are further classified into groups like cars, bikes, bus. Multi Support vector machine classifier is used to classify the vehicles for better; it works effectively even if the number of features is greater than the number of samples. The main aim of the paper is to develop an efficient algorithm that can count and classify the vehicles for better traffic surveillance.

II. RELATED WORK

From last decade, various methods of vehicle detection and classification were developed (Kastrinaki et al., 2003)[11]. Avery, Wang and Rutherford proposed digital image processing algorithm for length based vehicle classification. They used streams of images captured from un-calibrated video camera [12]. They actually compare the length of different vehicles in order to estimate the truck volumes and eliminated the needs of different complex calibration systems. They implemented length classification algorithm on trucks and got 92% accuracy under certain conditions. The objective in this phase is to detect moving vehicles in the scene. This operation is frequently based on the background subtraction (Yu et al., 2000; Mandellos et al., 2011; Xia et al., 2016)[13][14][15] or Optical Flow (Ji et al., 2006; Johansson et al., 2009; Hossen and Tuli, 2016)[16][17][18]. Background subtraction is a technique in the fields of image processing and computer vision wherein an image's foreground is extracted for further processing (object recognition etc.). This technique involves subtracting an image that contains the object, with the previous background image that has no foreground objects of interest. The area of the image plane where there is a significant difference within these images indicates the pixel location of the moving objects [19]. The second widely used method is Optical Flow (Aslani

and Mahdavi-Nasab, 2013). Optical flow is the pattern of apparent motion of objects, surfaces, and edges in a visual scene caused by the relative motion between an observer and a scene.

Among the issues widely known in video surveillance of road traffic, partial occlusions appear as a major problem which negatively influences the accuracy of video surveillance systems. Thus, various methods have been introduced to debug them. Also, the authors S. Xuefeng and R. Nevatia have presented a vehicle segmentation method to detect, track and classify moving vehicles in presence of occlusion in crowded scenario [20]. The authors used a vehicle outline patterns, camera adjustment and ground plane information for detection process. Secondly, Principal Component Analysis (PCA) is applied as a low-dimensional statistical method to measure the two histograms of each candidate, and support vector machine (SVM) is considered for real vehicle parts classification. Eventually, all classified parts shaped and connected as a parallelogram to represent the parts shapes for matching process. Also, a new method for vehicle detection based on shadows underneath vehicles information has proposed by Y. Iwasaki and H. Itoyama(2006)[21]. This method extracts the size features of vehicles from information that gathered from the distance between ends of front and rear tires for underneath shadow of vehicles to distinguish the existence of vehicles on the lanes.

III. PROPOSED WORK

System Architecture: Proposed system architecture is depicted in the following figure 1.

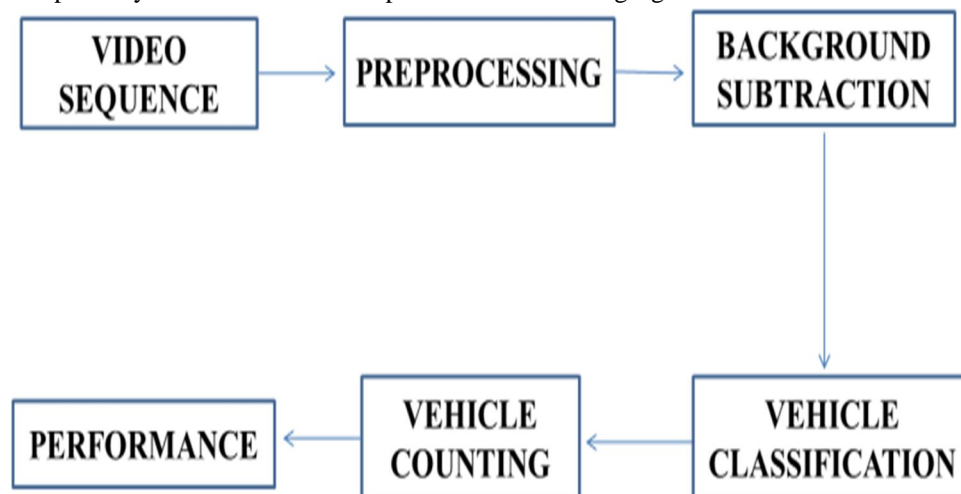


Figure 1.Overall architecture

The proposed system includes three main modules. Each module contains a set of techniques in order to have a good quality of the motion detection and vehicle classification modules. The main modules of the proposed method are:

- 1) *Background Modelling:* Background modeling is used in different application to model the background and to detect the moving objects in video surveillance. We propose an efficient approach for segmentation based on texture analysis, a 2D discrete cosine transform (DCT) is utilized to extract texture features in image block. We first split the input image into $M \times N$ blocks; calculate the distances between neighbor blocks by a set of largest energy signatures from DCT for each block. Then we merge blocks with smallest distances to form larger regions. The process will repeat until we got desired number of regions.
- 2) *Vehicle Classification:* Vehicle count and classification data are important for survey of traffic operation and transportation planning. There are various significant classification algorithms such as artificial neural networks (ANN), naïve bayes, support vector machine (SVM) etc. When comparing among the algorithms the SVM algorithm gives higher accuracy of classification since the training and classification is extremely efficient, they provide good accuracy in typical domains and kernel maps to a very-high dimensional space. Hence it is used to define the different types of vehicles (cars, bikes and bus) by extracting the features .The extracted features is trained and tested. The training features of the model of SVM classification are generated. The segmentation qualities of frames are important for vehicle classification.
- 3) *Vehicle Counting:* The Vehicle counting method has several advantages over other automatic systems. Vehicle counting process provides information about traffic flow, vehicle crash occurrences and traffic peak in roadways. A technique to attain these goals using digital image processing methods on camera video outputs present along roadway or highway. In this

proposed method, counting the vehicles is done by counting the number of bounding box present in the video frames respectively. The total count of vehicles in the frame is displayed at the left-top corner dynamically.

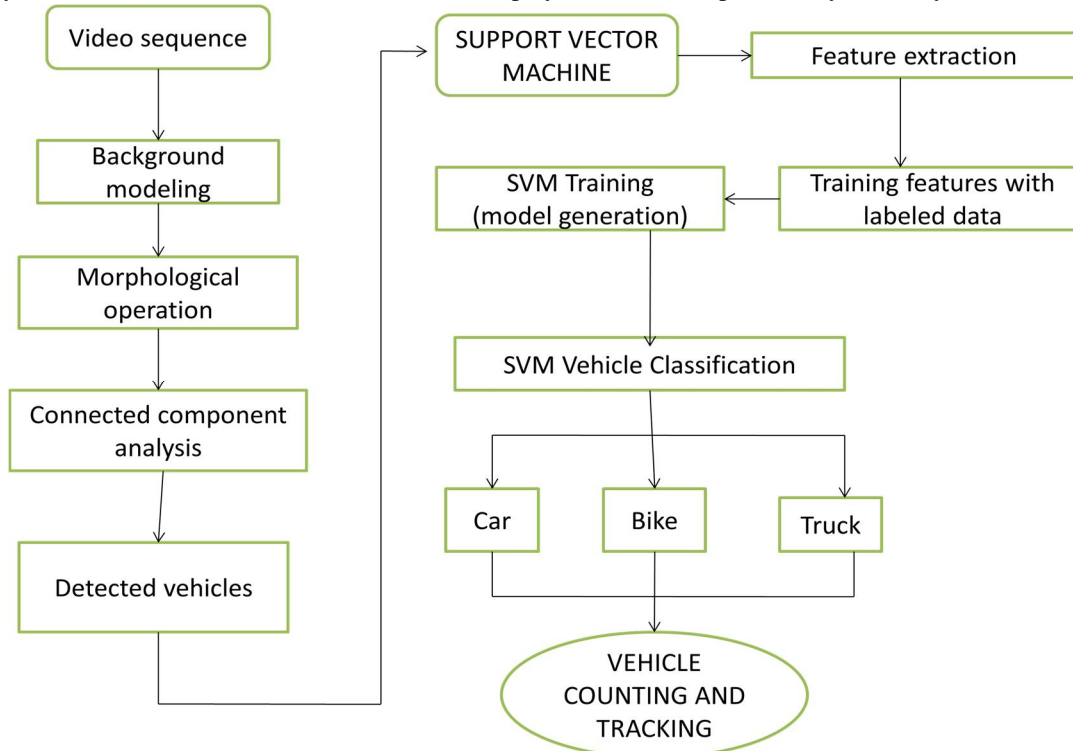


Figure 2.Flowchart of the proposed system

A. Vehicle Segmentation

- 1) *Segmentation phase:* The first step of the segmentation phase is extracting moving objects from the image sequence. There have been multiple proposed methods of background subtraction in the literature (Horprasert et al.,1999;Stauffer and grimson,1999;Kim et al.,2005).The main principle behind these method is to define a model corresponding to the static background in the scene by learning and subtract this model from the image sequence to isolate moving objects. A test was conducted to analyze the results of the background subtraction with these two methods. The first method models the background by distribution of a Gaussian per pixel (Fig. 3(b)). Mixture of Gaussians is a widely used approach for background modeling to detect moving objects from static cameras. The second method is based on background subtraction with discrete cosine transform (DTC) (Fig. 3(c)).DCT domain histogram is matched using Cb and Cr planes and motion vectors which are used to select the target object from the set of candidate objects. The test shows that the result given by the background subtraction with DTC is most efficient because moving objects corresponding to vehicles appear clearly in foreground mask with minimal mask.

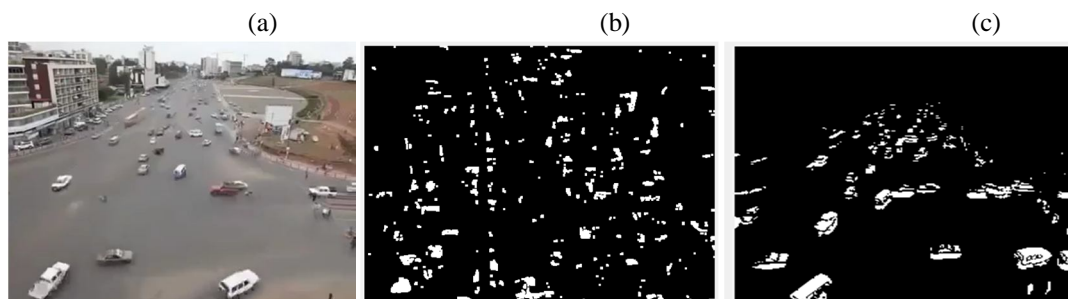


Figure 3.Background modeling

(a)Tested Video sequence

(b)Gaussian mixture model

(c)Background modeling with discrete cosine transforms

B. Vehicle Classification

- 1) **Multi-class SVM:** Most popular form of SVM usage is a binary classifier. The SVM can be extended to multi-class classification problems. The multi-class SVM can be used by creating multiple binary classifiers as shown in the figure 4. This method is similar to multinomial logistic regression, where we build a logistic model for each pair of class with base function.

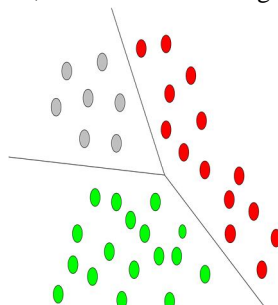


Figure 4. Multi-class SVM classification

Support vector machine (SVM) has emerged as a good classification technique and achieved excellent generalization performance in a variety of applications. From the below chart, comparing with other training and classification algorithms, the performance of SVM has the most advantages and accuracy in classifying the objects effectively.

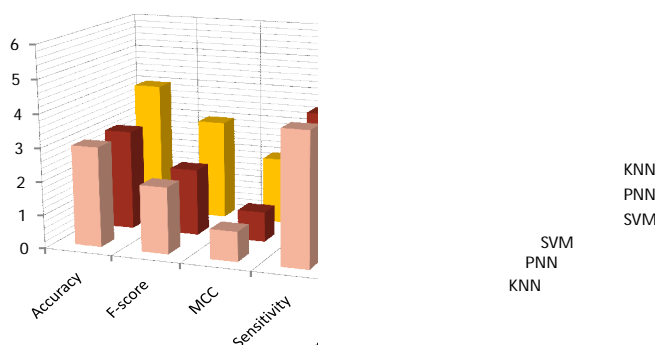


Figure 5 Comparison between training and classification algorithms

Where,

$$\begin{aligned}
 \text{Sensitivity} &= \frac{TP}{TP+FN} \times 100 \\
 \text{Specificity} &= \frac{TN}{TN+FP} \\
 \text{F-Score} &= \frac{2 \times \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \\
 \text{NPV} &= \frac{TN}{TN+FN} \\
 \text{MCC} &= \frac{(TP \times TN) - (FN \times FP)}{\sqrt{(TP+FN) \times (TN+FP) \times (TP+FP) \times (TN+FN)}}
 \end{aligned}$$

- 2) **Learning and training:** Vehicle classification helps to define the types of vehicle (car, bike, truck) crossing the road which is an indispensable tool in road traffic video surveillance systems. We use a multiclass Support Vector Machine (SVM) based method for vehicle classification. In order to classify the vehicles, a group of binary SVMs have been trained. This can be trained by simulation defined by two data sets, the training set and the testing set. From the testing data sets, the features of the vehicles are selected and later training is done for the selected features which further processed by the multi-class SVM training and hence the vehicles are classified based in accordance with their count. Finding the optimal hyperplane between the three

classes by maximizing the margin between the closest points of the three classes the support vector machine is defined. The goal of SVM is to create a flat boundary called a hyperplane, which divides the space to create homogenous partitions on either side with optimal hyperplane.

C. Vehicle counting and tracking

- 1) *Connected component analysis*: Connected component analysis involves the labeling of objects and highlighting them by drawing a bounding box around them. After the process of vehicle segmentation, bounding boxes is found for each connected component corresponding to a moving vehicle. Further the object filters the detected foreground by rejecting blobs respectively.
- 2) *Vehicle counting*: Vehicle counting gives information about the traffic load on a particular city highway. Automatic vehicle counting is an important in the automated traffic system. For counting the vehicles present in the current video frame, we can calculate by the number of bounding box of all the blobs, the number of bounding box of the moving vehicles gives the number of vehicles that have passed that particular path. Vehicle counting is important to estimate the traffic density and helpful to optimize the traffic flow.

$$\text{No. of bounding box} = \text{No. of vehicles}$$

The number of vehicles in each frame are estimated and displayed at the left top-corner of the video frame.

IV. RESULTS AND DISCUSSION

To evaluate the quality of this study, we reserved this section to represent the experimental results acquired during the execution of the proposed system. Then, we introduce a comparative study between our method and other existing methods.

A. Experimental result

For the testing, we used the video for the counting and classification of vehicle for the traffic surveillance. Figure 6 shows an image of video used for testing. The video has duration of 20 sec.



Figure 6. Testing video

In this chapter results are shown in figure 7 for the classification and counting of vehicle for traffic surveillance system.



Figure 7. Results of the proposed system

(a) Foreground detected using Background subtraction

(b) Classification and counting of vehicles based on SVM classification

B. Accuracy of traffic counting

To evaluate the efficiency of our proposed system, we conducted an analytic study of the counting and classification accuracy of vehicles. Table 1 shows the results of vehicle counting efficiency system.

TABLE 3
TRAFFIC COUNTING EFFICIENCY

Type of vehicle	Count	Error	Accuracy
Car	43	6	94.3%
Bus	20	5	94.25%
Bike	10	3	95%
Average			95.18%

C. Comparative study

A Comparative study on traffic surveillance video systems is developed in Table 4. This study was conducted to compare the counting and classifying efficiency of our proposed system to that measured in other existing systems.

TABLE 2
COMPARATIVE STUDY

Comparative methods	Guolin,Deyun and Jason (2008)	Sushmitha and Malviya (2013)	Raad, Ghazali and Loay (2014)	Mukesh Tiwari and Dr. Rakesh (2017)	Proposed method
Types of vehicles studied	Cars	Cars and Trucks	Cars	Cars, Bikes and Trucks	Cars, Bikes and trucks
Segmentation method	Frame subtraction and background update	Background subtraction	Background subtraction	Optical flow	Background subtraction with Discrete cosine transform
Classification method	X	Centroid method	Contour Tracking method	Silhouette tracking	Multi-SVM classification
Vehicle counting accuracy	88.6%	91%	92.04%	93%	95.18%

V. CONCLUSION

Traffic surveillance and detection of moving object provides information about the object behavior and object interaction since automated video surveillance systems modules such as object detection, object tracking, classification, efficiency in each module are particularly important. Greater amount of research has been done on the vehicle counting and detection but not much work is done on the vehicle classification .The proposed method can efficiently count and classify vehicles on highways and it can calculate traffic density on busy traffic roads for better monitoring. The result section shows that our proposed method can accomplish better counting accuracy when comparing with other existing systems. This proposed method can be enhanced to classify more vehicle types which influence to estimate the traffic density and consequently the robustness of the system in the future.

REFERENCES

- [1] R.Amali Therese Jenif, C.Akila,Dr. V.Kavitha, "Rapid Background Subtraction from video Sequence",IEEE International conference on computing, Electronic and Electrical Technologies 2012 978-1-4673-0210-4.
- [2] Thierry Bouwmans, El Hadi Zahzah," Robust PCA via Principal Component Pursuit: A review for a comparative evaluation in video surveillance" Elsevier Computer Vision and Image Understanding Volume 122, May 2014, Pages22–34
- [3] L. Maddalena, A. Petrosino, The SOBS algorithm: What are the limits? in: IEEE Workshop on Change Detection, CVPR 2012, June 2012.
- [4] M. Hofmann, P. Tiefenbacher, G. Rigoll, Background segmentation with feedback: The pixel-based adaptive segmenter, in: IEEE Workshop on Change Detection, CVPR 2012, June 2012.

- [5] O. Barnich, M. Van Droogenbroeck, ViBe: a powerful random technique to estimate the background in video sequences, in: International Conference on Acoustics, Speech, and Signal Processing, ICASSP 2009, April 2009, pp.945–948.
- [6] PL St-Charles, GA Bilodeau, "Improving Background Subtraction using Local Binary Similarity Patterns" Applications of Computer Vision (WACV), 2014 IEEE Computer Society Winter Conference, vol:1, pp:509-515
- [7] Tomasz Kryjak, Marek Gorgon, "Real-time Implementation of the ViBe Foreground Object Segmentation Algorithm", Proceedings of the 2013 Federated Conference on Computer Science and Information Systems pp. 591–596.
- [8] O. Barnichsz and M. Van Droogenbroeck, "Vibe: A universal background subtraction algorithm for video sequences," Image Processing, IEEE Transactions on, vol. 20, no. 6, pp. 1709–1724, 2011.
- [9] Brutzer, S., Hoferlin, B., Heidemann, G." Evaluation of background subtraction techniques for video surveillance ,Computer Vision and Pattern Recognition (CVPR), 2011 IEEE Conference, ISBN: 978-1-4577-0394-2 pp:193
- [10] C Patel ,R Patel "Gaussian Mixture Model Based Moving Object Detection from Video Sequence" International Conference and Workshop on Emerging Trends in Technology (ICWET 2011) – TCET, Mumbai, India
- [11] Kastrinaki, V., Zervakis, M. and Kalitzakis, K. (2003) A survey of video processing techniques for traffic applications. Image and Vision Computing, 21, 359-381
- [12] Ryan P. Avery, Yinhai Wang, and G. Scott Rutherford, "Length-Based Vehicle Classification Using Images from Un-calibrated Video Cameras", Intelligent Transportation Systems, 2004 Proceedings. The 7th International IEEE Conference
- [13] Yu, M., Jiang, G. and Yu, B. (2000) An integrative method for video based traffic parameter extraction in its. In Circuits and Systems, 2000. IEEE APCCAS 2000. The 2000 IEEE Asia Pacific Conference on (pp. 136-139). IEEE.
- [14] Mandellos, N. A., Keramitsoglou, I. and Kiranoudis, C. T. (2011) A background subtraction algorithm for detecting and tracking vehicles. Expert Systems with Applications, 38, 1619-1631.
- [15] Xia, Y., Shi, X., Song, G., Geng, Q. and Liu, Y. (2016) Towards improving quality of video-based vehicle counting method for traffic flow estimation. Signal Processing, 120, 672-681.
- [16] Hossen, M. K. and Tuli, S. H. (2016) A surveillance system based on motion detection and motion estimation using optical flow. In Informatics, Electronics and Vision (ICIEV), 2016 5th International Conference on (pp. 646-651). IEEE.
- [17] Ji, X., Wei, Z. and Feng, Y. (2006) Effective vehicle detection technique for traffic surveillance systems. Journal of Visual Communication and Image Representation, 7, 647-658.
- [18] Johansson, B., Wiklund, J., Forssen, P.-E. and Granlund, G. (2009) Combining shadow detection and simulation for estimation of vehicle size and position. Pattern Recognition Letters, 30, 751-759.
- [19] I. Haritaoglu, D. Harwood, and L. Davis. W4: Realtime surveillance of people and their activities. IEEE Transactions on Pattern Analysis and Machine Intelligence, 22(8):809–830, August 2000.
- [20] S. Xuefeng and R. Nevatia, "A model-based vehicle segmentation method for tracking," in Computer Vision, 2005. ICCV 2005. Tenth IEEE International Conference on, 2005, pp. 1124-1131 Vol. 2.
- [21] Y. Iwasaki and H. Itoyama, "Real-time Vehicle Detection Using Information of Shadows Underneath Vehicles," in Advances in Computer, Information, and Systems Sciences, and Engineering, K.Elleithy, et al., Eds., ed: Springer Netherlands, 2006, pp. 94-98.



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