ISSN: 2278 – 0211 (Online)

Analysis Of Classification And Tracking In Vehicles Using Shape Based Features

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Abstract:
Vehicle classification plays a prominent role in Electronic Toll Collection (ETC). The reason behind any method to incorporate into the system of ETC is to reduce the time at toll plazas and even the safety. Even many methods had been derived and implemented still we find some tackling and classification related problems. In this paper, a new algorithm has been proposed to avoid tackling and classification problems. In the proposed algorithm first the frame difference method is used to detect the moving regions from the highway scene. Some morphological operations are used to remove the shadow noise and to detect the moving object correctly. After vehicle detection, a region-based vehicle tracking method is used for building the correspondence between vehicles detected at different time instants. After vehicle tracking, we consider two parameters such as aspect ratio and compactness are used to classify and count the vehicles. Experimental results on different videos with different lighting conditions are used to demonstrate the effectiveness of our proposed system.

Key words: *Vehicle Classification, Vehicle Detection, Vehicle Tracking, Aspect Ratio, Compactness, ETC*

1.Introduction

An intelligent transportation system (ITS) is the application that incorporates electronic, computer, and communication technologies into vehicles and roadways for monitoring traffic conditions, reducing congestion, enhancing mobility, and so on. ITS is an evolving science and engineering discipline whose primary goal is to minimize the travel time of all travellers and merchandise while ensuring safety, through fair distribution of available resources, especially under the scenario of increasing travel speeds, and significantly large number of travellers, and a high demand for precise and timely information from travellers. To achieve its goal, ITS must bring about a seamless and natural integration of the different modes of transportation, including vehicular traffic, trains, cargo air transport, passenger air transport, marine ferries, and others through asynchronous distributed control and coordination algorithms. As a result of the integration, the traveller will (i) gain access to accurate status information of any transportation mode from any point in the system, (ii) compute the most efficient route or reroute across all different transportation modes by processing the available information through personalized decision aids, and (iii) be permitted to affect reservations, dynamically, even while en route, on any transportation system.

ITS encompasses the subareas of transportation management, which subsumes interstate roadways management and traffic signalling; travel management, which includes multimodal traveller information; public transportation and transit management; safety management, which subsumes incidents, railroad grade crossings, and emergency services; advanced vehicle control; and fare payment and toll collection. Traffic surveillance is one of the important issues in ITSs for traffic monitoring. The key goal of the traffic surveillance system is to estimate the desired traffic parameters through the detection, tracking and vehicle number counting process.

Nowadays, there is an instant need for the robust and reliable traffic surveillance system to improve traffic control and management with the problem of urban congestion spreads. Many traffic state parameters can be detected through traffic surveillance system, including traffic flow density, the length of the queue, average traffic speed and total vehicle in fixed time intervals. To achieve these goals, in past decades, there have been many approaches proposed for tackling related problems. Currently there are two kinds of traffic technologies. The dominant technology is loop sensor detection; this technology is efficient for vehicle speed and flow data collection. Although many detect devices such as closed loop, supersonic and radar are exist and widely used, the most important drawback of these equipments is their limitation in measuring some important traffic parameters and accurately assessing the traffic

condition. The first reason is that “blind” type of detection technology is employed. These sensors cannot provide full traffic scene information. Another very popular technique is a video monitoring system.
The vision-based approach has the advantages of easy maintenance and high flexibility in traffic monitoring and, thus, becomes one of the most popular techniques used in traffic surveillance system [1]. vehicles are the major objects in the traffic environment, many researchers have been investigated how to detect and classify vehicles. In past decades, numerous research projects aiming to detect traffic flow have been carried out in terms of measuring traffic performance. There are already several kinds of traffic flow detection methods. But there have been tackling and classification related problems. In previous work normal background subtraction method is used for detecting the moving vehicles which resulted tackling and classification problems. In order to avoid those problems a new algorithm has been developed in this paper. However, the main challenging issues to the success of vehicle detection and classification are from vehicle occlusion, perspective effects, and camera configuration [6]. There are many existing methods are proposed to tackle with these difficulties.
For many traffic surveillance systems, three major stages are used to estimate the desired traffic parameters of vehicles, i.e., vehicle detection, tracking and classification. The large increase of the vehicles there is a traffic jam and it become more critical day by day. So, the detection to vehicles is of great importance. For vehicle detection, we assume that the camera is stationary; most methods detect the vehicle by image difference.Then, different tracking schemes like the Kalman filter are designed to track each vehicle. After that, several vehicle features like shape, length, width, texture, etc., are extracted for vehicle classification.
An approach that uses parameterized 3D model is proposed in [3]. The adopted model for vehicle classification is a generic vehicle model based on the shape of a typical sedan. For the purpose of estimating vehicle parameters, we have to build the correspondence among the vehicles detected at the different frames by tracking schemes. The corners are detected as features for vehicle tracking in [4]. In [3], it uses a feature-based approach with occlusion reasoning for vehicle tracking in congested traffic scenes. Additionally, the vehicles are tracked through sub-features instead of entire vehicle to handle occlusion effect. More recently, a stochastic approach called particle filtering are widely used for tracking vehicles by relaxing the Gaussian assumption of vehicle motion [2].
The main objective of this paper is to present a robust traffic surveillance system for vehicle counting and classification. In order to avoid tackling and classification problems a new method has been implemented. The frame difference method is firstly used to detect the moving regions from the highway scene . After vehicle detection, a region-based vehicle tracking method is used for building the correspondence between vehicles detected at different time instants. The two parameters, such as aspect ratio and compactness are used to classify and count the vehicles.
The rest of this paper is organised as follows. In section II, we describe the overview of the proposed system. The methods of vehicle detection, vehicle tracking, vehicle classification and counting are introduced in sections III –V, respectively. Sections V give some experimental results. Finally, a conclusion and future work will be presented in section VII.

2.Overview

In this paper, we propose a new traffic surveillance system for detecting, tracking, and classifying vehicles from different video sequences. Figure 1 shows the flowchart of this proposed system. In the proposed system, different vehicles are first extracted through frame difference method. Unfortunately, due to shadows; several vehicles will be occluded together and cannot be well separated. This makes the further vehicle tracking and classification incorrect. To avoid this problem some morphological operations are used to remove the shadow noise and to detect the moving object correctly and shadow removal algorithm is used for obtaining more accurate segmentation results. After vehicle detection, a region-based vehicle tracking method is used for building the correspondence between vehicles detected at different time instants. After vehicle tracking the two parameters, such as aspect ratio and compactness are used to classify and count the vehicles.

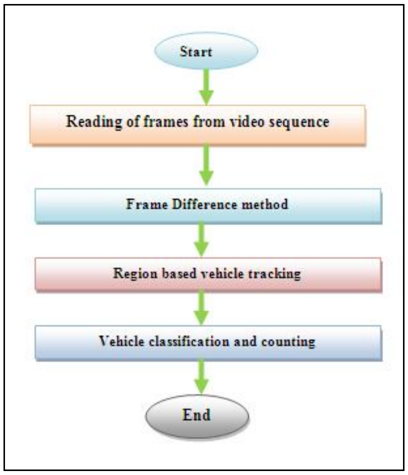


Figure 1: Flowchart Of Traffic Surveillance System

3.Vehicle Detection

In this section, we describe how to detect the moving vehicles on the highway. Firstly, the moving regions are segmented from the background by using frame difference technology. Then, the geometric properties of the segmented regions are used to filter out the false regions. In order to improve the accuracy of segmentation results, the pixels of shadow are also removed.

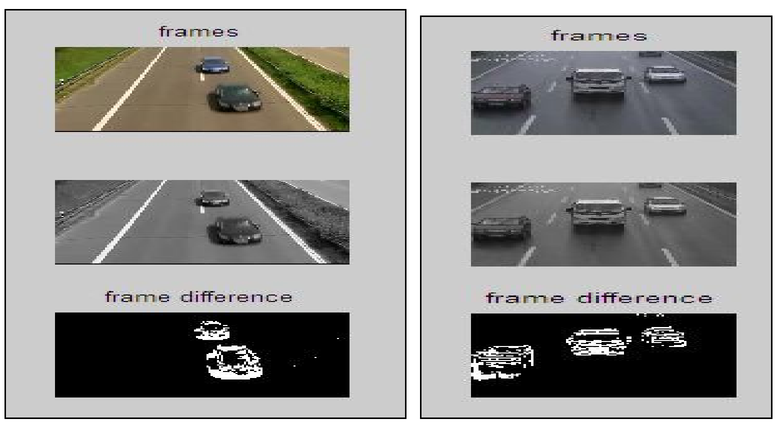
3.1.Vehicle Detection Using Frame Differencing

For classification each vehicle should be first detected and tracked from video frames. We propose a robust approach to detect moving objects for video surveillance applications. We demonstrate that a jointly use of frame by frame difference with a background subtraction algorithm allows us to have a strong and fast pixel foreground classification without the need of previous background learning. When the camera is static, different moving objects can be detected through frame difference method. The approach we choose was to perform frame differencing [7] on consecutive frames in the image acquisition loop, which identifies moving objects from the portion of a video frame that differs significantly from the previous frame. The frame method basically employs the image subtraction operator. The image subtraction operator [8] takes two images as input and produces as output a third image whose pixel values are simply those of the first image minus the corresponding pixel values from the second image. The subtraction of two images is performed straightforwardly in a single pass. The output pixel values are given by:

$$Q(i, j) = P1(i, j) - P2(i, j) \qquad (1)$$

There are many challenges in developing a good frame differencing algorithm for object detection. First, it must be robust against changes in illumination. Second, it should avoid detecting non-stationary background objects such as moving leaves, rain, snow, and shadows cast by moving objects. In our efforts to develop a high performance algorithm for object tracking we have tried to overcome the difficulties in our object detection module. Using frame differencing on frame-by-frame basis a moving object, if any, is detected with high accuracy and efficiency. The results of Frame difference in different videos are shown in Figure 2.

After identifying the moving pixels, the 8-connected component labelling algorithm is used to group the neighbouring moving pixels into the regions. As in [1], the regions with the size less than a pre-defined threshold are removed due to noise effect. However, the selection of the threshold is difficult. In this work, we propose the rules to filter out noisy regions automatically.



(a) Video 1: Frame Difference At Frame 61 & (b) Video 2: Frame Difference At Frame 80

Figure 2 The Results Of Frame Difference In Different Videos

Let $\bar{W}$ and σ_W be the mean and standard deviation of width of all detected regions. Similarly, $\bar{H}$ and σ_H are for height. For a particular region R_l, it will be considered as noisy region and eliminated if (2) is satisfied.

(1) $\left|W - \bar{W}\right| > \sigma_W \, and \left|H - \bar{H}\right| > \sigma_H$

(2)

(2) $\left|A_l - \bar{W}\,\bar{H}\right| > \sigma_W \times \sigma_H$

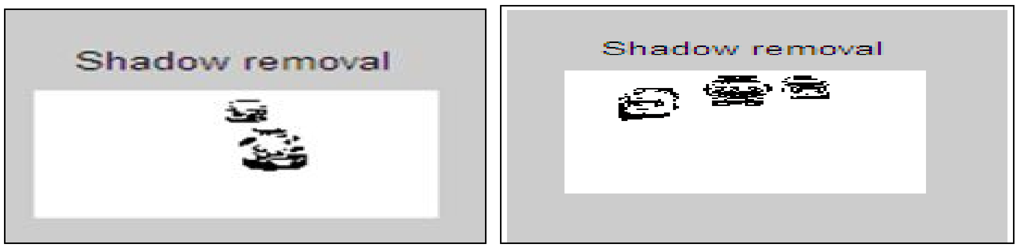
Where W, H and A_l are the width, height, and area of region R_l, respectively.

After that, we used the region growing algorithm [9] by taking the aforementioned regions as the seed to obtain more compact and accurate regions. The object of the region growing algorithm is to group their neighbouring pixels to form the larger regions. The pair of adjacent pixels is considered as neighbours if their intensity difference is less than a threshold Tr. The region growing process terminates if there are no any pixels which are merged.

3.2.Shadow Removal

Detecting moving objects in video sequences is very important in visual surveillance. The existence of cast-shadows would change the shape and size of the moving objects. Because the shadows usually move along the moving objects so that they may cause false classification, which can cause various unwanted behaviours such as object shape distortion and object merging when the video images are captured with a fixed camera, frame difference is a commonly used technique to segment moving objects. The foreground objects are identified if they differ significantly from the previous frame. However, the detecting results of moving objects are usually under the influence of cast-shadows. For these reasons, it is critical to detect and segment cast-shadows in order to describe moving objects correctly in visual surveillance and monitoring systems.

In this paper, morphological operations are used for identifying and removal of the shadow and to detect the moving object correctly. The result of shadow removal is shown in Figure 3.



(a)Video 1: Shadow Removal At Frame 54 & (b) Video 2: Shadow Removal At Frame 61

Figure 3: The Results Of Shadow Removal In Different Videos

4.Region-Based Vehicle Tracking

Once the object has been detected it is tracked by employing a region based vehicle tracking method. A vision-based traffic surveillance system needs to be able to track vehicles through the video sequence. Tracking eliminates multiple counts in vehicle counting applications. Moreover, the tracking information can also be used to derive other useful information like vehicle velocities. In applications like vehicle classification, the tracking information can also be used to refine the vehicle type and correct for errors caused due to occlusions.

- Tracking: For estimating the traffic parameters of vehicle, we have to find out the correspondence of detected vehicles at different time instants. The process for this purpose is called tracking.Some issues to be addressed in tracking process: Disappearance, Vehicle entrance, Splitting, Merging. These issues might occur when we consider region associated between time instant t-1 and t.
- Disappearance: Detected vehicle is no longer visible at t
- Vehicle entrance: A new vehicle is detected at t
- Splitting: Two vehicles are considered as 1 unit at t-1.The region might split into 2 regions at t.
- Merging: Multiple vehicles are detected at t-1.detected as a single region as t.

The region tracking method needs to be able to robustly handle these situations and work reliably even in the presence of these difficulties. We form an association graph between the regions from the previous frame and the regions in the current frame. We model the region tracking problem as a problem of finding the maximal weight graph. The association graph is a bipartite graph where each vertex corresponds to a region. All the vertices in one partition of this graph correspond to regions from the previous frame, P and all the vertices in the other partition correspond to regions in the current frame, C. An edge E_{ij} between vertices V_i and V_j indicates that the previous region P_i is associated with the current region C_j. A weight w is assigned to each edge E_{ij}. The weight of edge E_{ij} is calculated as

$$w(E_{ij}) = A(P_i \cap C_j) \qquad (3)$$

i.e., the weight of edge E_{ij} is the area of overlap between region P_i and region C_j. The weight of the graph G is defined as

$$w(G) = \sum_{E_{ij} \in G} E_{ij} \qquad (4)$$

Since the time period between two consecutive images is short, the same vehicle appearing at different time should overlap of each other. Consequently, the overlapping ratio is firstly used to remove the edges in the graph so that the computation complexity for finding the maximal weight matching can be greatly reduced. The weight of an edge is defined as the controlled distance between the two regions at different time as shown in Figure 4. The algorithm used in [10] is finally used to solve this problem so that the correspondence can be found to achieve the purpose of vehicle tracking.

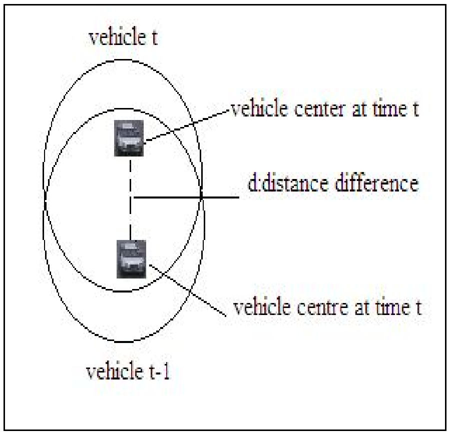


Figure 4: The Definition Of A Weight Associating With An Edge

5.Vehicle Classification And Counting

In the proposed system, the detected vehicle regions will be classified as car and truck or bus. After vehicle tracking, we consider two parameters for classifying and count the vehicles. Those two parameters are aspect ratio A_R and compactness C which are respectively defined as:

$$A_R = \frac{H}{W} \quad , \quad c = \frac{A_v}{W \times H} \qquad (5)$$

Where A_v Is The Area Of The Vehicle

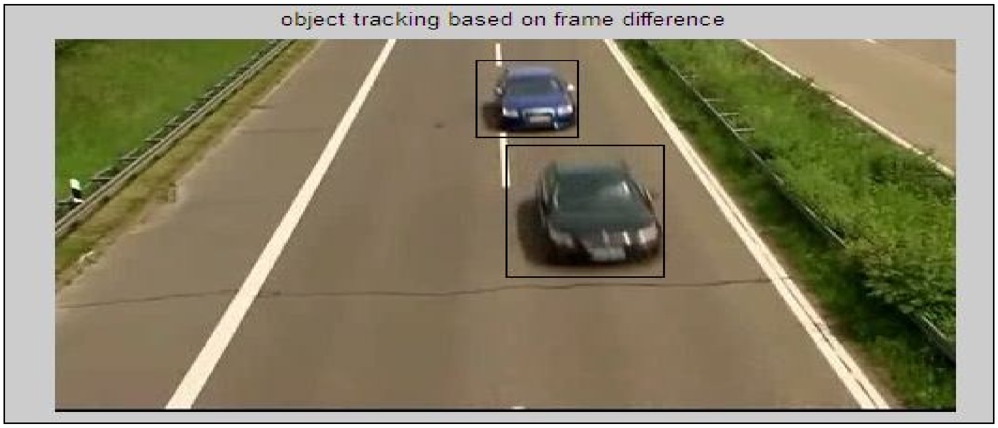
Because the height of truck and bus is larger than the one of car, it will have larger aspect ratio. Accordingly, the detected vehicle with aspect ratio smaller than a threshold T_a is firstly labelled as car. For further classifying between bus and truck, we analyze the foreground masks of bus and truck. Since the bus is general a convex object, the segmented foreground will be more compact than the truck. Accordingly, the region with compactness larger than a threshold T_c is classified as the bus. The classification rule of a detected vehicle is expressed as:

$$\begin{cases} \textbf{Car} \quad \textbf{if} \quad A_R < T_a \\ \textbf{Bus} \quad \textbf{if} \quad A_R \geq T_a \ \textbf{and} \ C \geq T_c \\ \textbf{Truck} \quad \textbf{otherwise} \end{cases} \qquad (6)$$

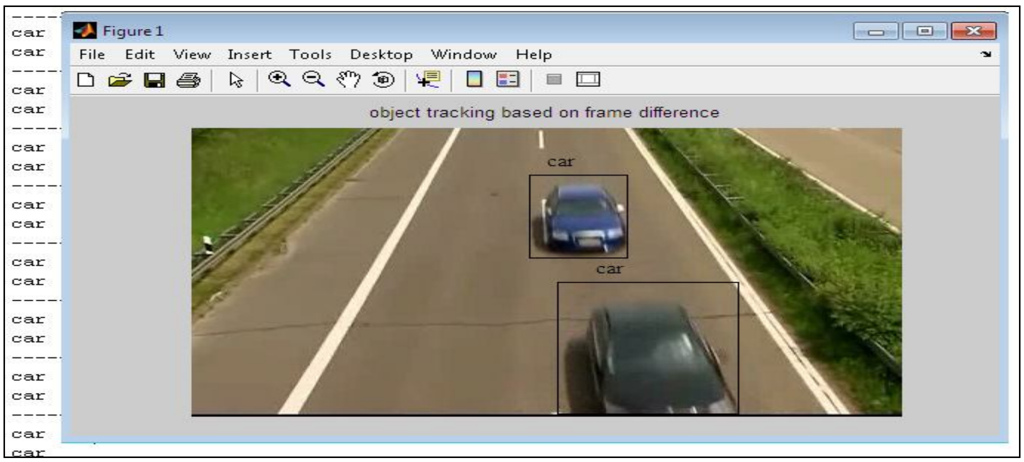
6.Experiment And Results

In this section, the traffic scenes on the highway are captured from Panasonic LUMIX DMC-FH25 Camera with image resolution 1280 x 720 pixels at 24 fps. The platform used to perform the proposed system is MATLAB 7.0.4. We collected two videos at different times in order to validate the proposed work with various illumination conditions.

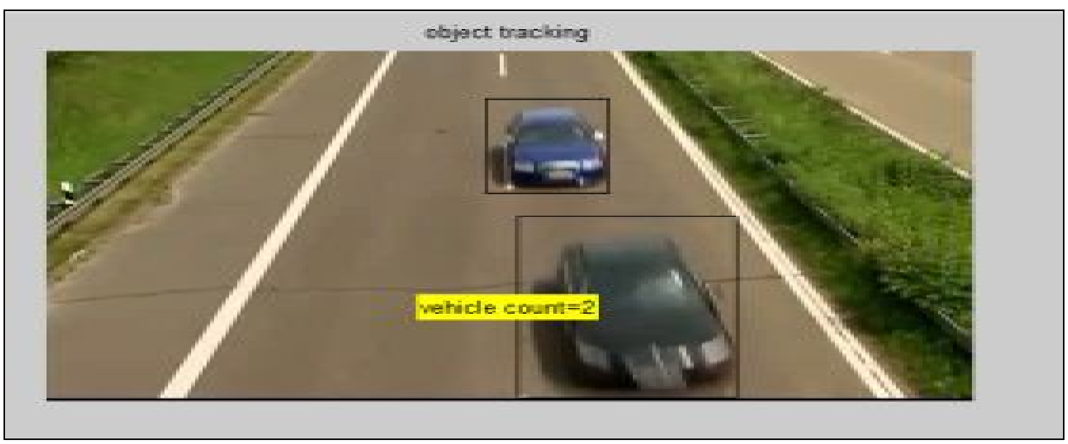
In the proposed algorithm, the frame difference method and some morphological operations are used to detect the moving vehicle correctly. After that, the region tracking problem is formulated as a problem of finding the maximal weight graph. To overcome this problem here we introduced the overlapping ratio of vehicle regions to remove invalid edge for saving computation time. Finally, two parameters such as aspect ratio and compactness are used for classification and counting the vehicles. For the purpose of annotating the classification results, the detected car and truck are shown on the left side of the image. The statics of number of vehicles passing through the highway is shown at the top of the image. Some experimental results are shown in Fig 5.



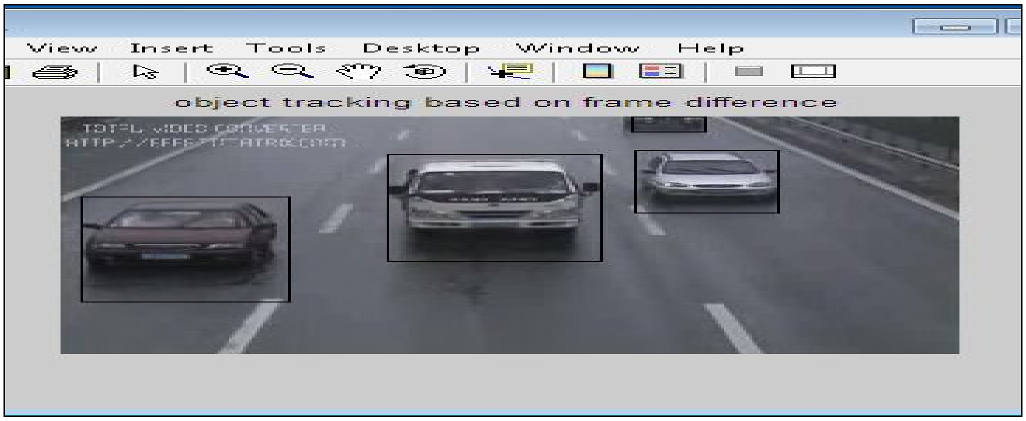
(a) Video 1:Object Tracking Based On Frame Difference At Frame 19



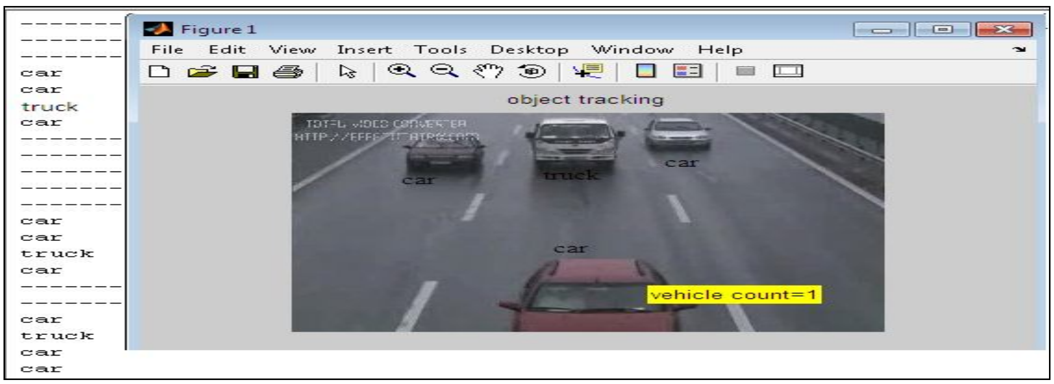
(b) Video 1: Vehicle Classification At Frame 30



(C) Video 1: Vehicle Counting At Frame 22



(d) Video 2:Object Tracking Based On Frame Difference At Frame 80



(e) Video 2:Vehicle Calassification At Frame 40

(f) Video 2: Vehicle Counting At Frame100

Figure 5: Some Experimental Results For The Captured 2 Videos

7.Conclusion And Future Work

In this paper, we proposed a new traffic surveillance system for detecting, tracking, and classifying vehicles from different video sequences. This algorithm presents a robust traffic surveillance system for vehicle counting and classification. The vehicles are classified into three categories: car, bus, and truck, according to two parameters.

Vehicle classification is used in ETC for collecting the appropriate toll and even to reduce the time at toll plazas. However the performance of this system is significantly affected by the selected thresholds. In the near further, Gaussian mixture methods used to detect the video object tracking and find the vehicle parameter estimation.

8.References

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