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Multiple Vehicles Detection Using A Hybrid Segmentation Technique

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Detection, Background Subtraction, threshold method, watershed transform, and shape analysis.

ABSTRACT

The visual analysis of moving objects has been an important computer vision research area. As the number of vehicles is increasing on the roads, the need for accurate detection of vehicles is rising. A hybrid segmentation method that combines background subtraction, threshold segmentation, morphological operators, and watershed segmentation is proposed in this paper.

The shadow has a vital effect on the performance of many fields like tracking, classification, detection, and shape analysis. The shadow presented in the data used in this paper was successfully removed using watershed and shape analysis. Since the connected vehicles touch each other in the boundary only, the watershed transform can correctly isolate these touching cars. The proposed system overcomes the over-segmentation drawbacks of the watershed transform by applying it to the gradient of the image rather than the image itself.

Finally, shape analysis is used to remove large shadow parts which lead to the detection of the vehicles only. An accuracy detection rate of 97% was reported from the highway video which is astonishing result compared to existing methods. The proposed algorithm was coded using MATLAB R2014b programming language. The accuracy and simplicity of the proposed system make it applicable for real-time traffic surveillance Applications.

كشف المركبات المتعددة باستخدام تقنيات تقسيم هجينة

الخلاصة

يعتبر التحليل البصري للأجسام المتحركة موضوعاً هاماً للبحث في مجال الكمبيوتر. فمع تزايد عدد المركبات في الطرق، تتزايد الحاجة إلى الكشف الدقيق عن هذه المركبات.هذا البحث يقترح طريقة تجزئة مختلطة تجمع بين عزل الخلفية، تجزئة بواسطة تحديد قيمة للتقسيم ، العمليات المورفولوجية، وتجزئة بطرية واترشيدز.

يعتبر الظل ذو تأثير حيوي على أداء العديد من المجالات مثل التتبع، التصنيف، الكشف، وتحليل الاشكال. تم إزالة الظل المعروض في البيانات المستخدمة في هذه الورقة باستخدام طريقتي تجزئة واترشيدز وتحليل الاشكال. وبما أن السيارات المتصلة تلمس بعضها البعض في الحافات فقط، فإن طريقة تجزئة واترشيدز يمكن أن تعزل بشكل صحيح هذه السيارات المتقاربة. ان النظام المقترح تغلب على العوائق المعروفة في طريقة تجزئة واترشيدز وهي التجزئة المفرطة بتطبيقه على صورة التدرج بدلا من الصورة نفسها.

في النهاية، تم استخدام تحليل الاشكال لإزالة أجزاء الظل الكبيرة وبذلك سوف يتم الكشف عن المركبات فقط. تم الحصول على معدل دقة كشف حوالي 97٪ من فيديو الطريق السريع المستخدم الذي هو نتيجة واعدة بالمقارنة مع الطرق السابقة. تم ترميز الخوارزمية المقترحة باستخدام اللغة البرمجية ماتلاب ان دقة وبساطة النظام المقترح جعلها قابلة للاستخدام في تطبيقات الواقعية لمراقبة حركة المرور.

الكلمات المفتاحية

كشف ، عزل الخلفية ، طريقة تحديد قيمة التقسيم ، طريقة واترشيدز ، تحليل الاشكال

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Introduction

The accurate detection of objects in traffic surveillance systems is an important task especially in intelligent transport systems applications [1]. The description of these objects becomes much easier after correctly detecting their shapes. One of the main problems in detection systems is the presence of the shadow of the moving object. The shadow becomes part of the moving object and separating it from the object will be a hard task especially when the color of the shadow has the same colors with certain regions of the object [2].

Currently, the three top methods that are used for moving object detection are background subtraction, frame differencing, and optical flow methods [1, 3]. The frame differencing method is considered the simplest and fastest method in which the difference between the last two or three consecutive frames was taken for moving regions detection [1]. The optical flow methods can get better detection of the moving objects compared to background subtraction; however, it requires a lot of calculations which is not suitable for real-time applications [3].

The Background Subtraction algorithm directly detects moving objects by subtracting the background from the current frame. Background based motion detection methods should have the ability to handle poor quality images, illumination changes, weather changes, movement of non-static background objects, object shadow regions, and multiple object motion [3].

The problem with the traditional background subtraction methods is calculation complexity and reduced accuracy with environmental changes [4]. This paper aims to propose a hybrid system that can handle the problems that traditional background subtraction method faces while speeding the process time. The proposed system can be categorized into the following operations: Segmentation, morphological operations, watershed transform, labeling, and shape analysis.

The rest of the paper is organized as follows: Section 2 gives an overview of the related works. In Section 3, the proposed system was explained. Section 4 presents experimentations results and discussion on the detection accuracy of vehicles using the highway video sequences. Finally, Section 5 provides the conclusion.

Literature Survey

Vehicle detection has been an important subject for researchers in the last years. Many researchers, [3, 5, 6, 7] proposed algorithms having their advantages and disadvantages based on segmentation techniques in general. The first and straightforward method used for detection was background subtraction and its improvement methods [3, 6, 7]. Segmentation, region tracking, and vehicle classification were used in [5] with an accuracy rate of 90% detection and 70% classification. A combination of a temporal difference and correlation matching based background subtraction method were presented in [6] with an accuracy of 94% of vehicles counting. Kalman filter with color and size features produced a good detection rate of 96% in [7]. Also, morphological operations and contour projection analysis were used with background subtraction method in [3]. However, these researchers didn't cover the shadow problem as their tested data was evident with no shadow present.

One of the most challenging issues which can affect the results of the vehicles detecting is the shadow. Different algorithms applied to detect and remove the shadow from images. For example, a Markov Random Field model with optimization was used to separate the background and shadow with no prior information needed [2], but the results were not good enough in complex scenes like the highway video. A color ratio model for shadow removal based on SNP (Statistical Non-Parametric) method was developed in [8] using prior information about the shadow form the tested highway video. A detection rate of 77.5% was obtained by testing the first 300 frames; however, this algorithm was not suitable when vehicles overlap each other in the frame or large shadow regions present.

The authors in [9] proposed a metrically trimmed mean Background Subtraction method with shadow removal in RGB color plane. The main object of their paper was increasing the shadow detection rate compared to [8] although the vehicle detection rate decreased. In [10], a gamma decoding followed by a threshold method with the background estimation model was presented. The developed system was able to detect multiple vehicles in daytime and nighttime.

Double subtraction method with geometrical attributes of the vehicles was used for shadow removal, and ghost vehicle detection was implemented in [11]. Although the results indicated a very good vehicle detection accuracy of (93%), the data set used didn't have any shadow or illumination changes. Inter-frame and edge detection, and background subtraction methods combined in [12]. An accuracy rate of (90%) of vehicle detection was evaluated in the complex traffic environment. Principle Component Analysis with Support Vector Machines used for classifying real vehicle parts. Also, it is possible to use a statistical approach for shadow detection in RGB space using Background subtraction method [13]. The accuracy rate for vehicle detection was low (83.5%) compared to the shadow detection (89%).

The Proposed System

Previous studies indicate that the existing of the shadow with the object causes a significant challenging problem for object detection and tracking systems. Shadow makes the detection of the object shape hard and connects more than one object. Since shadow removal algorithms make the computation more complicated and consume a lot of time, the proposed system is developed to accurately detect vehicles with simple calculations which make it applicable for real-time traffic surveillance systems. The proposed system can be categorized into the following operations: Segmentation (Adaptive Median Background model), morphological operations (gradient and opening operations), watershed transform, labeling (8-adjacency method), and shape analysis. Figure 1 shows the Framework of the proposed system.

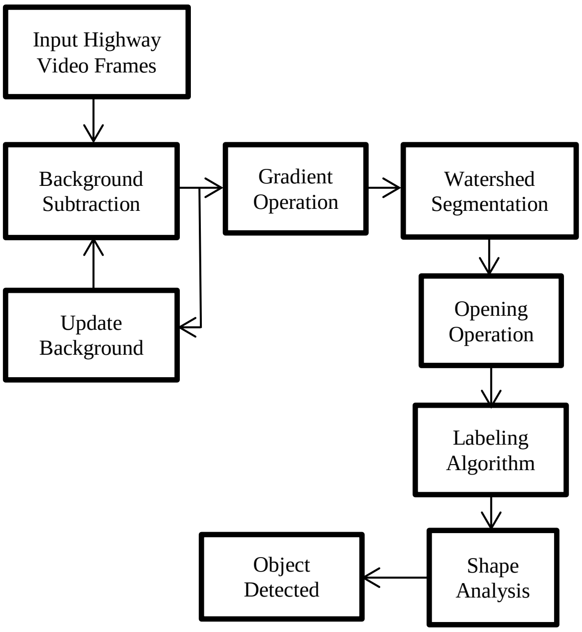

Figure 1: Framework of the proposed system

1. Segmentation (Background Subtraction)

Segmentation is the operation of separating the foreground objects from the background. Segmentation techniques can detect all the motions in consecutive frames. The Background Subtraction method was widely used for detecting moving objects in static and dynamic background situations. Background subtraction methods can be classified into three main groups: parametric, non-parametric, and predictive techniques [1]. The Gaussian mixture and median filter models are parametric background subtraction methods. The Gaussian mixture model is the conventional background subtraction algorithm used although it has a reduced accuracy with lighting changes. The median based model utilized in this paper because it provides more robust results with light changes since it gets the median of the previous frames all the time.

In Background subtraction algorithm, the Current Frame (CF) will be subtracted from the Current Background (CB) to get the Difference Image (DF).

$$\mathrm{DF_m} = \begin{cases} 1 & \text{if } /\mathrm{CF_m} - \mathrm{CB_m}/ \geq \mathrm{TH} \\ 0 & \text{otherwise} \end{cases} \quad (1)$$

Where TH is the threshold. The $\mathrm{DF_m}$ image is the binary mask of the frame m. Since CF and CB are both colored images, the difference value for any component should be greater than the specified threshold.

A dynamic threshold was used in the proposed system which can be calculated by [14]:

$$\mathrm{TH} = \mathrm{MED} + 3 * 1.4826 * \mathrm{MAD} \quad (2)$$

Where 1.4826 is the normalization factor for a Gaussian distribution, and MED is the median which equals:

$$\mathrm{MED} = \text{ median }_{\mathrm{x.y} \in \mathrm{CF}} \ \mathrm{D(x.y)} \quad (3)$$

Where $\mathrm{D(x.y)}$ is the absolute differences image which equals:

$$\mathrm{D(x.y)} = /\mathrm{CF(x.y)} - \mathrm{CB(x.y)}/ \quad (4)$$

And $\boldsymbol{MAD}$ is the median absolute deviation which is:

$$\mathrm{MAD} = \text{median }_{\mathrm{x.y} \in \mathrm{CF}} \ /\mathrm{D(x.y)} - \mathrm{MED}/ \quad (5)$$

2. Adaptive Background Method

The outdoor environment can change due to day-night, shadow, cloudy-sunny, rainy-snowy, or background objects changes [10]. For this reason, the background can never be static which makes the adaptive procedure necessary. Using a reliable model for selecting (CB) and updating it is the core of this method. In the proposed system, median filter method was used for selecting the background. The following equation was used:

$$CB_1 = Median\ (CF_k)\ .k = 1\ .\dots\dots\dots.n \quad (6)$$

Where CB_1 is the initial Background of the images, CF_k is the frame number k, and n is the number of frames initially used.

3. Morphological Gradient Operation

The morphological gradient of an image can be obtained by using dilation and erosion together with image subtraction [15]. The gradient of the image (G) is:

$$\mathrm{G} = (\mathrm{DF} \oplus \mathrm{SE}) - (\mathrm{DF} \ominus \mathrm{SE}) \quad (7)$$

Where SE is the structuring element, and $\ominus$ and $\oplus$ denote erosion and dilation, respectively.

The morphological gradient removes the boundaries between regions which are considered parts of shadow in this case.

4. Watershed Segmentation Method

Watershed is a region growing based segmentation technique widely used in separating connected components. Segmentation based on watersheds produces more stable results having separated connected components compared to the primary segmentation methods: edge detection, thresholding, and region growing [15]. Watersheds visualize an image in three dimensions which are the two spatial coordinates versus intensity. Detecting nearly uniform objects from the background is considered one of the primary applications of this transform [15]. Since Watershed segmentation method has a disadvantage of over-segmentation, many techniques applied before this step to reduce the regions and eliminate this problem. Besides, watersheds were applied to gradient instead of the image to segment the regions of the image correctly [16].

The following mathematical procedure will be used to determine watershed lines [15]:

Let $M_1 . M_2 . \dots \dots . M_R$ be set denoting the coordinates of the points in the regional minima of an image $G(x.y)$ which is the gradient image. Let $C(M_i)$ be a set denoting the coordinates of the points in the catchment basin associated with regional minimum M_i.

Let $T[n]$ represents the set of coordinates $(s.t)$ that lays below the plane $g(x.y) = n$. That is

$$T[n] = \{ (s.t) \mid g(s.t) < n \} \qquad (8)$$

Where $n = min + 1$ to $+1$, n is the flooding process step.

Let $C_n(M_i)$ denotes the set of coordinates of points in the catchment basin associated with minimum M_i that is flooded at stage n. Then $C_n(M_i)$, which is a binary image, can be represented by:

$$C_n(M_i) = C(M_i) \cap T[n] \qquad (9)$$

and let

$$C[n] = \bigcup_{i=1}^{R} C_n(M_i) \qquad (10)$$

Where $C[n]$ is the union of the flooded catchment basins at sate n. Then, the union of all catchment basins ($C[max + 1]$) is:

$$C[max + 1] = \bigcup_{i=1}^{R} C(M_i) \qquad (11)$$

The algorithm for finding watershed lines is initialized with $C[min + 1] = T[min + 1]$, then the algorithm proceeds by computing $C[n]$ from $C[n - 1]$. The result will be a marker image WG that contains zero marker values of watershed line pixels.

5. Morphological Opening Operation

The resulted images WG can be enhanced by using opening process. The opening operation can be used to find objects that fit a particular structuring element. According to [15], the opening operation decreases the size of the items to the scale of the features of the structure element SE, and the opening has negligible effects on the characteristics of objects and the background.

The opening is the dilation of the erosion of an image G by a structuring element SE:

$$WG \text{ o } SE = (WG \ominus SE) \oplus SE \qquad (12)$$

A rectangular structuring element used for enhancing the image, which keeps rectangular shape components and removes non-rectangular objects.

6. Labeling Algorithm

Labeling algorithm is used to identify all the connected components in the binary image WG_m. First, the 8-adjacency were used to determine the related components. Then the area of each component will be calculated to illuminate small connected regions.

$$F_m(x.y) = \begin{cases} c & \text{if the pixel at } (x.y) \text{ belongs to } c \\ 0 & \text{otherwise} \end{cases} \qquad (13)$$

Here c = 1, 2, 3, 4, …… represents the connected component group number. The resulted F_m will have all the connected components.

7. Shape Analysis Technique

Shape analysis techniques detect stationary objects instead of all moving regions. The shape of the vehicle will be used to decide whether the detected object is a vehicle or non-vehicle object. For shape detection, the selected features should be distinctive, non-redundant, and has less sensitivity to weather changes [4]. Four features were used to describe the shape of the vehicle: the area, the width, the length, and the rectangularity. For the rectangularity feature, the ratio of the length to the width was used. For the area feature, the expected area size of the vehicle will change when the vehicle becomes closer. For this reason, different size feature was used in various line locations as the vehicle size increases while coming closer.

8. Object Representation

The objects can be described by using the centroid and a rectangular window surrounding the object. This description is considered a combination of point and geometric shape methods. The flowchart of the proposed system is shown in Fig.2.

Results and Discussion

To illustrate the performance of the proposed algorithm in this paper, image sequences of highway I video (available at http://cvrr.ucsd.edu:88/aton/shadow) were tested. The first 250 frames from this video were used for testing which has a total no. of 59 vehicles that pass through the sequence. Since each vehicle needed less than 25 frames to travel throughout the video from the upper to the bottom side, using 250 frames to test the proposed system was sufficient. Subjective and objective measurements were used for the proposed system.

Two kinds of objective measurements were used in this paper to evaluate the performance of the proposed system. These measurements are related to precision and recall measurements. Precision measures the ability of the system to detect moving objects according to the outcomes, while recall measures the ability of the system to identify moving objects according to the condition [11].

The first measurement was pixel-wise for shadow and foreground detection accuracy while the second measurement was object-wise for vehicle detection accuracy.

The first performance measurement used was the shadow detection rate (η), and shadow discrimination rate (ζ). These measurements are widely used for evaluation shadow detection algorithms as in [8], [9], and [10]. They can be defined as:

$$\eta = \frac{TP_{sh}}{TP_{sh} + FN_{sh}} \qquad (14)$$

$$\zeta = \frac{TP_{f}}{TP_{f} + FN_{f}} \qquad (15)$$

Where TP refers to the number of correctly determined pixels as shadow (sh) or vehicles (f), and FN refers to the number of errors of pixels when shadow (sh) or vehicle (f) misclassified.

For this measurement, the ground truth masks (available at http://arma.sourceforge.net/shadows) were used to determine actual shadow and vehicle pixels. The available mask for frames (45, 65, 85, 105, 125, 165, and 185) were used to evaluate this measurement. The average shadow detection rate (η) was (84%) which is comparable to the previous techniques while the average discrimination rate (ζ) was (93.7%) which is superior to previous methods. Since the object of this paper is the accurate detection of vehicles and not the shadow, the shadow discrimination rate is more important. So, the proposed system was able to detect vehicles better than previous methods.

Table (1): Comparison between different algorithms (First subjective measure)

Methods	The shadow detection rate (η)	The shadow discrimination rate (ζ)
Song and Tai [8] (2007)	77.5 %	72.2 %
Ye et al. [9] (2012)	80.55 %	86.33 %
Taha et al. [10] (2014)	92 %	88 %
Proposed Method (2017)	84 %	93.7 %

The second performance measurement used was the foreground detection rate (DR) and accuracy of detection rate (AR). These measurements commonly used by many researchers as in [2, 5, 7, 11, 12, 13], where:

$$DR = \frac{TP}{TP + FN} \qquad (16)$$

$$AR = \frac{TP}{TP + FP} \qquad (17)$$

Where TP is the number of correctly classified vehicles, FN is the number of missed vehicles, and FP is the number of additional classified objects as vehicles. Here, FP represents the total no. of detection where no car presented and the no. of vehicles detected as two. In case of detecting one vehicle as two objects, the first one is considered the object, and the other detection occurred is considered additional detection where no car presents.

In general, the total no. of vehicles appeared in the (250) frames were 781 vehicles. The proposed algorithm was able to detect 758 cars correctly and missed 23 of them. Hence, $TP = 758$, and $FN = 23$. On the other hand, we had two detection cases where no vehicle presented and only the shadow of a vehicle was there. This means$FP = 2$. The mean of the accuracy of detection results was obtained by analyzing the first 250 frame of the video sequences. The results indicate that the proposed method has the best foreground detection (97%) and accuracy of detection (99.7%) rates compared to previous algorithms.

Table (2): Comparison between different algorithms (Second subjective measure)

Methods	Presence of Shadow	Fore-ground detection rate (DR)	Accuracy of detection rate (AR)
Benedek and Sziranyi [2], (2006)	Yes	83.1 %	88.5 %
Taha et al. [10], (2014)	Yes	92 %	88 %
Hardas et al. [13], (2015)	Yes	83.5 %	89 %
Hashmi et al. [11], (2015)	No	91 %	92.4 %
Proposed (2017)	Yes	97 %	99.7 %

For subjective measure, the results of the proposed system for several frames were presented in Fig. 1. A centroid point and a rectangular window were used to identify the detected objects as shown in Fig. 3. In Fig. 4, the ground truth masks for vehicles, the detected vehicles and the missed parts of the vehicles for frames (85), (145), and (185) were presented. It is clear that the system was able to recognize the vehicles correctly with (97%) although some parts of the vehicles missed during the detection process.

Figure 5 shows the results of applying watershed transform during the process of frame no. 140. It is clear that watershed transform was able to segment these vehicles connected in the boundary. The used of Watershed transform in the proposed system improved the detection rate and increased the ability to distinguish connected components. Furthermore, the original frame no. 140 image, the estimated background, and the resulted image were shown in Fig. 6. All the vehicles in this frame were detected correctly although they were very close.

Since the proposed method failed to detect one of the vehicles in 23 cases, it was important to present some of these cases in Fig. 7. The system failed to detect these vehicles because they were in the corner of the frame and only half of the vehicle presented. Since not all the vehicle was clearly presented, shape analysis wasn't able to detect these vehicles. Finally, the problem of identifying two connected vehicles as one vehicle was shown in Fig. 8. These frames have the same problem of having vehicles in the corner touching other vehicles in vertical. Besides, these examples have the miss detection of vehicles in the same frame.

Conclusion

This paper introduces an approach for multiple vehicle detection based on a hybrid segmentation method that combines background subtraction, threshold segmentation, morphological operators, and watershed segmentation. Watershed transform improved the performance of the system and increased the ability to distinguish most of the connected vehicles cases by removing the presented shadows. In addition, watershed transform isolated the connected vehicles correctly.

Two kinds of objective performance measurements were used in this paper. The first measurement was pixel-wise for shadow and foreground detection accuracy while the second measurement was object-wise for vehicle detection accuracy. An accuracy detection rate of 97% was evaluated from the highway video used which is an astonishing result compared to the existing methods. The precision and simplicity of the proposed system will help on the development of the real-time intelligent transportation systems including the traffic monitoring and enforcement applications.

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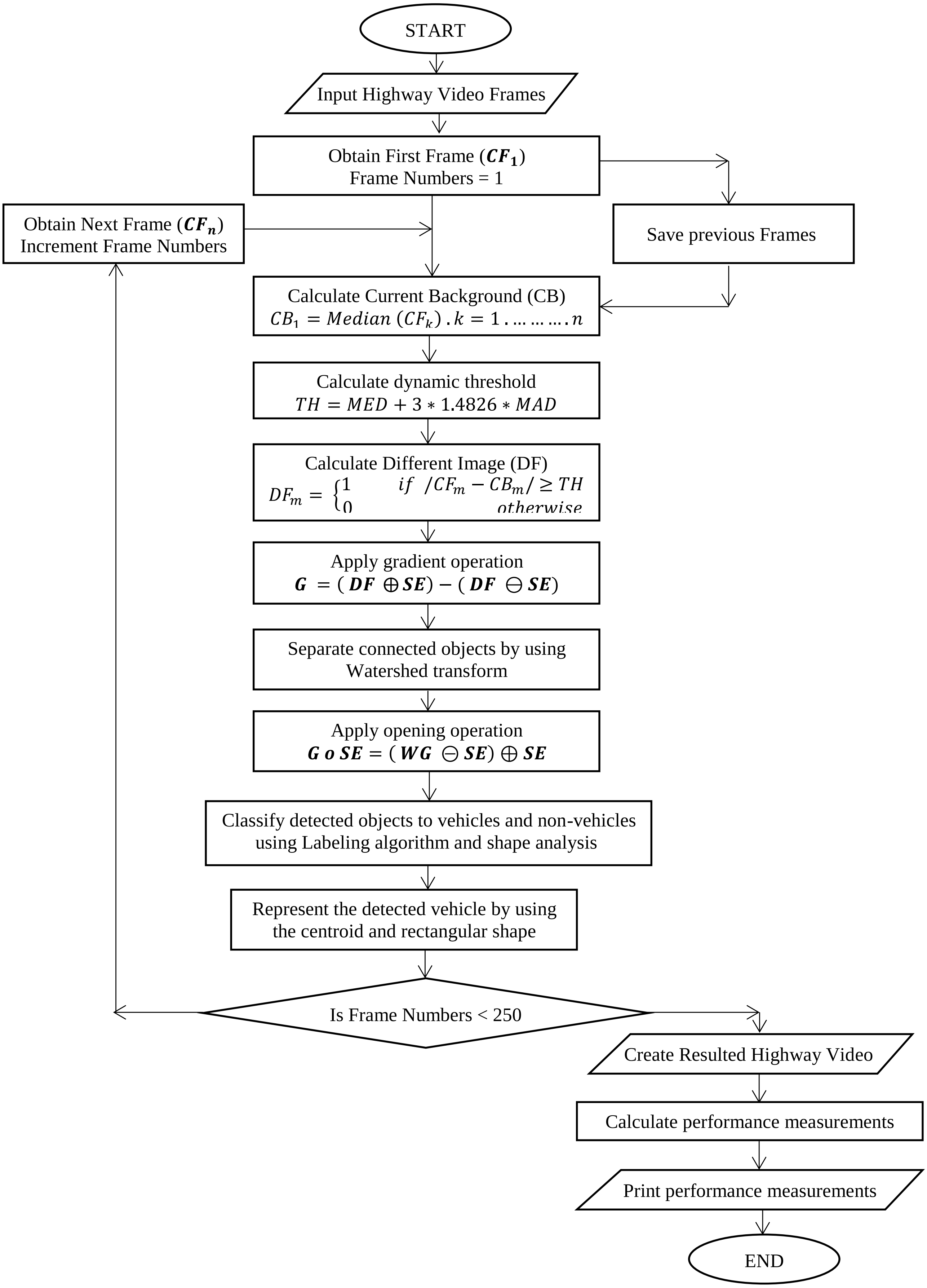


Figure 2: Flowchart of the proposed system

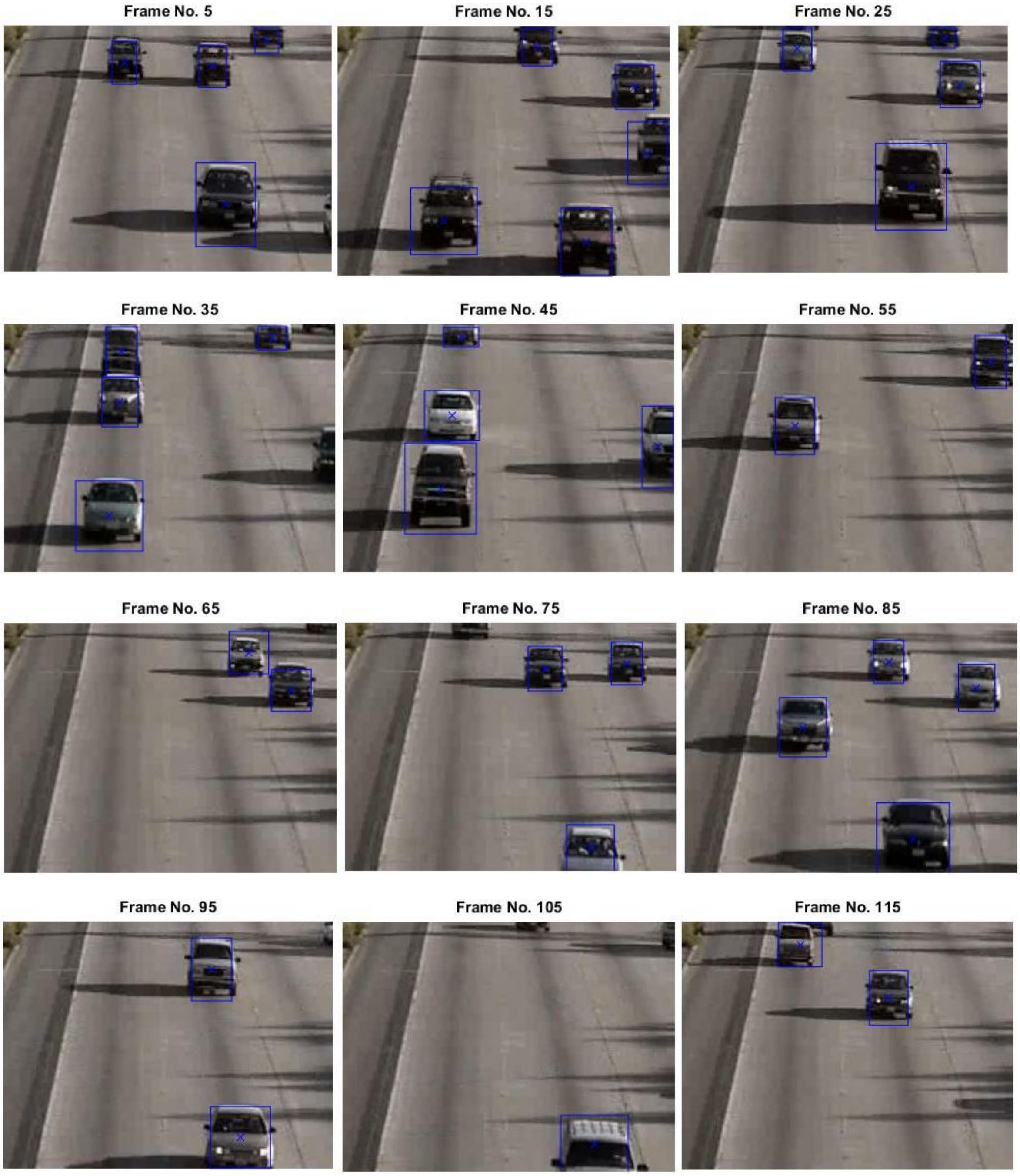
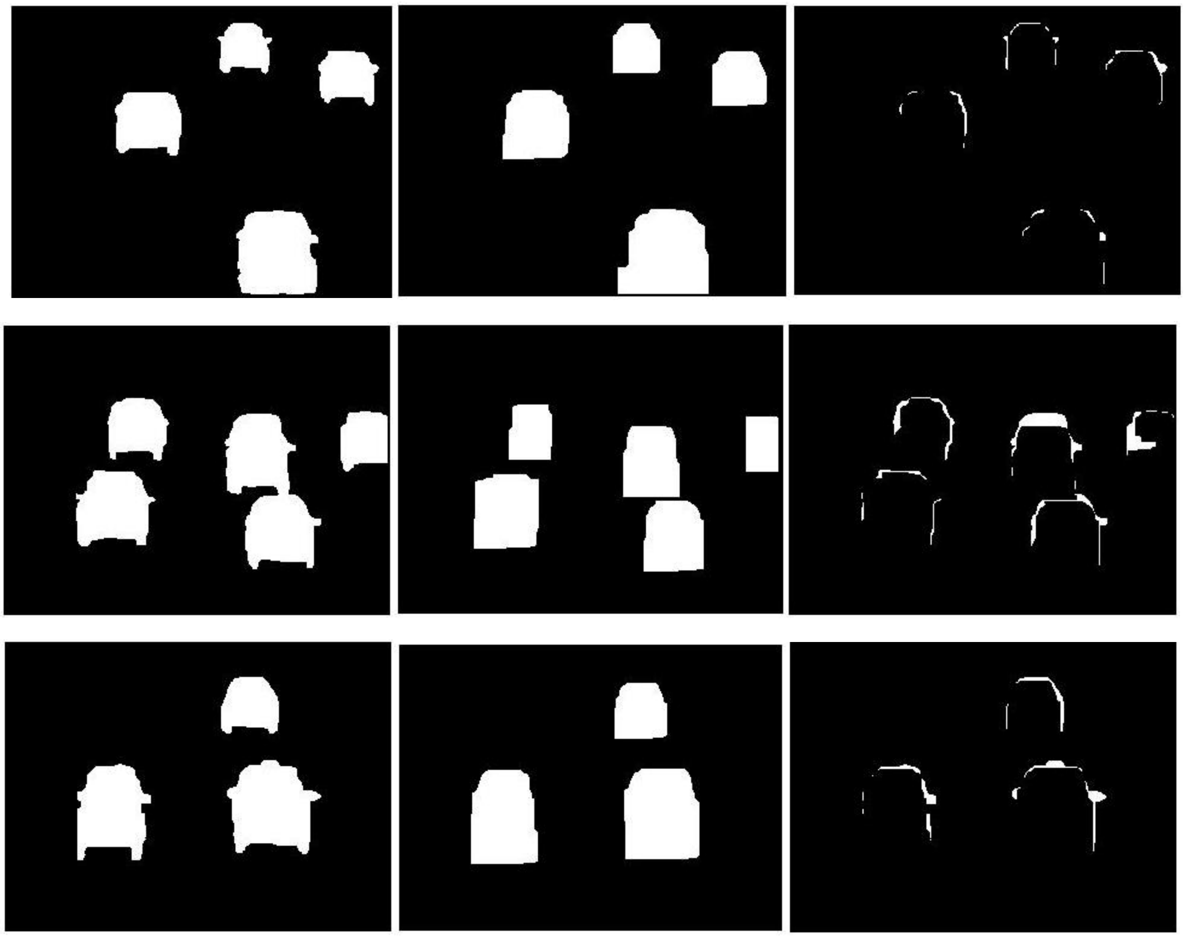
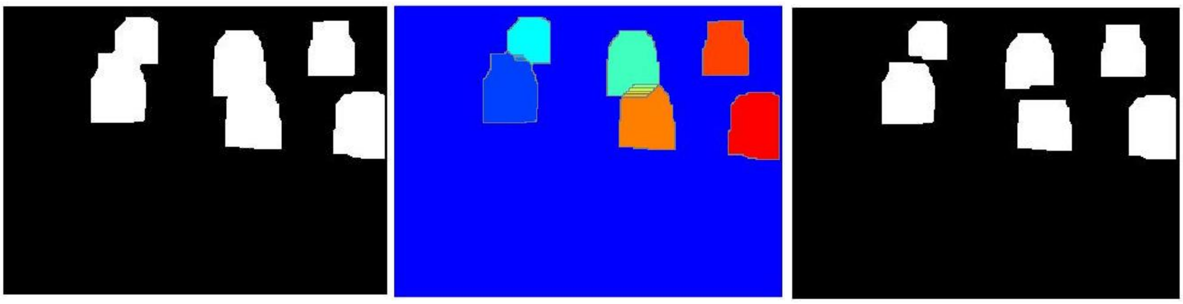


Figure 3: Proposed system detection results for some frames



(a) (b) (c)

Figure 4: Comparison between detected vehicle shapes and the ground truth mask for frame numbers (85), (145), and (185) respectively Ground truth mask for vehicles (b) the detection mask of the proposed algorithm (c) the missed parts of the detected vehicles



(a) Gradient Image Mask **(b) Watershed Transform Result** **(c) Watershed Binary Result**

Figure 5: Frame No. 140 Watershed transform affect result

(a) Original frame **(b) Estimated Background** **(c) Detection Result**

Figure 6: Frame No. 140 Complete Result

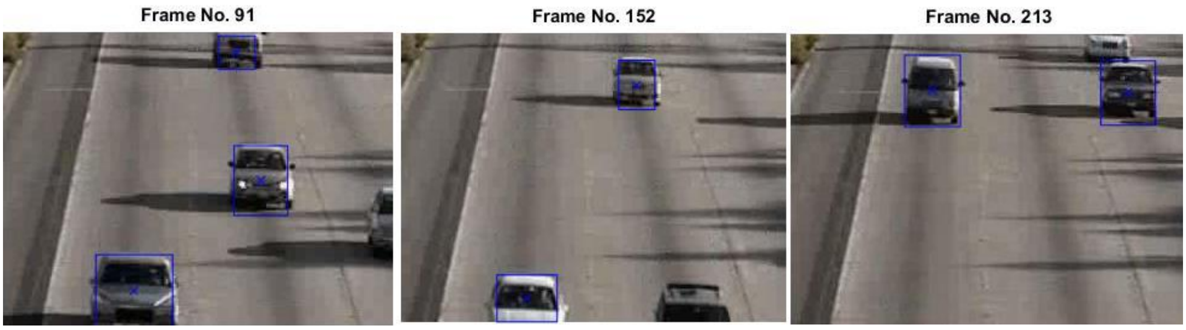


Figure 7: Example of cases when vehicles not detected

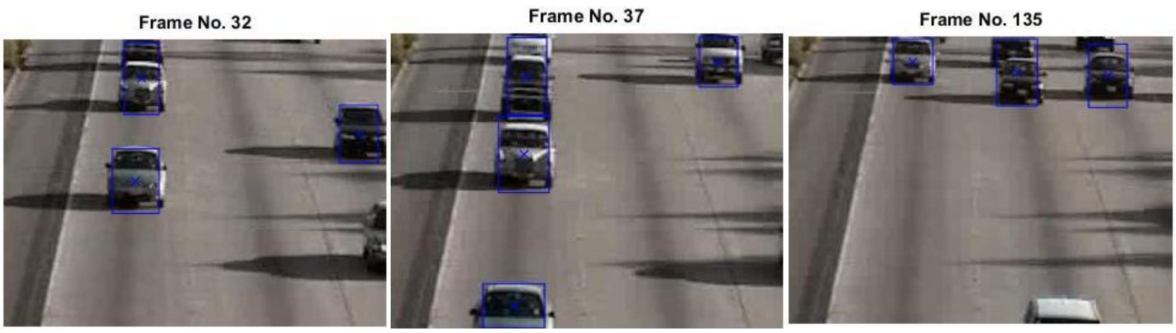


Figure 8: Examples of cases when two vehicles detected as one vehicle