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REAL-TIME SYSTEM BASED ON FEATURE EXTRACTION FOR VEHICLE DETECTION AND CLASSIFICATION

Zakaria Moutakki^{1,2}, Imad Mohamed Ouloul¹, Karim Afdel¹, Abdellah Amghar¹

¹*Laboratory of Metrology and Information Processing, Department of Physics, Faculty of sciences,
University Ibn Zohr, B.P 8106, Agadir, Morocco*

²*zakaria.moutakki@edu.uiz.ac.ma*

Today, Road traffic video surveillance becomes the centre of several concerns. It presents an important way for analysis of road traffic in highways. Road traffic video surveillance can help to resolve many problems which can influence road safety. This paper presents a real-time management and control system which serve to analyze road traffic using a stationary camera. The proposed system can measure the quantity and characteristics of traffic in real time based on three modules, segmentation, classification and vehicle counting. Our contribution consists of developing a feature-based counting system for vehicle detection and recognition under the conditions which present a challenge in recent systems, such as occlusions, and illumination conditions. Our method can perform vehicle detection and classification by eliminating the influence of many factors on system efficiency. The obtained results show that the system proposed in this paper provides a counting rate higher than that of some existing methods.

Keywords: Intelligent transportation systems, Vehicle detection, Occlusion handling, Vehicle classification, Background subtraction, Feature extraction

1. Introduction

In Morocco, the road is the most significant support for people mobility and transport of goods. The road is the first mode of transportation for 90% of individuals and 75% of products. Every year, road network continues to grow thanks to the high priority allowed at the national level to road infrastructures. Against this remarkable development of infrastructures, road traffic control and analysis remains modest. Traffic surveillance systems are usually based on the following control tools: Portable radars, patrol radars, and fixed radars (Un-Habitat, 2013). These systems do not allow to intervening immediately on the scene of the misdemeanour, and do not provide the necessary information for operators to ensure the fluidity, the reliability and the safety of displacements, without skipping that these systems are expensive in installation and maintenance (Barendregt and Van Der Kemp, 1988; Mimbela and Klein, 2000). Thus, many problems appear at the level of road traffic circulation such as traffic jams and accidents.

The application of video surveillance techniques in road traffic analysis can assure good results compared to traditional systems (Kastrinaki *et al.*, 2003). Based on surveillance cameras, video surveillance systems can be a valuable tool to manage all tasks related to road traffic. Based on the information which may be collected using these systems, vehicle counting and tracking in real time becomes less complicated and more efficient.

The contribution to solve the problems presented previously was our motive to design a video surveillance system of road traffic. Based on a stationary camera on the road, our real time system can generate a set of information about vehicles flow which crosses the road. The produced results will be useful to take necessary security measures to ensure circulation fluidity. The performance of a real-time system is related to its capacity to detect vehicles and recognize their types as well as its robustness. Consequently, we have established a set of techniques designed to increase vehicle detection and recognition accuracy.

The developed method in this paper starts with a segmentation module of frames coming from the camera. This module is based on background subtraction as a first step, followed by filtering techniques to reduce segmentation noise. In the second module, we extract a set of characteristics related to the shape of moving objects in order to characterize and classify these objects. Vehicle counting and tracking are the goals of the last module.

The rest of paper is organized as follows. The following section presents related work. Section 3 shows a conception of the method which describes the different modules used to count and track vehicles. Section 4 describes the results achieved and their comparison with some existing methods. Finally, section 5 is dedicated to draw a general conclusion.

2. Literature review

During the last decade, traffic surveillance systems have become among the leading applications of video surveillance at the planetary level due to vehicle traffic increase. Thus, numerous studies were

conducted in this field. The primary purpose of most traffic monitoring systems includes the following tasks: Motion detection, vehicle classification, vehicle counting and tracking. The motion detection phase aims to segment the regions of interest based generally on two methods: (1) Background subtraction (Wan *et al.*, 2014; Sobral and Vacavant, 2014); (2) Optical flow (Frias-Velazquez *et al.*, 2015; Chauhan and Krishan, 2013). Classification module aims to classify vehicles to their appropriate type. Most of classification methods are based on feature extraction (Hsieh *et al.*, 2006; Jung and Ho, 1999) from moving objects. The extracted features are usually related to the moving object shape, colour, and texture. Ince (2011) proposes a vehicle counting method based on background subtraction and invariant moments. A mixture of Gaussian models is used to perform the foreground estimation. Vehicle classification is performed by computing moment invariant features of the foreground mask. In (Chen *et al.*, 2007), T.H. Chen proposes a vehicle counting system based on three modules: Object segmentation, blob analysis, and vehicle tracking. This system in (Lai *et al.*, 2010) use a three-step technique comprised of vehicle extraction, vehicle tracking, and classification. The method uses background subtraction to extract the foreground mask containing vehicles region. Filtering and shadow removal are then performed based on geometric parameters. After vehicle detection and tracking, vehicle classification is realized using two shape features called aspect ratio and level of compactness.

Vehicle video surveillance systems know certain constraints due to various problems such as shadows, illumination conditions and occlusions. Numerous studies were proposed to reduce the influence of these problems on the efficiency of vehicle detection and classification systems. In (Tian *et al.*, 2015; Satzoda and Trivedi, 2016; Reilly *et al.*, 2013; Sanin *et al.*, 2012), the authors present a survey and a comparative study of shadow removal methods. The analysed methods are classified to four categories: texture, physical, chromaticity, and geometry. In (Faro *et al.*, 2011), a vehicle detection and tracking system is proposed. The system utilizes luminosity sensors and one fixed camera. The proposed method can handle illumination changes and occlusions based on luminosity information and the features of the detected vehicles. Kanhere and Birchfield (2008) propose a real-time segmentation and tracking system. The system operates at low camera angles using stable features. Based on the feature points, the method can detect and track the partially occluded objects.

3. Proposed system

The system consists of three parts: Image segmentation, feature extraction, vehicle counting and tracking. The image segmentation starts with motion detection using background subtraction to eliminate the static background which contains the stationary objects in the road. This step is followed by a set of filtering techniques of segmentation mask to remove the noisy and the blurry image. Canny edge detector is then performed to detect the contours in image sequence. The detected contours will be subject of a box modelling method.

In feature extraction module, we will characterize the boxes associated with vehicles by a set of parameters. This step aims to perform two important tasks:

- Classify vehicles according to their types.
- Detect partial occlusions of vehicles.

Classification process is based on preliminary study applied to a vehicle image database in order to determine feature values associated with vehicle types. Thus, each vehicle detected in the first phase is classified depending on the values of the calculated parameters. In the last module, these vehicles are counted during their movement in the scene.

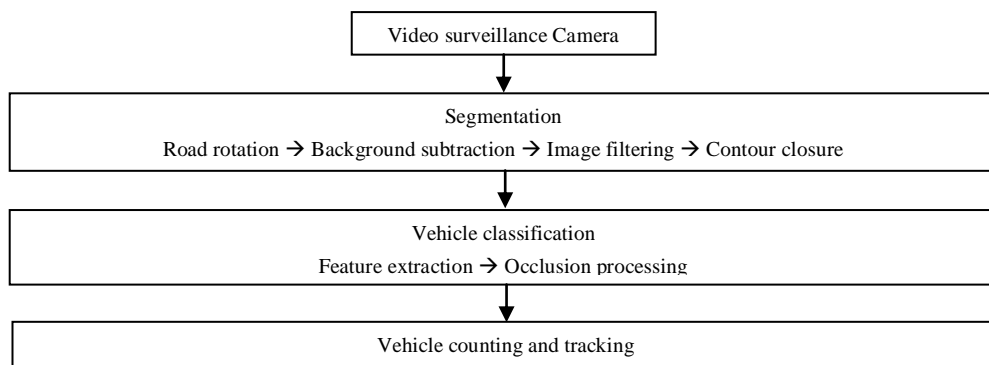


Figure 1. Flowchart of the proposed system

3.1. Video sequence rotation

Road inclination angle compared to vision field axis of surveillance camera influences on the vehicle detection efficiency. Indeed, for some camera positions, it is possible that a false detection can reproduce. A preliminary study is performed to define the inclination angle associated to the highest detection rate. The result of this study showed that when road direction coincides with the axis of vision field of surveillance camera, we have the highest detection rate.

The rotation algorithm is composed of following steps:

- Detection of roadsides direction using Hough transforms (Ballard, 1981). This operation will be applied one time and only in first frame.
- Angle computation between detected roadside and the vision axis of surveillance camera.
- Video sequence rotation respecting that road direction coincides with the axis of vision.

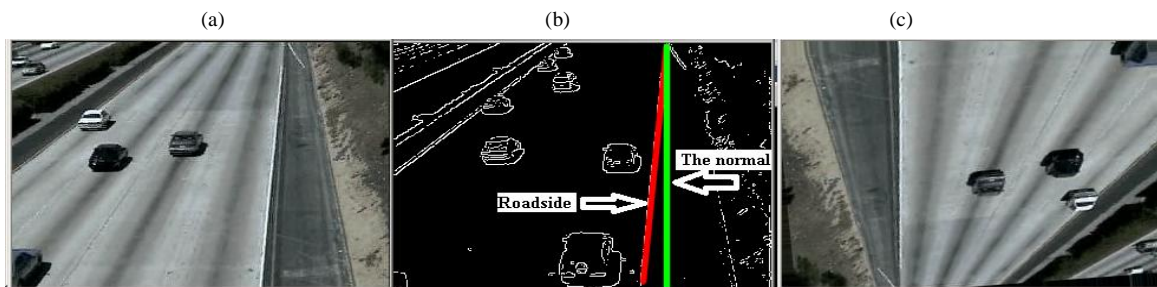


Figure 2. Video rotation: (a) First frame, (b) Line detection using Hough Transform, (c) Rotation result

3.2. Image segmentation

3.2.1. Background subtraction

In many road traffic video surveillance systems, motion detection process in a video sequence is based mostly on background subtraction. The basic idea of the concept is to determine a model of background corresponding to static regions of video sequence by training. The difference between background model and observed image is then performed to bring out mobile elements in a foreground mask. In our case, the camera is stationary, which means that the background model contains the static objects in the scene (road, trees, and road signs). The foreground mask contains the moving objects.

Numerous subtraction background methods exist in the literature (Wang *et al.*, 2012; Kim *et al.*, 2005). Among these methods, we used Mixture of Gaussian Model (Stauffer and Grimson, 1999). Taking into consideration the multi-modal aspect, Stauffer et al. propose a method based on modelling with a mixture of N Gaussian for each pixel with $2 \leq N \leq 5$. For $n = \{1, \dots, N\}$, each element of Gaussian mixture is represented by an average μ_n , standard deviation σ_n and a weight α_n ($\sum_n \alpha_n = 1$). Foreground mask contains some amount of noise due to segmentation step. To remove the noisy and blurry image, morphological operations, such as opening and closing, are applied.



Figure 3. Background subtraction using Mixture of Gaussian method

3.2.2. Filtering and contour detection

Segmentation mask still contains residual noise. That can have an adverse impact on vehicle detection and tracking rate. To eliminate this noise, we propose to model the detected contours with boxes. For that purpose, we use firstly Canny edge detector (Canny, 1986) to detect vehicle contours. Then, we compute the coordinates of contours. The coordinates is then used to draw boxes. We obtain a mask containing vehicles modelled by boxes (Fig. 4).

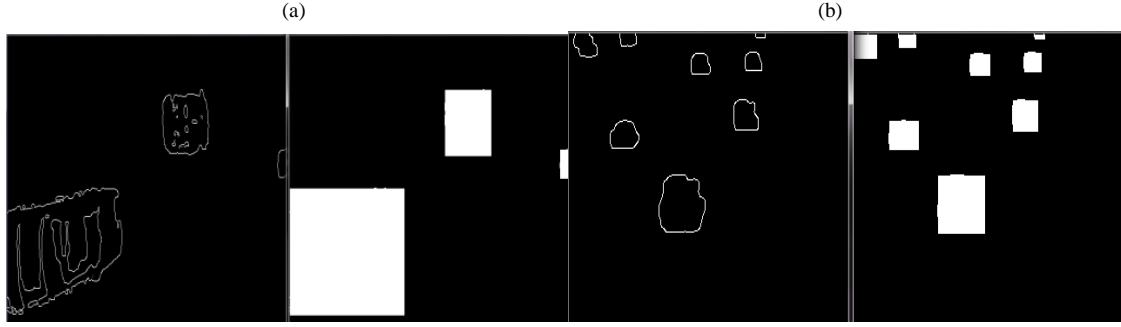


Figure 4. Results of box modelling technique
(a): Single-directional situation 1; (b): Single-directional situation 2

3.3. Vehicle classification

In classification process, the first task consists of classifying vehicles to their types based on extracted features from vehicle shape. An approach to detect and eliminate the partial occlusions is also performed. This approach is added to classification process in order to improve vehicle counting efficiency.

Feature extraction of vehicles can be performed using several parameters such as the shape (Ali *et al.*, 2013; Huang *et al.*, 2012), the colour, and the texture. In our system, we focused on shape to establish two parameters which can describe the moving vehicles. The two parameters used are related to length and width of detected boxes in segmentation phase. That means that the values of parameters vary according to detected vehicle type.

$$R1 = \frac{\text{Height}}{\text{Width}}, \quad (1)$$

$$R2 = \frac{((\text{Height} + \text{Width}) * 2)^2}{(\text{Height} * \text{Width})}. \quad (2)$$

In the above equations, Height, Width denote the height, width, of the detected box, respectively. The parameters R1 and R2 present two different combinations of Height and Width in order to establish parameters characterizing each moving object. The choice of combinations is related to the stability against vehicle movement in the scene and the variation according to the vehicle type.

Based on preliminary study applied to a vehicle image database containing 6500 images as shown in Figure 5, we were able to analyze the variations of parameters R1 and R2 depending on various classes of vehicles. We conclude that the values of parameters vary on defined intervals according to vehicle type (Bike, car), except when there is a vehicle occlusion (case 1 and case 2 in Table 1).

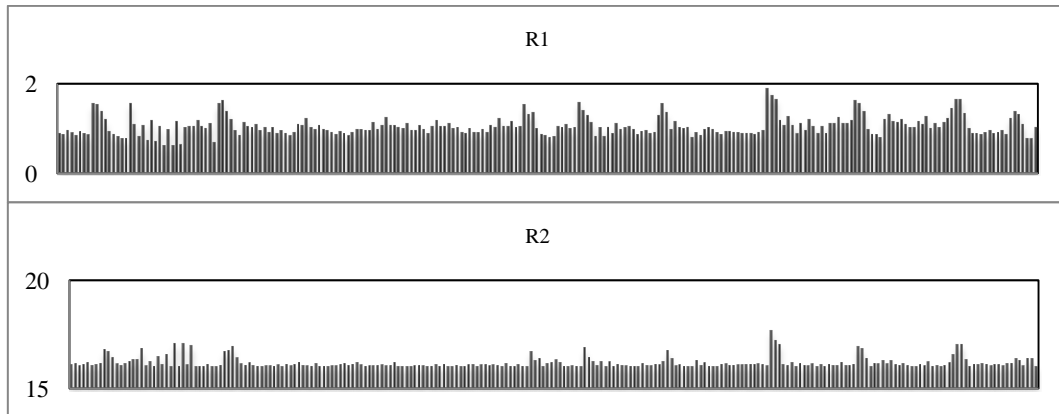




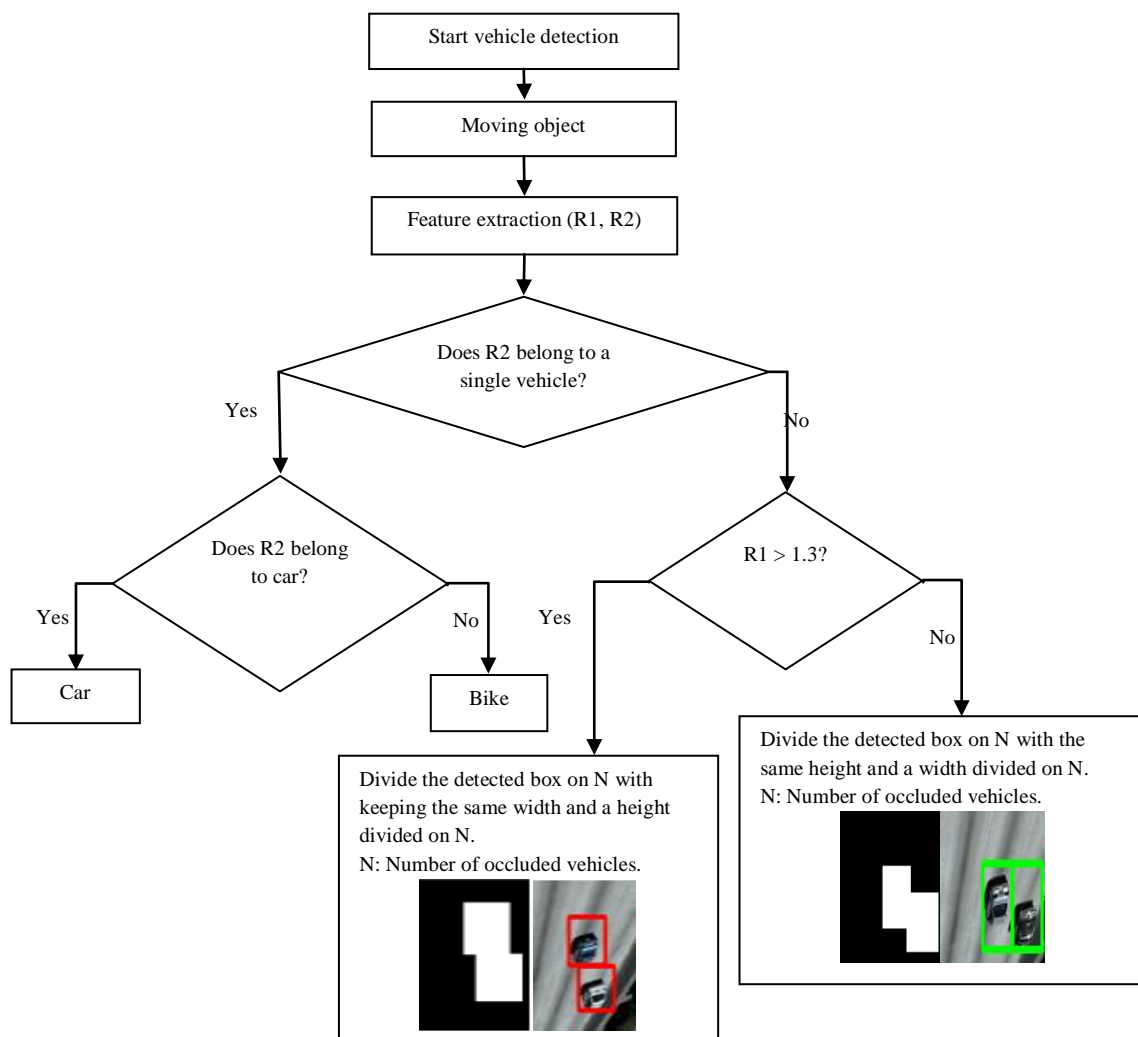


Figure 5. Results of the preliminary study

Table 1. Classification intervals

Vehicle type	Sample Image	R1	R2
Car		0.8 – 1.3	16 -16.5
Bike		1.5 – 1.8	17 – 18.5
Case 1		0.603	17.04
Case 2		1.75	19.25

We concluded that when R2 value belongs to the interval (16-16.5), the moving vehicle is a car. When the value of R2 belongs to the interval (17-18.5), the moving vehicle is a bike. Otherwise, if R2 value does not belong to any determined interval previously, there is one or more vehicle occlusion present in the scene. In this situation, we analyse R1 value. If R1 value is higher than 1.3, the box associated with the partial occlusion will be divided into two boxes based on height. Otherwise, we divide the box based on width (Fig. 6).

*Figure 6.* Flowchart of vehicle classification module

3.4. Vehicle counting and tracking

Figure 7 reveals the established zone for vehicle video surveillance. Two lines A and B present the borders of the zone. Every vehicle passing through this area will be counted and tracked.

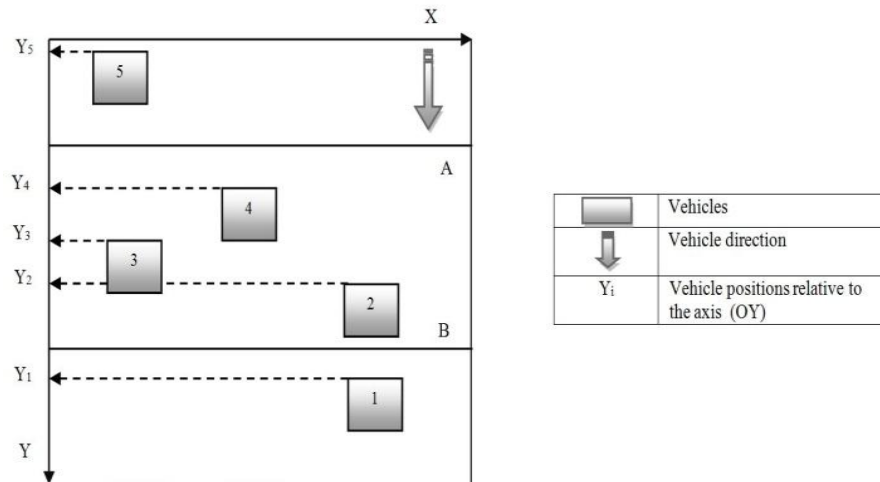


Figure 7. Surveillance zone

The process consists of knowing at any moment the number of vehicles crossing surveillance zone and their positions according to axis (OY). Segmentation module calculates these positions and save them in a one dimensional table. Thus, we can conclude recent and previous positions of each vehicle and if a new vehicle is present on the road. Vehicle counting process will depend on this result. Based on classification phase, we introduce two variables. Each variable is used to count the number of a defined type of vehicles.

In the tracking and counting system, the table comparison is the most important module. The inputs of this block are the table (Fig. 8) and V the current number of objects in the surveillance area AB, V also presents the number of positions added to the table at each frame.

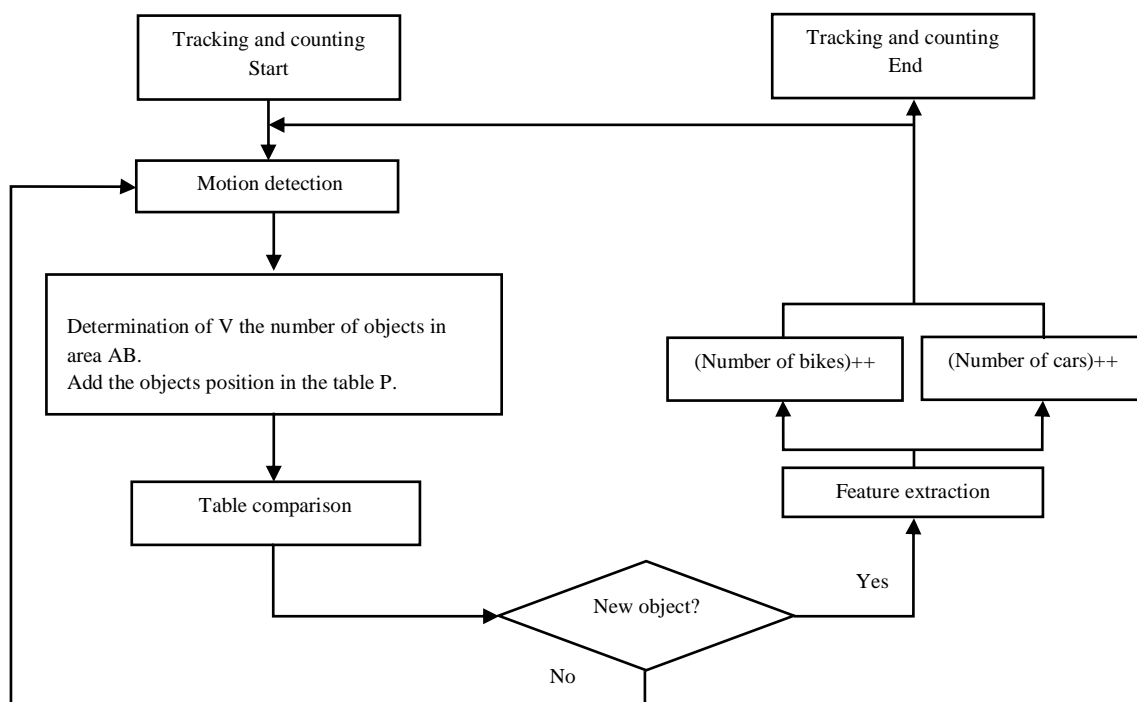


Figure 8. Illustration of proposed method in counting and tracking module

4. Experimental results

4.1. System implantation

Proposed System was tested in different video sequences. The difference between tested videos appears in several parameters such as distance between road and camera, road inclination angle and illumination conditions. Figure 9 presents the results obtained during realized system operation. Blue segments define the surveillance zone. The provided bounding boxes take two colours depending on the type of detected vehicles. Above these boxes appears a number indicating the number of vehicles passing through the road since the start of the algorithm execution.

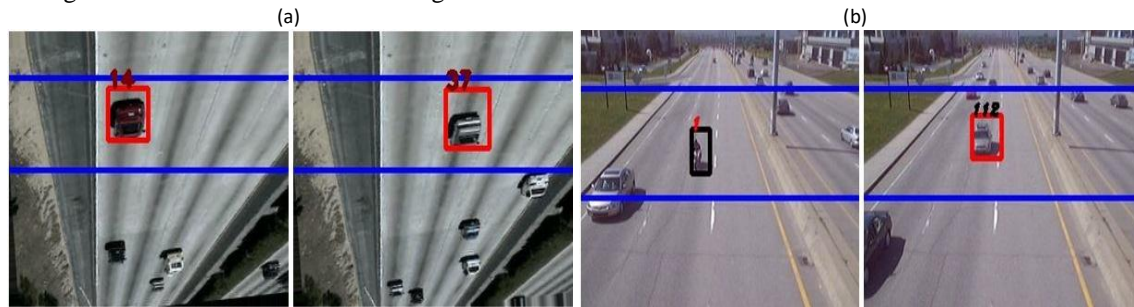


Figure 9. Results of proposed method
(a) Video 1 (b) Video 2

4.2. System test in GRAM-RTM dataset

GRAM-RTM dataset (Guerrero-Gomez-Olmedo *et al.* 2013) is a benchmark for multi-vehicles tracking in real-time. Certain changes were made to the system to adapt it to GRAM-RTM dataset. Such as the video surveillance zone this will be defined using a mask (Fig. 10).



Figure 10. Mask used to define the surveillance zone

The intervals of the coefficients R1 and R2 associated with the different classes determined will vary. The implementation of the system in another scene with a different position of camera involves this change because the both coefficients have a direct relation to the height and width of the detected vehicles. Thus, the classification intervals defined to classify the cars, bikes and partial occlusions will take new values as is shown in (Table 2).

Table 2. Classification intervals for GRAM dataset





Video test	Classes	Image Sample	R1	R2
Video 1	Car		0.2 - 0.6	15 - 16
	Bike		1.6 - 2.5	17 - 19
Video 2	Car		0.5 - 1.4	15 - 17.5
	Occlusion		1.75	17.5 - 25

Figure 11 presents the results obtained during the execution of the realized system. The provided bounding boxes take two colours relatively to the type of the detected vehicle. Above these rectangles appears a number indicating the number of vehicles passing through the scene.

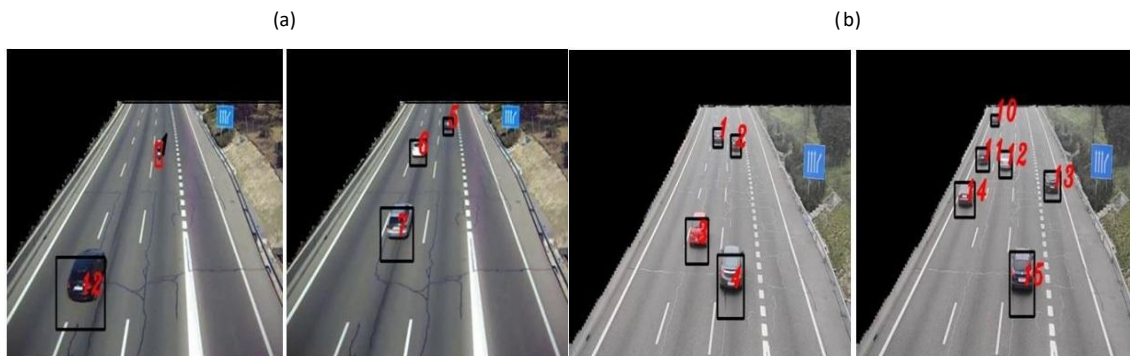


Figure 11. Results of proposed method in GRAM dataset
(a) Video 1; (b) Video 2

4.3. Performance evaluation

4.3.1. Vehicle counting accuracy

An analytical study was conducted to calculate the vehicle counting accuracy to test the efficiency of our system. Table 3 presents the results calculated at each block of the segmentation phase and after the technique of partial occlusion elimination based on feature extraction. The average accuracy measured in the test conducted on three different roads had as value 98.7%.

Table 3. Vehicle counting accuracy in different scenes

Video test	Real number of vehicles	Vehicles number using Canny	Vehicles number with box modelling	Vehicles number after classification	Accuracy
1 st video sequence	5	30	6	5	100%
2 nd video sequence	38	45	36	37	97.36%
3 rd video sequence	162	176	170	160	98.76%
Average					98.7%

4.3.2. Comparative methods

The robustness of any method is not related only to the precision of the realized system but also to the comparison of the results with other existing methods which treat the same field. Table 4 presents the result of this comparison.

Table 4. Results of comparative study

Comparative methods	(Huang <i>et al.</i> , 2012)	(Lei <i>et al.</i> , 2008)	(Pornpanomchai <i>et al.</i> , 2008)	(Mohana <i>et al.</i> , 2009)	Proposed method
Studied types of vehicles	Cars and bikes	Cars	Cars	Cars	Cars and bikes
Segmentation methods	Background subtraction	Background subtraction	Background subtraction	Optical flow	Background subtraction
Classification methods	Feature extraction	X	X	X	Feature extraction
Measured accuracy of vehicle counting	98.6%	Scene 1: 90.41% Scene 2: 70.31% Scene 3: 98.39% Scene 4: 80.00%	Afternoon: 91.98% Evening: 96.35%	94.04%	98.7%

5. Conclusions

This paper has proposed a real-time vehicle analysis and counting system for vehicle video surveillance. The proposed system is able to detect, locate, and automatically recognize vehicles in video sequences. In other words, the system can measure the quantity and characteristics of vehicles in real-time based on three modules, segmentation, detection and classification.

Despite the considerable success in the segmentation process, there are some problems during the experiments that cannot be overlooked for performance evaluation. Contrary to the preliminary hypothesis, the effects of inhomogeneous vehicle architecture seem to play an important role in noise generation during the detection phase. This led us back to apply a mask for closing contours to eliminate such disturbances. Thus, the quality of filtering is increased considerably which leads to an optimization in the overall efficiency of the system.

In the classification phase, the system is able to classify vehicles into two classes (car, bike) using feature extraction. However, some difficulties are observed during the experiments because of vehicle occlusions. The extracted features are used also to classify vehicle occlusions in order to eliminate them. As a result, the designed system has successfully eliminated the majority of vehicle occlusions.

The results of the proposed method reached a value of 98.7% as average measured at three different scenes. Which indicates that the system is efficient as a reliable vehicle counting tool for traffic video surveillance systems. In addition, the system is characterized by reasonable robustness against illumination changes and objects size. Nevertheless, the provided results demonstrate that the counting methodology in traditional road traffic video surveillance systems based on the camera can be improved in terms of accuracy by implementing the proposed method of detection and classification.

Further studies could be conducted in the future to demonstrate the effectiveness of the proposed method on a much larger test scale. Following this work, many perspectives are possible, the most important being without doubt the realization of an embedded system based on FPGA in order to test the entire system in road scenes in real time and for long periods.

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