Visual Motorcycle Detection and Tracking Algorithms

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Abstract: - Although the motorcycle is a popular and convenient means of transportation, it is difficult for researchers in intelligent transportation systems to detect and recognize, and there has been little published work on the subject. This paper describes a real-time motorcycle monitoring system to detect, recognize, and track moving motorcycles in sequences of traffic images. Because a motorcycle may overlap other vehicles in some image sequences, the system proposes an occlusive detection and segmentation method to separate and identify motorcycles. Since motorcycle riders in many countries must wear helmets, helmet detection and search methods are used to ensure that a helmet exists on the moving object identified as a motorcycle. The performance of the proposed system was evaluated using test video data collected under various weather and lighting conditions. Experimental results show that the proposed method is effective for traffic images captured any time of the day or night with an average correct motorcycle detection rate of greater than 90% under various weather conditions.

Key-Words: - Motorcycle detection, Visual, Tracking, Occlusion, Segmentation, Traffic monitoring.

1 Introduction

An intelligent transportation system (ITS) is an advanced application that combines electronics, communications, computers, and sensor technologies. An ITS integrates vehicles, people, and roadway information with traffic management strategies to provide real-time information for increasing safety, efficiency, and comfort in public traffic systems. In past decades, there have been many methods for solving vehicle detection and recognition problems in ITSs [1-10]. The vision-based method has the advantages of low hardware cost and high scalability compared to other methods of traffic surveillance, and therefore is one of the most popular techniques used in ITSs for traffic surveillance.

A background extraction algorithm offers excellent pre-processing for traffic observation and surveillance. It reduces unimportant information in image sequences and speeds up the processing time. Change detection [1, 2] is the simplest method for segmenting moving objects. An adaptive background update method [3] has been proposed for obtaining the background image over a period of time. He *et al.* [4] used a Gaussian distribution to model each point of the background image, and took the mean value of each pixel during a period of time as the background image. Stauffer and other researchers [11-13] used spectral features such as intensity or color distributions at each pixel to model the background. Some spatial features have also been used to adapt to different illumination conditions [14-16]. These methods are able to obtain background images over a long period of time. Chiu *et al.* [5] used a probability-based background extraction algorithm to extract the color background and segment the moving objects efficiently in real time. In this paper, we use the same algorithm [5] to extract the background image and segment the moving objects.

Once the moving objects have been segmented, the next step is to determine which of them motorcycles are. However, solving the problems of object occlusion that often follow moving object segmentation has proven to be difficult for ITS researchers. Recently, several approaches to vehicle occlusion have been proposed for traffic monitoring. Pang *et al.* [6] proposed a cubical model of the foreground image to detect occlusion and separate merged vehicles. Song *et al.* [7] used vehicle shape models, camera calibration, and ground-plane knowledge to detect, track, and classify moving vehicles in the presence of occlusions. However, these approaches do not specifically consider motorcycle detection and occlusion segmentation. Tai and Song [8] proposed an automatic contour initialization method to track vehicles of various

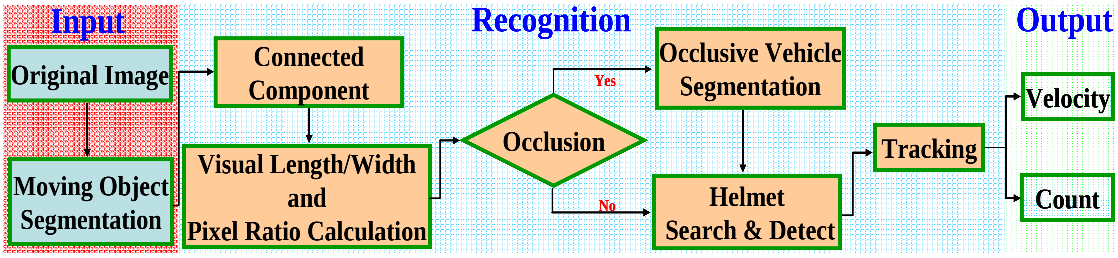


Fig.1 Flowchart of the proposed system

sizes; this method used a detection region to predict the position and size of vehicles. Using the size of objects to differentiate between automobiles and motorcycles is very intuitive as motorcycles will be detected as small objects. However, a detected vehicle may be broken into fragments due to the detection method or illumination conditions, and these small fragments will be detected as many motorcycles. The paper did not specifically consider the occlusion segmentation of motorcycles.

There are many mixed-traffic problems yet to be solved, including capacity estimation, passenger car equivalency of motorcycles estimation, and signal design [17]. Since motorcycle detection and segmentation are key elements in this sort of problems, this paper proposes a vision-based motorcycle monitoring system to detect and track motorcycles with occlusion segmentation.

The organization of the rest of this paper is as follows. Section 2 presents a system overview. Section 3 describes the motorcycle recognition and occlusive segmentation algorithms. Section 4 introduces the motorcycle-tracking algorithm. Experimental results and conclusions are given in Sections 5 and 6.

2 Overview of the proposed system

A flowchart of the real-time vision-based motorcycle monitoring system is shown in Fig.1. The first phase of the proposed system is the moving object segmentation. In this paper, we use the algorithm proposed by Chiu *et al*. [5] to extract the background image and obtain the moving objects, which are detected by subtracting the background from an input image. The second phase of the proposed system is the recognition of moving objects. After the moving object segmentation, the moving objects are processed by connected component labeling [9] to be the bounding boxes, which include much of each object's outline. Using a motorcycle's size, which is a distinguishing and stable characteristic, the proposed method checks whether the motorcycle overlaps another vehicle using the visual length, the visual width, and the pixel ratio. The visual length and width were proposed by Chiu *et al*. [10]. In the last phase, the velocity and motorcycle count are output by the proposed system. The following sections describe the method in more detail.

3 Recognition and occlusive segmentation algorithms

Based on the specific features of motorcycles and helmets, we use four parameters (visual length, visual width, pixel ratio, and helmet shape) to recognize a motorcycle and to solve the occlusive problems between a motorcycle and other vehicles. A pixel is a unit of length and width in the image, and it is influenced by the position of the object. According to the definition given by Chiu *et al*. [10], we can compute the visual length and width of the object outline, regardless of the object's position. The imaging geometry is used to calculate the visual length, D_h as shown in Fig.2.

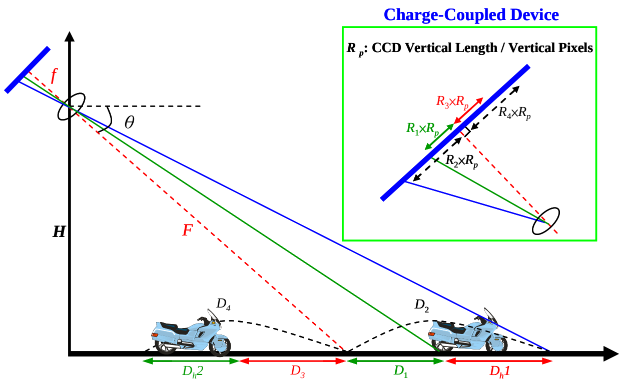


Fig.2 Optical geometry between the image and the ground

The parameters D_h1 and D_h2, whose units are meters, are the visual length of an object and are defined as

$$D_h1 = D_2 - D_1$$
$$= \frac{R_p H}{\sin\theta}\left(\frac{R_2}{f\sin\theta - R_2 R_p\cos\theta} - \frac{R_1}{f\sin\theta - R_1 R_p\cos\theta}\right) \quad (1)$$

and

$$D_h 2 = D_4 - D_3 = \frac{R_p H}{\sin\theta}\left(\frac{R_4}{f\sin\theta + R_4 R_p \cos\theta} - \frac{R_3}{f\sin\theta + R_3 R_p \cos\theta}\right), \quad (2)$$

where D_h1 is the visual length of the object above the dotted line F, which is the optical axis of a charge-coupled device (CCD) camera. Parameters R_2 and R_1 are the pixel lengths in the image plane, and R_p is the average pixel length of the CCD camera. The H is the altitude of the camera, f is the focus length of the lens, and θ is the angle of depression of the camera.

In the same way, the visual length D_h2 can be calculated by Eq. 2. The D_h2 is the visual length of the object below the optical axis, and R_4 and R_3 are the pixel lengths in the image plane.

The visual width of an object is defined as

$$D_w 1 = \frac{R_w\left(\frac{H}{\sin\theta} + D_1\cos\theta\right)}{f},$$
$$D_w 2 = \frac{R_w\left(\frac{H}{\sin\theta} - D_4\cos\theta\right)}{f}, \quad (3)$$

where D_w1 is the visual width when the object is above the optical axis and D_w2 is the visual width when the object is below the optical axis. The R_w is the pixel width of the object width in the image plane.

After connected component labeling, each moving object is marked by a bounding box. In the proposed method, the pixel ratio of a bounding box is defined as

$$\text{Pixel Ratio} = \frac{\text{The total pixels of the object in the bounding box}}{\text{The area of the bounding box}} \quad (4)$$

According to different vehicle models, experimental results show that the visual length and width of different vehicle models are approximately 6 m and 2 m respectively, while the visual length and width of motorcycles are about 3 and 1.2 m. If a motorcycle overlaps with another motorcycle or a vehicle, the occlusive motorcycle in the bounding boxes should be segmented before the next step. If the visual length, visual width, and pixel ratio conform to the conditions

$$\begin{cases} 2m < \text{visual length} < 4m \\ 1m < \text{visual width} < 2m \\ 0.6 < \text{Pixel Ratio} \end{cases} \quad (5)$$

the object represents a motorcycle. At the same time, the system will create an area to be searched for the helmet of the motorcycle rider using a single-helmet detection method.

The single-helmet detection method is as follows.

Step1. Count object's pixels to determine the horizontal projection histogram.

Step2. Extract the helmet region (R_h) from locations in the horizontal projection histogram above the midpoint where the histogram counting values are less than 25 pixels.

Step3. Find the center (X, Y) and the horizontal and vertical radii R_x and R_y of R_h.

Step4. Find the edges ($e_i, e_j \in R_h$) of R_h using Canny edge detection [18].

Step5. Compute the distance D,

$$D = \sqrt{(X-e_i)^2 + (Y-e_j)^2}, \ (e_i, e_j) \in R_h .$$

Step6. Increase the accumulator *Count* by one when the condition $(R_x - 1 \le D \le R_x + 1)$ or $(R_y - 1 \le D \le R_y + 1)$ is met.

Step7. If $\frac{Count}{2\pi[(R_x + R_y)/2]} > 0.7$ then R_h is a circle.
Else, R_h is not a circle.

If a bounding box contains more than one motorcycle, the motorcycle cannot be successfully recognized in the region. In the following, we will discuss the details of how to separate an occlusive motorcycle. For an occlusive object, we can generalize five occlusive classes as follows.

Class I: Vehicle-motorcycle vertical occlusion and segmentation

$$\begin{cases} 6m < \text{visual length} < 10m \\ 2m < \text{visual width} < 4m \\ \text{Pixel Ratio} < 0.6 \end{cases} \quad (6)$$

When the visual length, visual width, and pixel ratio conform to the conditions in (6), the object in the bounding box belongs to vehicle-motorcycle vertical occlusion. A motorcycle is either in front of or behind another vehicle. This occlusion includes six cases, which are shown in Fig.3.

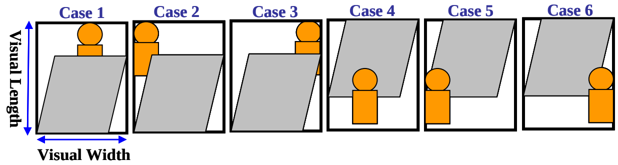


Fig.3 Six cases of vehicle-motorcycle vertical occlusion (Class I)

In this class, the horizontal projection of the object in the bounding box is computed to find the position of the motorcycle. If the projection values vary from small to large, from top to bottom, the occlusion belongs to cases 1-3; otherwise, the occlusion belongs to cases 4-6.

In cases 1-3, the motorcycle rider is located at the top of the moving object. The segmentation point is defined as the difference of the neighboring horizontal projection values that are greater than

15 pixels. The helmet of the motorcycle rider will be detected by the single-helmet detection method. The detailed processes are shown in Fig.4.

In cases 4-6, the helmet of the motorcycle rider overlaps a vehicle. The position of the helmet cannot be located directly. Therefore, the search area is searched for the position of the helmet. The length of the search area is defined as 2 m to 5 m of the visual length above the bottom of the bounding box. The width of the search area is defined as the width of the bounding box. The helmet is detected in the search area by the multi-helmet search method, which will be introduced at the end of this section. The detailed processes are shown in Fig.5.

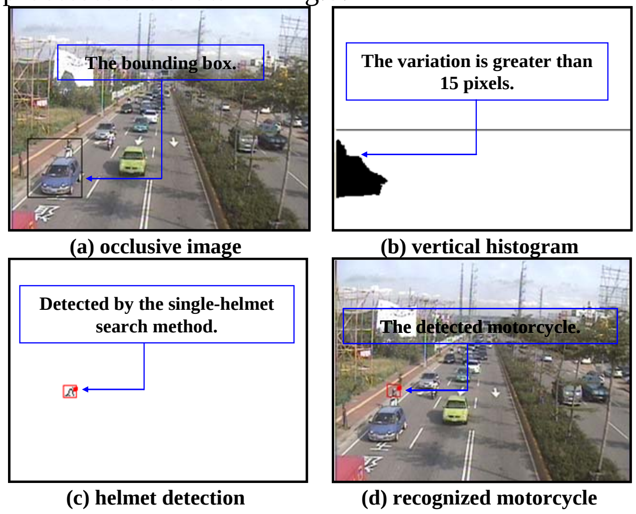


Fig.4 Processes of vertical vehicle-motorcycle occlusion detection and segmentation (cases 1-3)

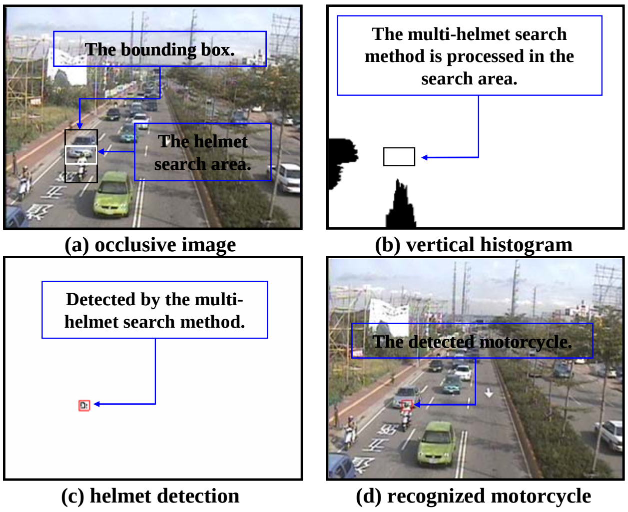


Fig.5 Processes of vertical vehicle-motorcycle occlusion detection and segmentation (cases 4-6)

Class II: Vehicle-motorcycle horizontal occlusion and segmentation

$$\begin{cases} 5m < \text{visual length} < 7m \\ 2m < \text{visual width} < 4m \\ \text{Pixel Ratio} < 0.6 \end{cases} \tag{7}$$

When the visual length, visual width, and pixel ratio conform to (7), the moving object is part of a vehicle-motorcycle horizontal occlusion. A motorcycle overlaps a vehicle to the right or left. This occlusion includes two cases, which are shown in Fig.6.

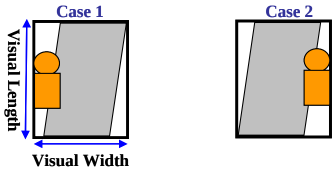


Fig.6 Class II

In this class, the vertical projection histogram of the moving object in a bounding box is computed to determine the position of the motorcycle. The motorcycle is segmented by the valley of the vertical projection. The helmet of the motorcycle rider will be detected by the single-helmet detection method. The details are shown in Fig.7.

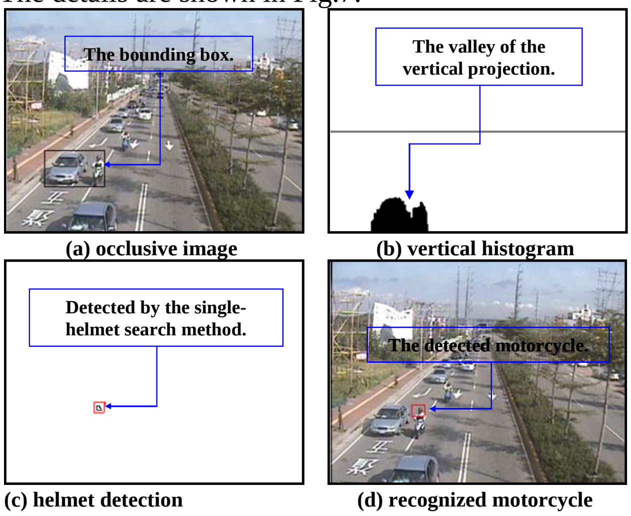


Fig.7 Processes of vehicle-motorcycle horizontal occlusion detection and segmentation

Class III: Motorcycle-motorcycle horizontal occlusion and segmentation

$$\begin{cases} 2m < \text{visual length} < 4m \\ 3m < \text{visual width} < 5m \\ 0.6 < \text{Pixel Ratio} \end{cases} \tag{8}$$

When the visual length, visual width, and pixel ratio conform to (8), the moving object is part of a motorcycle-motorcycle horizontal occlusion. Two motorcycles are side by side on the road, as shown in Fig.8.

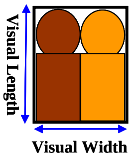
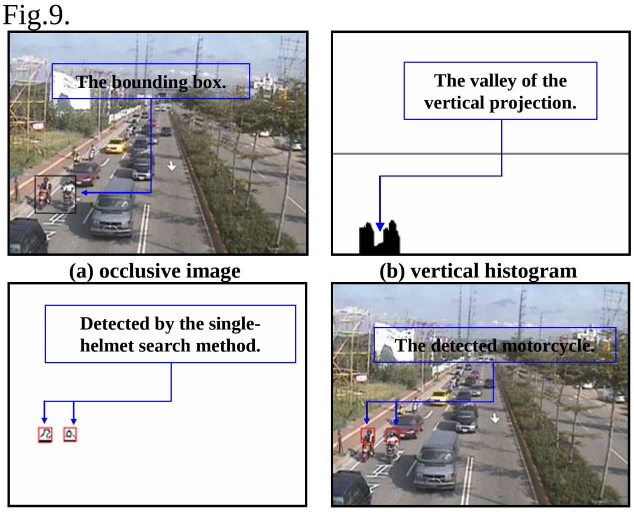


Fig.8 Class III

In this class, the vertical projection histogram of the moving object in a bounding box is computed to find the valley between the motorcycles. The vertical projection is segmented by the valley of the vertical projection. Both the motorcycles can be determined after the segmentation and the helmets of the motorcycle riders will be detected by the single-helmet detection method. The details are shown in Fig.9.



(a) occlusive image (b) vertical histogram

(c) helmet detection (d) recognized motorcycle

Fig.9 Processes of motorcycle-motorcycle horizontal occlusion detection and segmentation

Class IV: Motorcycle-motorcycle vertical occlusion and segmentation

$$\begin{cases} 4m < \text{visual length} < 7m \\ 1m < \text{visual width} < 2m \\ 0.6 < \text{Pixel Ratio} \end{cases} \tag{9}$$

When the visual length, visual width, and pixel ratio conform to (9), the object is part of a motorcycle-motorcycle vertical occlusion. The front rider overlaps with the rear rider, as shown in Fig.10.

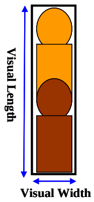
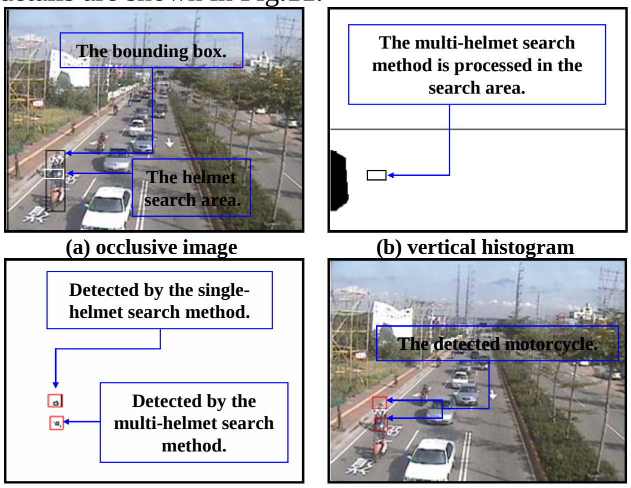


Fig.10 Class IV

The helmet position of the front rider cannot be located directly. Therefore, a search area is searched for the helmet position. The search area is defined as 2 m to 5 m of the visual length above the bottom of the bounding box. The width of the search area is defined as the width of the bounding box. The multi-helmet search method is applied to the search area to find the helmet of the front rider. The rear rider is found by the single-helmet detection method. The details are shown in Fig.11.



(a) occlusive image (b) vertical histogram

(c) helmet detection (d) recognized motorcycle

Fig.11 Processes of motorcycle-motorcycle vertical occlusion detection and segmentation

Class V: Motorcycle-motorcycle diagonal occlusion and segmentation

$$\begin{cases} 4m < \text{visual length} < 7m \\ 2m < \text{visual width} < 3.5m \\ \text{Pixel Ratio} < 0.6 \end{cases} \tag{10}$$

When the visual length, visual width, and pixel ratio conform to (10), the object is part of a motorcycle-motorcycle diagonal occlusion. One motorcycle diagonally overlaps another motorcycle. This occlusion includes two cases, which are shown in Fig.12.

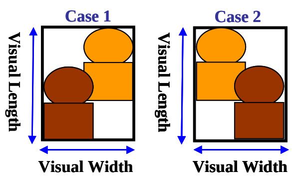
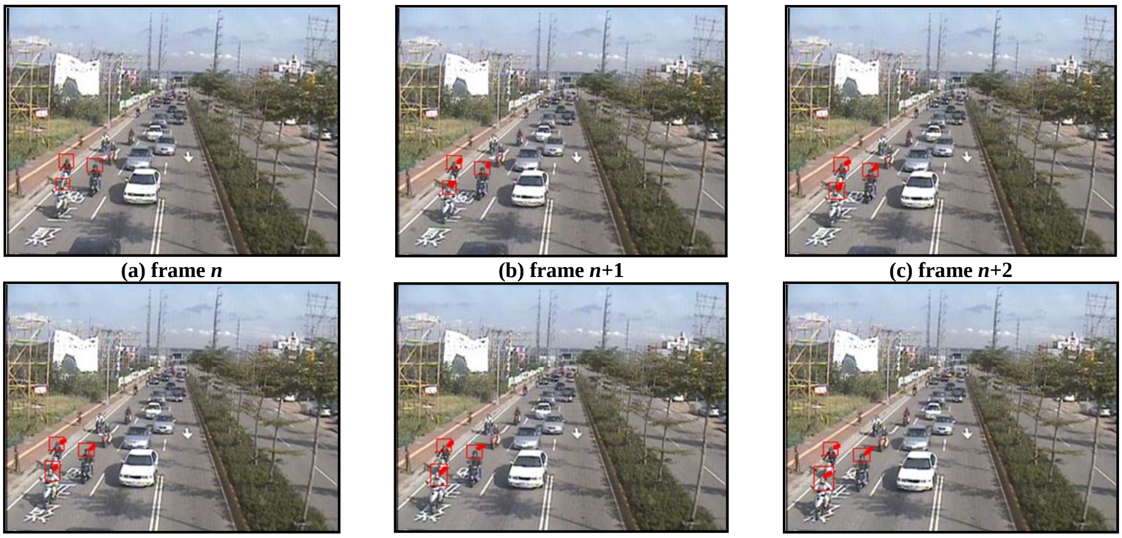


Fig.12 Class V

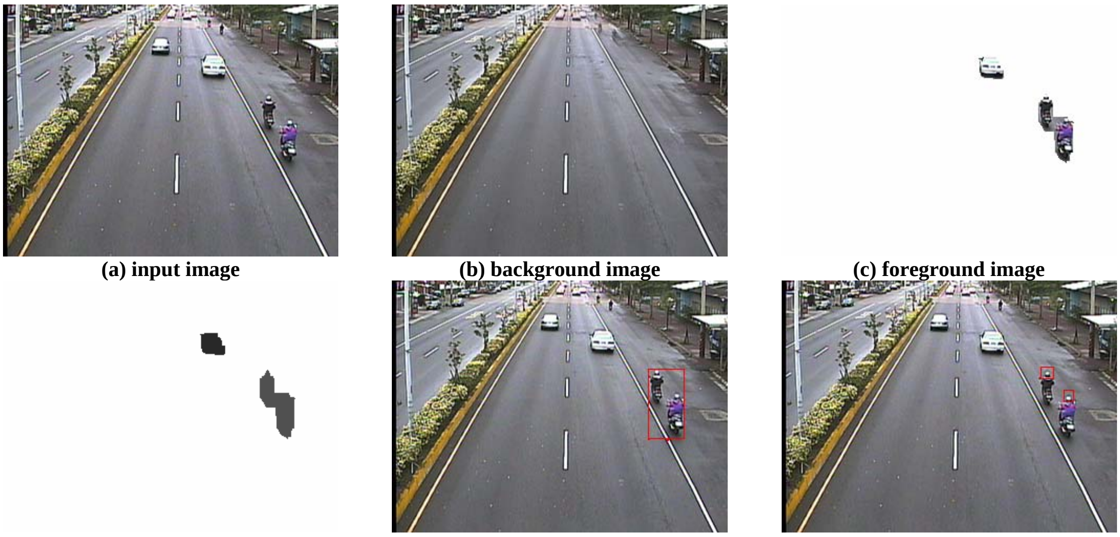
In this class, the front rider overlaps with the rear rider. The algorithm to detect and search for the helmets of both riders is same as the algorithm of class IV.

When the motorcycle rider overlaps with another motorcycle or vehicle, the width and length of the search area are defined by classes I, IV, and V, and set to W (pixels) set to W (pixels) and L (pixels),



(a) frame *n* **(b) frame *n*+1** **(c) frame *n*+2**
(d) frame *n*+3 **(e) frame *n*+4** **(f) frame *n*+5**

Fig.13 Motorcycle-tracking results in sequential images



(a) input image **(b) background image** **(c) foreground image**
(d) labeling image **(e) occlusion image** **(f) segmented vehicles**

Fig.14 Occlusive segmentation processes

respectively. The multi-helmet search method is as follows:

Step1. Determine the pixel width $R_w = RH_w$ that is the diameter of the helmet. RH_w is computed from Eq. (3) by setting the visual width D_w1 to 25 cm.

Step2. Extract the edge pixels (e_i, e_j) in the search area i = 0 - (W-1) and j = 0 - (L-1) using Canny edge detection [18].

Step3. In the search area, set a search window $W(x_m, y_n)$, where $m = \frac{1}{2}RH_w \sim (W - \frac{1}{2}RH_w)$ and $n = \frac{1}{2}RH_w \sim (L - \frac{1}{2}RH_w)$.

Step4. Compute the distance $D_{i,j}$ for each (x_m, y_n), $D_{i,j} = \sqrt{(x_m - e_i)^2 + (y_n - e_j)^2}$, $\forall$ (e_i, e_j).

Step5. For $\forall(e_i, e_j)$, increase the accumulator *Count* by one when the condition $\left(\frac{1}{2}RH_w - 1 \le D_{i,j} \le \frac{1}{2}RH_w + 1\right)$ is met.

Step6. Find the maximum value of *Count*, denoted $Count_{max}$, from (x_m, y_n).

Step7. If $\frac{Count_{\max}}{\pi \times RH_w} > 0.7$, the helmet is detected. Else, the helmet is not found.

4 Tracking algorithm

After the segmentation and recognition procedures, the center of the motorcycle driver's helmet is defined as a reference point. The tracking method uses the concept of velocity and displacement to ensure the next reference point is the tracked motorcycle. In the sequence frames, the distance in the n^{th} frame *Dis* between a predictive point and a reference point is defined as

$$Dis = \sqrt{\left(x_n^{'} - x_n\right)^2 + \left(y_n^{'} - y_n\right)^2} \,, \qquad (11)$$

where $\left(x_n^{'}, y_n^{'}\right)$ and $\left(x_n, y_n\right)$ are the coordinates of the predictive point and the reference point in the n^{th} frame, respectively.

The predictive point is predicted by the reference point of the $(n-1)^{th}$ frame according to the motion of the motorcycle. We use the predictive point to predict the coordinate of the reference point in the n^{th} frame. Therefore, when the reference point of the n^{th} frame has the minimum distance to the predictive point, the reference point could be the matching point. Otherwise, the reference point with the minimum distance of the other reference points will be checked until the best match is found.

The predictive point is predicted by the displacement, which is computed by the velocity and the acceleration of the reference point. The coordinate $\left(x_n^{'}, y_n^{'}\right)$ of the predictive point in the n^{th} frame is

$$\left(x_n^{'}, y_n^{'}\right) = \left(x_{n-1}, y_{n-1}\right) + \left(\Delta S_n(x), \Delta S_n(y)\right). \qquad (12)$$

The coordinate $\left(x_{n-1}, y_{n-1}\right)$ is the reference point of the same vehicle in the $(n-1)^{th}$ frame. The parameters $\Delta S_n(x)$ and $\Delta S_n(y)$ are the displacements of the *x* and *y* coordinates. The displacements are calculated from

$$\Delta S_n(Co) = v_{n-1}(Co)\cdot\left(t_n - t_{n-1}\right) + \frac{1}{2} a_{n-1}(Co)\cdot\left(t_n - t_{n-1}\right)^2 , \qquad (13)$$

where $v_{n-1}(Co) = \left(Co_{n-1} - Co_{n-2}\right)/\left(t_{n-1} - t_{n-2}\right)$, $a_{n-1}(Co) = \left(v_{n-1}(Co) - v_{n-2}(Co)\right)/\left(t_{n-1} - t_{n-2}\right)$, and *Co*=*x* or *y*. The $v_{n-1}(Co)$ and $v_{n-2}(Co)$ are the velocities of the reference point in frames (n – 1) and (*n* – 2), $a_{n-1}(Co)$ is the acceleration of the reference point in frame (*n – 1*), and t_n, t_{n-1}, and t_{n-2} are snapshots in time of frames *n*, (*n – 1*), and (*n – 2*), respectively.

The tracking system uses the time interval between sequential images and the displacement of the reference point to track the motorcycles. This method is quite appropriate for capture systems with variable capture speeds. Figure 13 shows the tracking results after segmentation and detection. There are three motorcycles in the detection zone, and two of them belong to occlusive case IV. In Fig. 13, the helmet of each rider is detected by the proposed system and marked by a red square. Furthermore, the trajectory of each helmet center is described by a thick red line. Figure 14 shows the occlusive segmentation processes in the system. Figure 14(a) depicts the current input image while Fig. 14(b) depicts the current background image. After object segmentation, the moving objects can be segmented as shown in Fig. 14(c). The moving object image from rows 0 - 40 will be deleted to remove the unwanted output. Figure 14(d) gives the labeling image with different gray levels after the connected component labeling. Figure 14(e) shows the bounding box that satisfies Class V, the motorcycle-motorcycle diagonal occlusion. Figure 14(f) illustrates the result after segmentation and recognition.

5 Experimental results

Test images were captured by the stationary CCD camera shown in Fig.15, which was mounted over the Jhong-Hua road (24°45'54" N, 120°54'50" E) in Hsinchu, Taiwan. The analog image was converted to digital data by a frame grabber operating at 30 frames per second installed in a Pentium IV 2.6-GHz 512-MB personal computer system. Microsoft Visual C++ was used for the development environment.

Fig.15 Set up and location of the stationary CCD camera (*H*=6 m, θ=14°, *f*=8 mm, R_p=6 mm/240 pixels)

The interface of the proposed system is shown in Fig.16. The output of the interface gives the total motorcycle count and the motorcycle velocities for each lane. The lane marks are initially set by the user. The time required to process one frame (320 pixels wide by 240 pixels high, 24-bit RGB) was between 28×10^{-3} and 32×10^{-3} s.

This paper describes a real-time vision-based motorcycle monitoring system for extracting real-time traffic parameters. To evaluate the performance of the proposed system, we used more than 7 days of test images collected under various weather and lighting conditions. This included one continuous 14-hr test sequence.

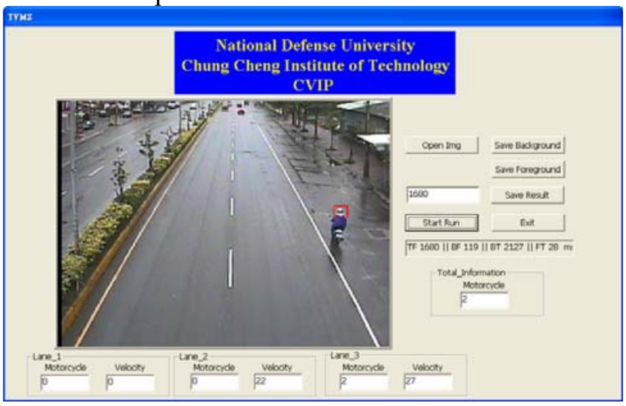


Fig.16 Proposed system interface

Figure 17 shows the detection results of the proposed system obtained during the continuous 14-hour test sequence, which consisted of 1,512,000 frames captured from 6:00 a.m. to 8:00 p.m. on Mar. 6, 2007. The environmental lighting conditions changed continuously throughout the day. According to weather reports from the Central Weather Bureau in Taiwan, the sunrise and sunset for the test day were 06:15 a.m. and 6:00 p.m. The maximum flow of motorcycles was 386 per hour between 7:00 and 9:00 a.m. The average motorcycle detection rate was 96.7% during the day and 80.2% at night. Most of the detection errors and false detections were due to motorcycles with fragmented edges at night because the small outline of a motorcycle was not seen accurately in low illumination conditions, and there was possible interference from the reflected lights of vehicles. During the daytime, the missed and false detections were mainly caused by the color of the motorcycles or their riders, which blended into the road surface.

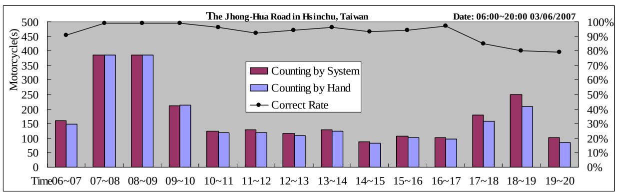
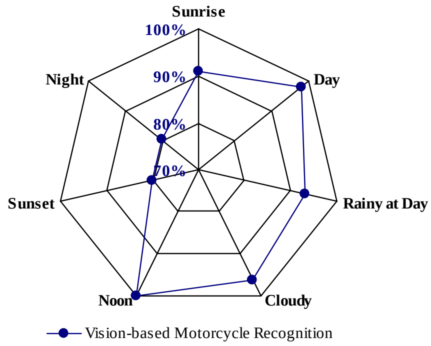


Fig.17 Motorcycle detection results for continuous 14-hr test sequence

Figures 18 and 19 show motorcycle detection results under various weather conditions. The experimental environment included rain and fog, and the average motorcycle detection rate was above 85%. The recognition rate under low-light conditions was lower because external light sources such as headlights and rear lights caused the motorcycle outlines to become blurred or missing.

The detection region was set to rows 41 - 230. When a moving object enters the detection region, the system starts to detect and recognize the helmets of motorcycle riders. In Fig.19, each detected helmet is indicated by a cyan or red bounding box. Cyan indicates a detected helmet. To prevent false detection, the helmet of a rider must be detected more than five times before the motorcycle is confirmed. When this happens, the bounding box of the helmet is drawn in red.

The velocity estimated by the proposed system was compared to the velocity measured by a laser gun (Stalker Lidar). This device is a very popular hand-held police laser used to determine vehicle speed. Figure 20 compares the velocity calculated by the proposed system with that determined by the laser gun and shows that the detection errors of the motorcycle velocity are within ±5 km/hr.



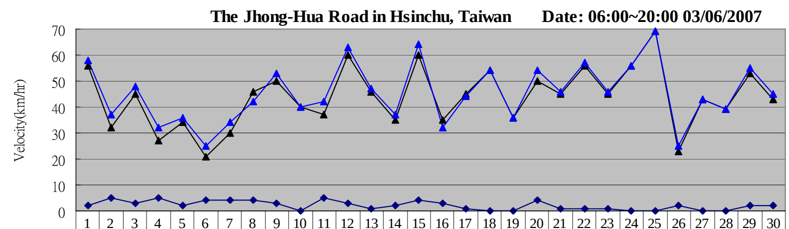
	Environmental Condition			
	Sunrise	Day	Rainy at Day	
Correct Rate	91%	96%	93%	
	Cloudy	Noon	Sunset	Night
Correct Rate	96%	100%	80.2%	80%

Fig.18 Motorcycle detection results for various weather conditions

6 Conclusions

We described a real-time vision-based motorcycle monitoring system that can be used to detect and track motorcycles in a sequence of images. The system used a moving object detection method and resolved occlusive problems using a proposed occlusive detection and segmentation method. Each motorcycle was detected by proposed helmet detection or search methods. The proposed occlusive detection and segmentation method used the visual length, visual width, and pixel ratio to identify classes of motorcycle occlusions and segment the motorcycle from each occlusive class. Because the size of the helmet can be computed by Eq.(3) or estimated automatically from the horizontal projection, the helmet detection and search methods could identify helmets in different locations in a frame. This system overcame various issues raised by the complexity of occlusive segmentation and helmet detection problems. Experimental results obtained with complex road images revealed that the proposed system could successfully segment and detect various occlusions. Occlusive problems with motorcycles in traffic jams will be the subject of future work.

Fig.19 Experimental results under various weather conditions



	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30
Vision-Based	56	32	45	27	34	21	30	46	50	40	37	60	46	35	60	35	45	54	36	50	45	56	45	56	69	23	43	39	53	43
Stalker LIDAR	58	37	48	32	36	25	34	42	53	40	42	63	47	37	64	32	44	54	36	54	46	57	46	56	69	25	43	39	55	45
Error	2	5	3	5	2	4	4	4	3	0	5	3	1	2	4	3	1	0	0	4	1	1	1	0	0	2	0	0	2	2

Sample motorcycle's NO.

Fig.20 Comparison of calculated motorcycle velocity with that measured by a laser gun

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