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Feature-Based Vehicle Flow Analysis and Measurement for a Real-Time Traffic Surveillance System

Deng-Yuan Huang[1], Chao-Ho Chen[2], Wu-Chih Hu[3], Shu-Chung Yi[4] and Yu-Feng Lin[5]

[1]Department of Electrical Engineering
Dayeh University
Ag. Loukas, 65404, Kavala, Greece
168 University Rd., Dacun, Changhua 515, Taiwan (R.O.C.)
kevin@mail.dyu.edu.tw

[2]Department of Electronic Engineering
National Kaohsiung University of Applied Sciences,
415 Chien Kung Rd., Kaohsiung 807,Taiwan (R.O.C.)
thouho; 1094320136@kuas.edu.tw

[3]Department of Computer Science and Information Engineering,
National Penghu University of Science and Technology
300 Liu-Ho Rd., Makung, Penghu 880, Taiwan (R.O.C.)
wchu@npu.edu.tw

[4]Department of Computer Science and Information Engineering,
National Changhua University of Education
Changhua City, 500, Taiwan (R.O.C.)

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Abstract. *A feature-based vehicle flow analysis and measurement system is proposed for a real-time traffic surveillance system. The system includes moving object segmentation, background updating, feature extraction, and vehicle tracking and classification. Moving object segmentation is firstused to extract the contour of vehicles. By analyzing the contours of vehicles and their corresponding minimal bounding box, salient discriminative features of vehicles are obtained. The tracking of moving targets is then achieved by comparing extracted features and by measuring the minimum distance between two consecutive images. To increase the accuracy of vehicle classification, the temporal correlation of moving objects tracked between video frames is taken into consideration. In addition, the velocity of each vehicle and the vehicle flow through the field of vision are calculated by analyzing the features of vehicles. Experimental results show that classification rates of 96.4% and 92.7% for cars and bikes, respectively, can be achieved using the feature of aspect ratio. The bikes here refer to motorcycles, scooters, or bicycles. The average accuracy of vehicle flow measurement of 96.9% is obtained, indicating the feasibility of the proposed method.*
Keywords: Vehicle counting, Vehicle detection, Object segmentation, Background subtraction, Motion detection, Feature extraction.

1. **Introduction.** the past decades, traffic Congestion has become a major concern in a modern society due to the increase of vehicles.Solutions include widening roads and banning cars from central business districts. However, traffic congestion remains a serious problem due to the limitations of road construction and expansion. Numerous studies have thus been conducted on intelligent transportation systems (ITSs), which integrate microelectronics, AI, robotics, sensing, communication, and control. ITSs are considered to have the most potential for solving the problems of traffic congestion, where real-time machine vision that can augment drivers visual capabilities is the most attractive technology in ITSs.

In general, traffic-flow monitoring systems can be divided into two categories. One is the traditional embedded system with a voltage return circuit. This type of system is reliable but the cost of implementation is relatively high. In addition, roads need to be dug up for installation and maintenance, which greatly influence traffic mobility. The other is a hanging type system that uses sensors such as cameras, radar, and infrared sensors. Camera-based systems are most attractive due to their lower cost of installation and maintenance compared to those of other systems. In this paper, we propose a camera-based vehicle flow analysis and measurement system that can be used for real-time traffic control and monitoring, which are important for ITSs.

The fundamental task of most video processing algorithms is to extract the regions of interest (ROIs) of moving objects. Video images are segmented into moving objects (or foregrounds) and the remaining parts (or backgrounds) to facilitate subsequent tracking procedures. Motion segmentation in video sequences focuses on detecting regions corresponding to moving objects such as cars and bikes; it can be categorized as: (1) background subtraction [1]-[4], (2) temporal differencing [5]-[7], (3) optical flow [8], and (4) block motion estimation [9]. Background subtraction can extract the most feature pixels but it is extremely sensitive to lighting changes. Temporal differencing is suitable to dynamic environments but its performance to extract relevant feature data is not satisfied. Optical flow can detect moving objects in the presence of camera motion but its computational complexity is very high. Block motion estimation can reduce the computational complexity of the optical flow method but the accuracy may be also decreased.

Motion detection in many tracking systems involves background subtraction. Lighting variations in a scene can cause serious problems formany background subtraction methods. Ridderet al. [1][3] modeled each pixel in a background with a Kalman filter to allow their system to adapt to lighting changes in a scene. In their method, the background estimator performs well for human body tracking in real-world scenes with illumination changes due to daylight or moving clouds or both. Although their method uses a pixel-wise automatic threshold, it recovers slowly and cannot handle bimodal backgrounds well. Generally, there are two types of Gaussian method for background subtraction: a single Gaussian and a mixture of Gaussians [2]. A mixture of Gaussians is more suitable than a single Gaussian for dealing with slow lighting changes, slow moving objects, and camera noise. Basically, a mixture of Gaussians can represent the color distribution of each pixel to handle variations due to factors such as lighting, shadows, and camera noise. By updating parameters, their system can track people and cars in outdoor environments. Moreover, another application for ship detection by background subtraction was presented by Hu et al. [4].

Based on frame differencing, moving targets can be extracted from a real-time video stream using the pixel-wise difference between consecutive frames. This approach can classify humans, vehicles, and background clusters [5]-[7]. Once classified, targets are tracked bya combination of temporal differencing and template matching. The improved approach makes the segmentation of moving objects more compact by using two difference images obtained from three consecutive frames in video sequences, where the two difference images are processed using a logical AND operation. For obtaining the better segmentation result, another scheme utilizes both methods of adaptive background subtraction and temporal differencing for moving objects detection.

Garlic and Loncaric [8] used optical flow to extract the feature vectors in a video sequence. The feature vectors extracted are further clustered using a K-means clustering algorithm to determine the characteristic image regions, which allows the detection of a moving object in video images. Chen et al. [9] proposed a multipath search with flatted-hexagon pattern for block motion estimation to achieve adjustable speed and accuracy in the block matching algorithm. This method can greatly reduce the computational complexity of optical flow even though it may slightly decrease the performance of optical flow.

To detect cars and bikes in traffic surveillance sequences, background initialization, foreground detection, and background updating are three essential procedures. Object tracking methods can be classified as region-based tracking [10], active contour-based tracking [11][12], feature-based tracking [13]-[15], and model-based tracking [16][17]. Among these methods, feature-based tracking is most widely used due to its robustness; even with partial occlusion, some of the features of moving objects are still visible, and the approach can adapt to varying illumination, such as daylight, twilight, or night-time conditions. In general, the features of a moving object can be classified as: (1) global feature-based, such as the center of gravity, color, and area [13]; (2) local feature-based, such as segments and vertices [14]; and (3) dependence graph-based [15], such as structure changes between features. However, since tracking performance highly depends on the selection of features, the problem of grouping, i.e., what set of features belongs to a moving object, is introduced. In this paper, several salient features are presented for classifying cars and bikes in video images, and counting and analysis processes are proposed.

Morris and Trivedi [18] proposed a real-time highway monitoring system called VECTOR for tracking and classifying vehicles from live video streams. In their method, the front-end ofthe system includes object detection by adaptive background subtraction, Kalman filter-based tracking, and vehicle classification with tracking details. During object detection, blob features of an object are extracted, such as area, bounding ellipse, and image moments, and transformed using linear discriminant analysis (LDA). The reduced feature set is then applied to classify vehicles into 8 main classes using a weighted K nearest neighboring (wKNN) method. Efforts have been made to improve the performance of the VECTOR system by adding real-time situational awareness to highway monitoring for high-level activity and behavior analysis [19]. A path prediction module was proposed to detect abnormal trajectories and to predict future intent of drivers, where the spatio-temporal motion characteristics of motion paths are encoded by a hidden Markovmodel (HMM).

In recent years, traffic monitoring systems have been presented to automatically extract important traffic parameters using only cameras. These systems often combine tracking, object classification, traffic parameter extraction, and event detection. For these systems, visual tracking is important for measuring vehicle flow at intersections, which can be used to improve urban mobility efficiency. Moreover, vehicle path trajectories are statistically predicted for behavior analysis in a driver assistance system (DAS). In [20], a framework for tracking and categorizing multiple vehicles using Markov chain Monte-Carlo particle filters (MCMC PF) was proposed to classify moving objects into motorcycles, cars, light trucks, and heavy trucks. The method has also been applied to the tracking of pedestrians [21].

Lai et al. [22] developed a traffic surveillance system that includes three phases: vehicle region extraction, vehicle tracking, and classification. In their method, the background subtraction method is used to segment foreground regions from highway scenes. Geometric features and a shadow-removal algorithm are used to remove false regions and to improve segmentation accuracy, respectively. The graph-based tracking method is often adopted to determinethe correspondence between vehicles detected at different instances.Two measures, suchas aspect ratio and compactness, are usedto performthe classification of vehicles. More recently, a stochastic approach called particle filtering [23], which is also known as the sequential Monte Carlo method, has been widely used in video object tracking; it relaxes the Gaussian assumption of vehicle motion due to the nonlinearity of the state transition.

Traffic vehicle counting is important in traffic scene analysis. Wakabayashi and Aoki [24] proposed a traffic flow measurement system that uses a pair of stereo slit cameras. However, they did not extract vehicle type and velocity, which are important parameters for traffic surveillance. Therefore, the present study proposes a traffic surveillance system that can determine vehicle type and velocity besides vehicle counting.

The rest of this paper is organized as follows. In Section 2, we outline the proposed method for vehicle flow counting, which includes vehicle segmentation, background updating, feature extraction, vehicle tracking, and vehicle classification. Section 3 describes the experimental results and their evaluations. Finally, the conclusion is given in Section 4.

2. **The Proposed Method.** A flowchart of the proposed method for vehicle flow analysis and measurement is shown in Fig. 1. Moving objects are first segmented from a sequence of video images using the schemes of motion detection and background updating. Motion detection is used to analyze the temporal correlation of moving objectsin successive frames. A frame

difference mask and a background subtraction mask are utilized to acquire the initial object mask on which the problem of stationary objects in backgrounds can be solved. Moreover, boundary refinement is introduced to reduce the influence of shadows and the problem of residual background. Each segmented object, denoting a vehicle, is then bounded by a rectangle; the height, width, and area of the rectangle are regarded as important features of that vehicle. Based on these salient features, each vehicle can befurther classified as a car or a bike.

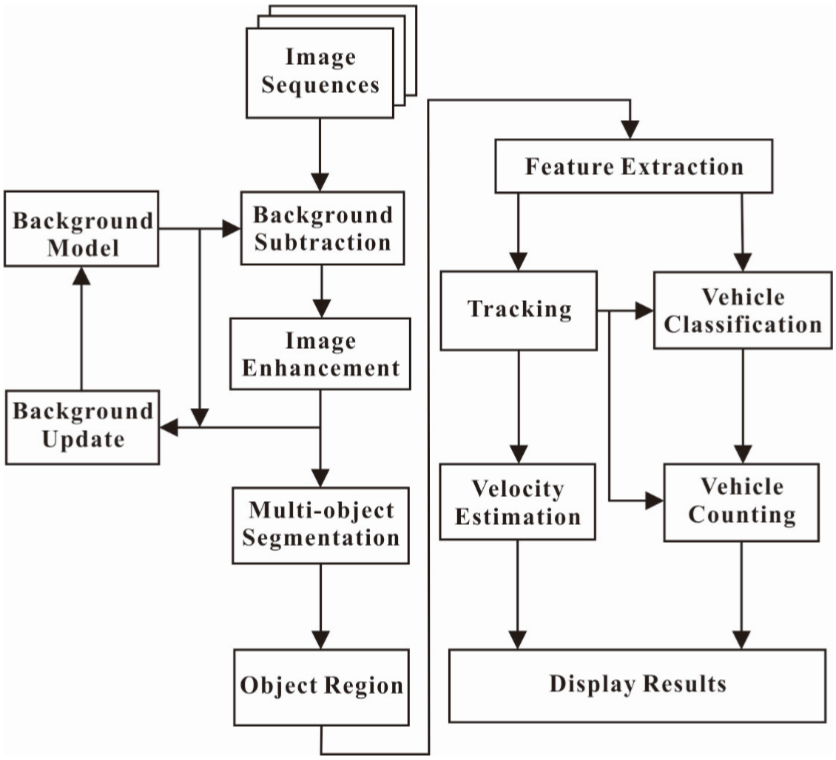


Figure 1. Flowchart of the proposed method for vehicle flow analysisand measurement

2.1. **Vehicle segmentation.** Video cameras for a traffic surveillance system are often mounted at major roads in a modern city. Since the background in videos is almost stationary, background subtraction [1]-[4] is thus suitable for detecting moving objects such as pedestrians or vehicles. Since the performance of vehicle segmentation highly depends on the extraction of a reliable background, the reference mask is established using background subtraction and then background updating to prevent the background information from containing those of moving targets. In this paper, we used the temporal information of the mean and standard deviation of gray level distribution in consecutive frames to model the background for each point, and updating is adaptively proceeded, by which the gray level providinga maximum occurrence probability is then assigned to that of the absolute background for that point. As to the detailed information of how to build this model, the readers can refer to our previously published paper [25].

Once background mask is established, foreground objects such as cars and bikes can be readily extracted by the proposed multi-object segmentation algorithm, as illustrated in Fig.2. In the proposed method, we first scanned the binary image from left to right and row by row, as shown in Fig. 2(a), to obtain two larger regions with moving objects. Next, we scanned these two regions from top to bottom and column by column, as shown in Fig. 2(b), to obtained four smaller regions having moving objects. Finally, we scanned these four regions again from left to right and row by row, as shown in Fig. 2(c), to obtain the minimum bounding box of each moving object. The resulting segmentation of each moving object is shown in Fig. 2(d). Figure 3 shows the resulting segmentation of cars and bikes under different traffic situations by the proposed approach.

2.2. **Vehicle feature extraction.** Numerous features can be extracted from a moving target, such as texture, color, and shape. These features can be roughly classified as spatial features or temporal features. Spatial features are often used to discriminate objects at a given time, and temporal features are used for recognizing an object at different points in time. To recognize targets, it is necessary to obtain specific features that can discriminate between various moving objects.

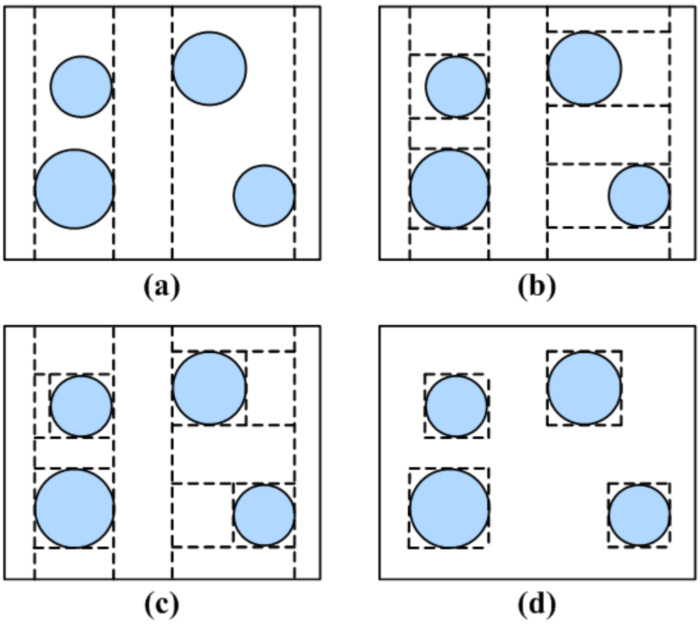


FIGURE 2. Illustrations of the proposed multi-object segmentation algorithm

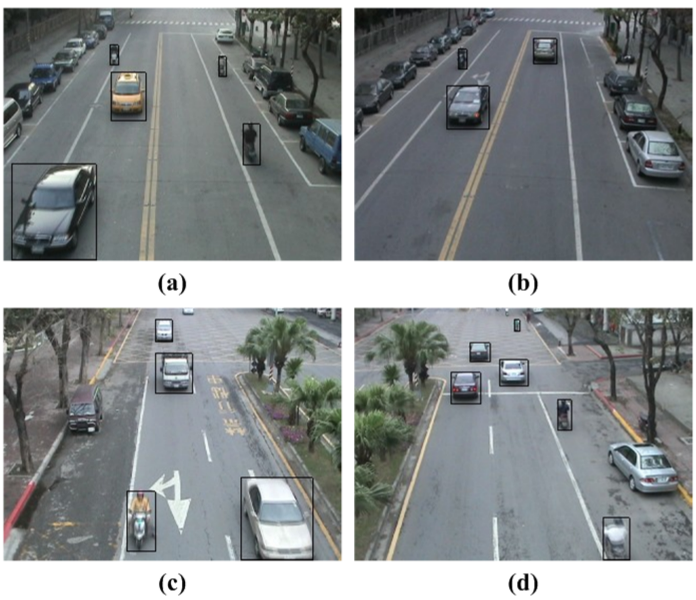


FIGURE 3. Resulting segmentation of cars and bikes under different traffic situations

For a moving vehicle, features such as perimeter and area may vary with timedue to the use of a fixed video camera. To reduce the effect of feature variation, an analysis of the boundingbox of amoving object is introduced [26]. Features that are less varying with motion, such as compactness, aspect ratio, and area ratio, are often utilized for steady trackingof moving objects. The definitions of these features are given as:

$$Compactness = \frac{Perimeter^2}{Area} \tag{1}$$

$$Aspect\ Ratio = \frac{Height}{Width} \tag{2}$$

$$Area\ Ratio = \frac{Area}{ROI} \tag{3}$$

In the above equations, Perimeter is the length of the boundary of a moving object, and Area denotes its corresponding area. Height, Width, and ROI denote the height, width, and area (i.e., Height*Width) of the bounding box, respectively. To aim at tracking and counting moving objects, the centroid of each moving object is also calculated, which is defined as:

$$x_c = \frac{\sum\limits_{(x,y)\in R} \sum x}{\sum\limits_{(x,y)\in R} \sum 1}, y_c = \frac{\sum\limits_{(x,y)\in R} \sum y}{\sum\limits_{(x,y)\in R} \sum 1} \tag{4}$$

Where (x_c, y_c) is the centroid of the moving object and R is the set of pixels in the moving object. Among the three features, the distributions of aspect ratio of cars and bikes for a period time in a video sequence are shown in Fig. 4(a) and (b), respectively. As shown in Fig. 4, the values of aspect ratio around 1.2 for cars and 2.0 for bikes, respectively, can be observed, which are quite different between them, indicating the strong discriminative power of aspect ratio for cars and bikes when using in a traffic surveillance system.

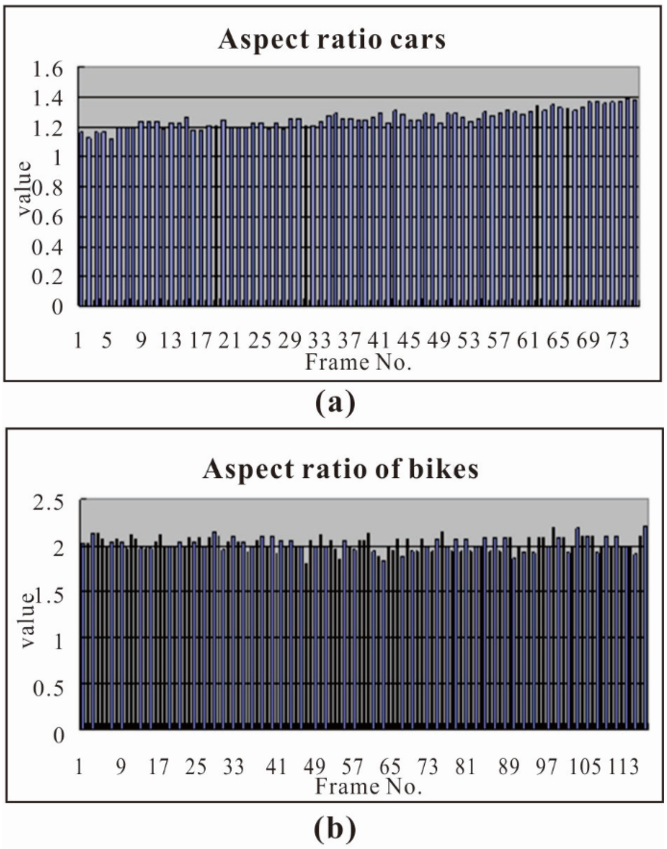


Figure 4. Resulting segmentation of cars and bikes under different traffic situations

2.3. Vehicle tracking. In this work, a feature-based approach for vehicle analysis and counting is presented to track the moving objects of cars and bikes. For bikes, they can be motorcycles, scooters, and bicycles. The proposed algorithm for vehicle tracking is given as follows.

1. Assume that the moving objects detected are the targets to be tracked.
2. Assume that the template list is initially empty. If moving objects are detected in the current frame, they are added to the template list, as shown in Fig. 5(a) and (b).
3. If the template list has some records of moving objects, there are two possibilities for the detected moving object:
   (a) The moving objects have already been recorded in the template list.
   (b) The moving objects are new. If this is the case, the moving objects detected are added to the template list, as shown in Fig. 5(c) and (d).
4. If a moving object that is recorded in the template list is not found in the current frame, there are two possibilities.
   (a) The moving object has left the monitoring region of the video camera.
   (b) Tracking failure has occurred.
   For both cases, the record of the moving object is removed from the template list, as shown in Fig. 5(e) and (f).
5. The tracking process is repeated for each input frame to ensure that the records in the template list match the moving objects detected in the current frame, as shown in Fig. 5(g).

A flowchart of the proposed method for vehicle tracking is shown in Fig. 6. To achieve vehicle counting in a traffic surveillance system, the tracking of every moving vehicle between successive image frames is required.Once finishingthe segmentation of moving objects, we can extract the ROIs of targets and their bounding boxes in which the centroidscan also be obtained. Intuitively, two moving objects that are spatially closest in adjacent frames are correlated; therefore, Euclidean distance (ED) is suitable to measure the distance between the centroids of these two objects. Additionally, the vehicle features of compactness, aspect ratio, and area ratio arealso considered to improve the tracking performance of moving objects. For each moving object in the current frame, an object with the minimum distance and the most similar features between consecutive frames is searched for the previous frame. The criteria for object matching are defined in Eqs. (5) and (6), respectively.

$$\rho = \prod_{m} \left(\left| f_n^m(t) - f_n^m(t-1) \right| \right) < Th_{track} \tag{5}$$

$$dist\left(ctd(t), ctd(t-1)\right) = \sqrt{\left(x_c(t) - x_c(t-1)\right)^2 + \left(y_c(t) - y_c(t-1)\right)^2} \tag{6}$$

where ρ is a tracking parameter, m is the feature index to denote compactness, aspect ratio, or area ratio, n is the number of moving objects, $f(t)$ is the object feature in the current frame, $f(t-1)$ is the object feature in the previous frame, and Th_{track} is a threshold that is determined from experimental results. If $dist$ is the minimum in their sets, and the criterion of $\rho < Th_{track}$, is satisfied, the object in the current frame is considered to bethat in the previous frame. Results of the proposed method for vehicle tracking are shown in Fig. 7.

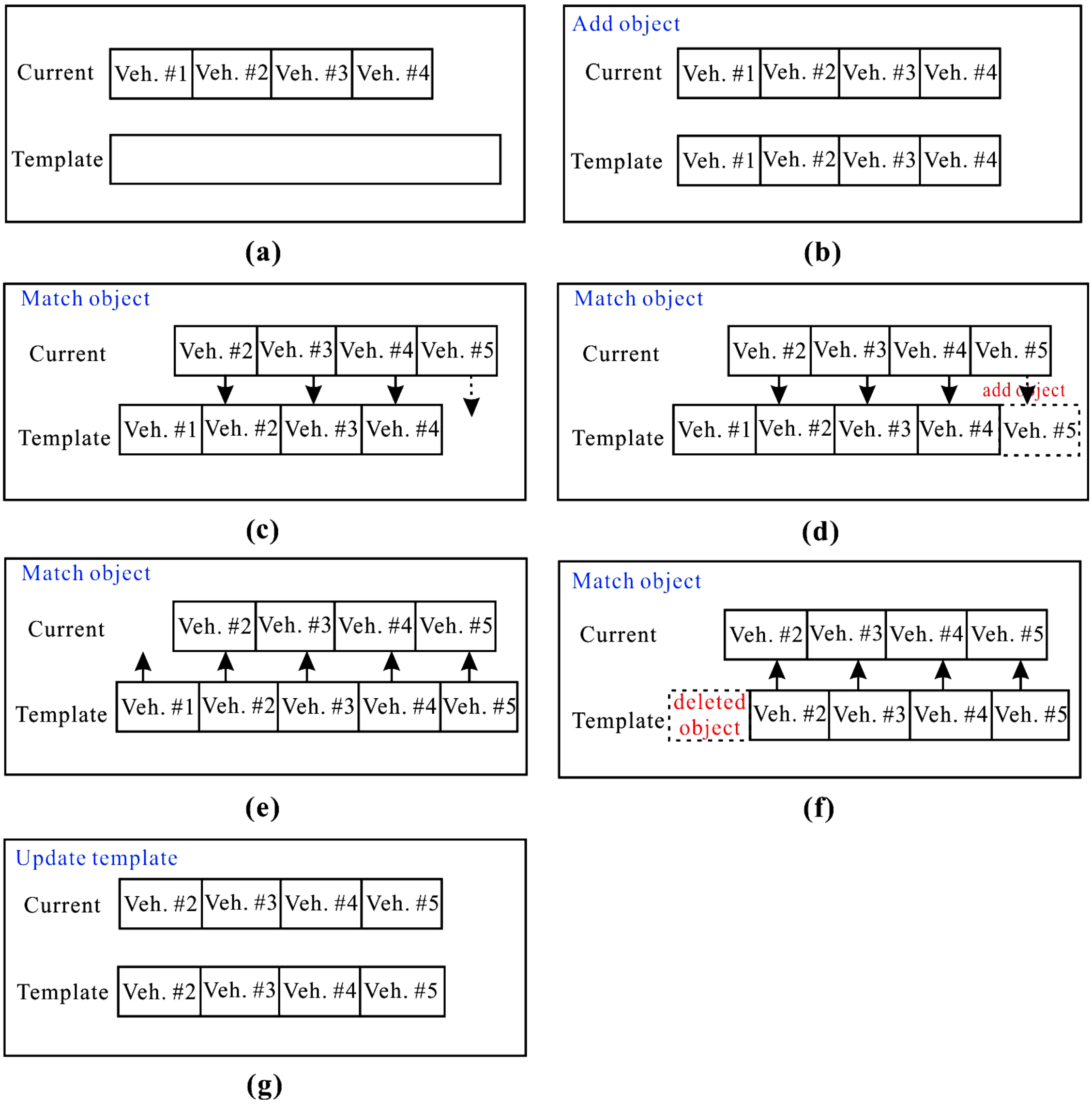


FIGURE 5. Illustration of the principle of the proposed vehicle tracking algorithm

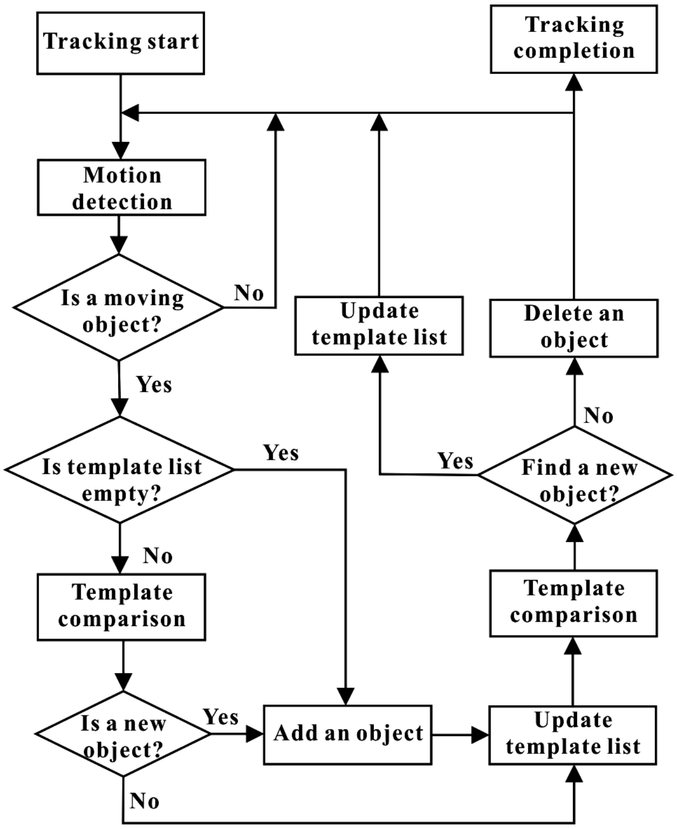


FIGURE 6. Flowchart of the proposed method for vehicle tracking

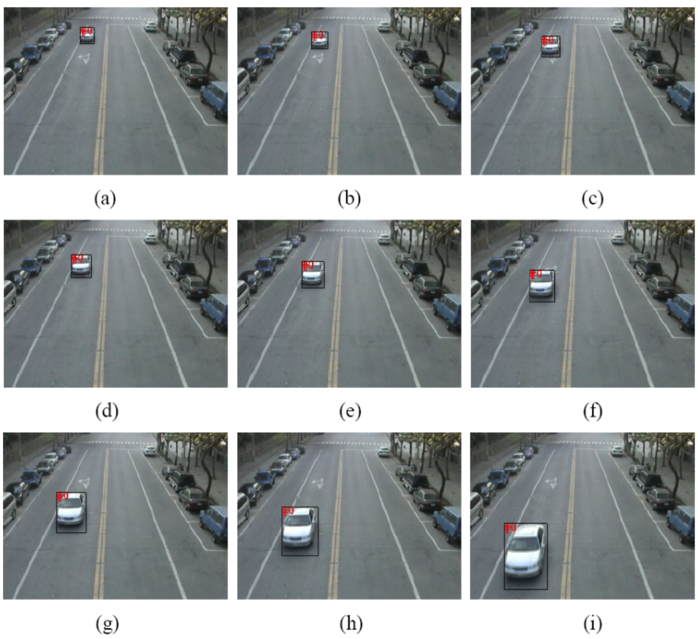


FIGURE 7. Results of the proposed method for vehicle tracking from ((a)-(c)) a relatively far distance, ((d)-(f)) a middle distance, and ((g)-(i)) a near distance from a fixed video camera.

2.4. **Vehicle classification.** In some countries, there are only two lanes for automobiles and bikes. Thus, the proposed method classifies extracted vehicles as either cars or bikes. To overcome the problem of using only one reference frame [26, 27], the proposed method extracts several features, such as compactness, aspect ratio, and area ratio, from various frames to achieve a robust and highly accurate classification of moving objects. In our work, two accumulators, called Acc_Car and Acc_Bike, are used to sum up the features extracted from cars and bikes in video images, respectively. If the extracted feature is regarded as belonging to a car, the accumulator of Acc_Car is increased by one; otherwise, the accumulator of Acc_Bike is increased by one. After a period of time, the final value of the accumulators of Acc_Car and Acc_Bikeis used to determineof the typeof vehicle. Fig. 8 shows a flowchart of the proposed method for vehicle classification. The value of threshold is optimally set from experimental results.

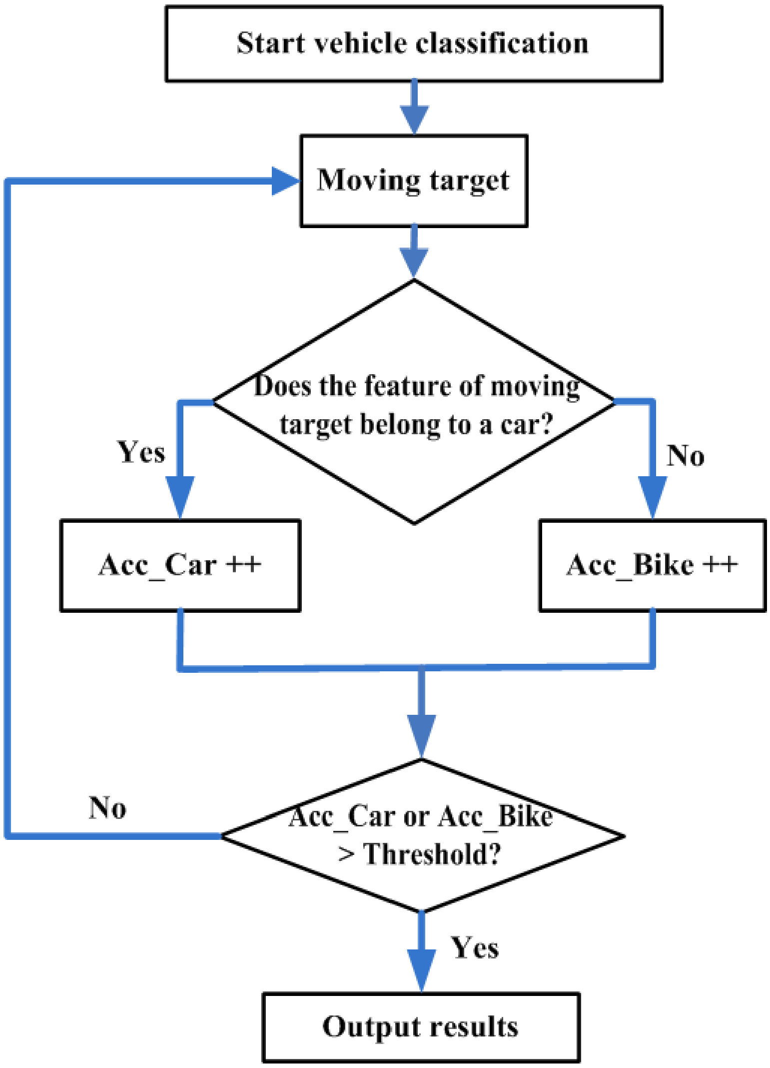


FIGURE 8. Flowchart of the proposed method for vehicle classification

Figure 9 shows the results of the proposed method for vehicle classification under different traffic situations. Fig. 9(a) and (b) illustrates the classification results of two different unidirectional flows in different situations, and Fig. 9(c) and (d) shows the results of classifying each vehicle in two bidirectional flows from different views on the same road.

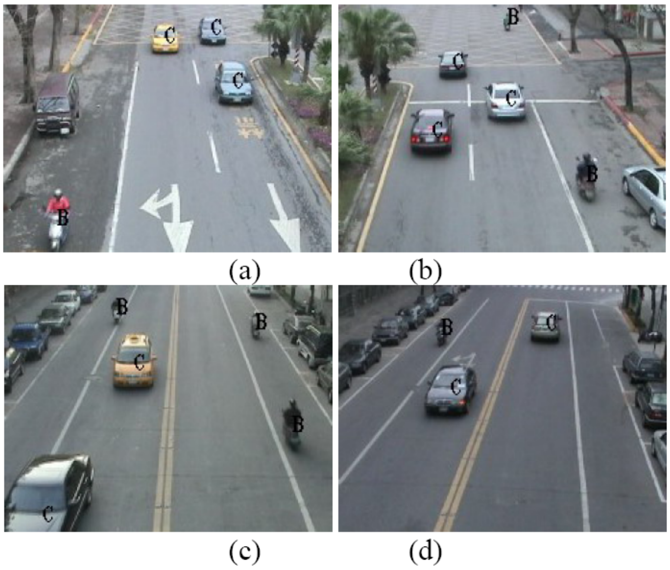


FIGURE 9. Results of vehicle classification under different traffic situations: (a) unidirectional flow in situation-1, (b) unidirectional flow in situation-2, (c) bidirectional flow in situation-1, and (d) bidirectional flow in situation-2. (Symbols C and B represent cars and bikes, respectively.)

2.5. **Vehicle flow analysis and measurement.** To achieve automatic bidirectional counting of vehicles, the proposed method uses two base lines, as shown in Fig. 10. The system also calculates the velocity of the vehicles in the counting process. When vehicles pass through area R2, the frame is recorded. The moving vehicle is counted when it passes the base line.By measuring the distance between base lines on the actual road and using the frame rate of the camera, the velocity can be calculated when the vehicle passes through area R2. The velocity of the vehicle is computed using:

$$v = \frac{S \times F}{F_n} \tag{7}$$

Where S is the distance between base lines on the actual road, F is theframe rate of the video sequence, and Fn is the frame number at which the vehicle passed the detection area.

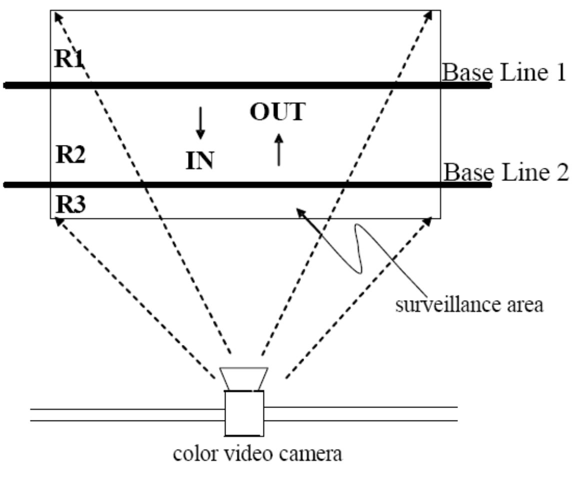
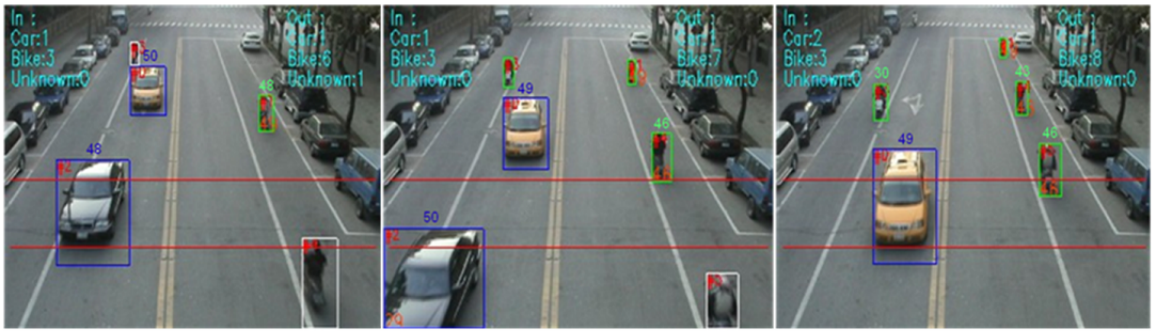


FIGURE 10. Setting of the video camera for the proposed system of vehicle flow analysis and measurement

3. **Experimental Results.** An implementation of the system was tested in several representative situations containing various car flows. A color video camera was set up on an overpass above the road section under surveillance. The video format was 320*240 pixels at a capture rate of 30 frames per second. Figure 11 shows the practical result of the proposed vehicle flow analysis system in the bi-directional two-lane way. The result includes vehicle classification, car number, bike number, and their speeds. The subfigure (a) shows the result of the 1575-th frame in which one car and three bikes have been counted in the in-direction on the upper-left corner and one car and six bikes have been counted in the out-direction on the upper-right corner. In addition, speeds (km/h) of these vehicles are calculated and labeled on the upper of the bounding-box of each vehicle. From the 1575-th frame to 1625-th frame, car number increases from 1 to 2 in the in-direction and bike number increases from 6 to 8 in the out-direction, as shown from the subfigure (a) to (c). From these subfigures, the vehicles can be classified correctly, both numbers of car and bike can be counted accurately, and the vehicles speed can be calculated under a tolerance of 5 (km/h) in the proposed vehicle flow analysis system.



(a) (b) (c)

FIGURE 11. The results of the proposed vehicle flow analysis algorithm in the bi-directional two-lane way at: (a) 1575-th frame; (b) 1600-th frame; (c) 1625-th frame.

To evaluate the importance of features, such as aspect ratio, area ratio, and compactness, the mean values of these features for cars and bikeswere calculated using 375 car samples and 431 bike samples, respectively. The values of aspect ratio, area ratio, and compactness were 1.46, 0.84, and 13.12 and 2.15, 0.65, and 17.12 for cars and bikes, respectively. Hence, the ratios of these three features, defined as separability, are 1.47, 1.29, and 1.30, respectively, where the values were calculated using (high value/low value) of the features. Clearly, the separability of cars and bikes is largest when using the feature of aspect ratio, implying that aspect ratio is the most suitable feature for classifying cars and bikes.

To evaluate the effect of the type of feature on the performance of vehicle classification, 317 vehicle samples (138 cars and 179 bikes) in a video image sequence were used. Table 1 shows the effect of the type of feature on the performance of vehicle classification for cars and bikes. For the test image sequence, the system tracked and classified most cars successfully using the aspect ratio and the area ratio. In the proposed system, the best classification rates (96.4% and 92.7% for cars and bikes, respectively) are achieved when using the aspect ratio, which was expected since aspect ratio has the largest separability for cars and bikes, as described earlier.

For a fair evaluation of vehicle analysis and counting, three situations of vehicle flow with different movement directions were simulated; he results are listed in Table 2. In the table, CarFlow1 denotes the bidirectional flow shown in Fig. 9(c) and (d), and CarFlow2 and CarFlow3 represent the unidirectional flowsshown in Fig. 9(a) and (b), respectively. The results show that the average counting accuracy for the three situations is 96.9%. Furthermore, for velocity measurement, the estimation error is less than 5 km/h.

TABLE 1. Effect of feature type on the performance of vehicle classification for cars and bikes.

		Aspect ratio		Area ratio		Compactness		Total
		Car	Bike	Car	Bike	Car	Bike	
Number of actual vehicles	Car	133	5	129	9	106	32	138
	Bike	13	166	66	113	58	121	179
Accuracy (%)	Car	96.4	3.6	93.5	6.5	76.8	23.2	100
	Bike	7.3	92.7	36.9	63.1	32.4	67.6	100

TABLE 2. Results of vehicle counting for cars and bikes.

	Vehicle type	Count	Error	Accuracy (%)
CarFlow1	Car	5	0	100.0%
	Bike	21	1	95.2%
CarFlow2	Car	14	1	92.9%
	Bike	15	1	93.3%
CarFlow3	Car	19	0	100.0%
	Bike	18	0	100.0%
Average				96.9%

To make a fair comparison with existing vehicle counting algorithms is quite difficult because comparison bases such as weather, luminance conditions and scenes of the test video sequences used are quite different. Hence, a qualitative instead of quantitative comparison of the proposed method with existing algorithms is a possible way to be conducted. The comparisons in terms of vehicle type, object segmentation, background modeling, vehicle classification, velocity estimation, and counting accuracyof vehicles are carried out and tabulated in Table 3. As observed from this table, the counting accuracy on an average of cars and bikes of 96.9% indicates the feasibility of the proposed method when comparing to other existing vehicle counting algorithms.

TABLE 3. Comparative results of the proposed method and the other three vehicle counting algorithms

Comparative algorithms	[28]	[29]	[30]	The proposed method
Vehicle type	Cars only	Cars only	Cars only	Cars and bikes
Object segmentation	Background subtraction	Background subtraction	Optical flow	Background subtraction
Background modeling	Adaptive background estimation	N/A	No need	Adaptive background estimation
Vehicle classification	×	×	×	⊙
Velocity estimation	×	×	×	⊙ (Estimation error is less than 5 km/h)
Vehicle counting accuracy	Scene 1: 90.41% Scene 2: 70.31% Scene 3: 98.39% Scene 4: 80.00%	Afternoon: 91.98% Evening: 96.35%	94.04% on an average	96.9% on an average

Note: The symbol ⊙ represents to have such function, the symbol × denotes no such function, and N/A means not available.

4. **Conclusion.** This paper presents a feature-based method of vehicle analysis and counting for bidirectional roads in a real-time traffic surveillance system. Vehicle features, such as the aspect ratio, area ratio, and compactness, are extracted from a video sequence and used to categorize vehicles as cars or bikes. A simple and efficient tracking algorithm is introduced to robustly track vehicles. Classification rates of 96.4% and 92.7% for cars and bikes, respectively, are achieved using the feature of aspect ratio. The counting accuracy on an average of 96.9% of cars and bikes was obtained by the proposed method of vehicle analysis and counting. Furthermore, the estimation error of vehicle velocity is less than 5 km/h.

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