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職稱	教授	會議時間	100 年 7 月 18 日至 100 年 7 月 21 日
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發表論文題目	Pedestrian and Vehicle Classification Surveillance System for Street-Crossing Safety		

一、參加會議經過

The 2011 International Conference on Image Processing, Computer Vision, and Pattern Recognition國際研討會於100/7/18—100/7/21在美國拉斯維加斯召開。論文收錄於Microsoft Academic Seaarch 。此會議論文接受率約24%，論文品質相當不錯。本人擔任其中一個session的session chair，並口頭發表論文，會後引起許多迴響，詳參下圖。

二、與會心得

本次2011 International Conference on Image Processing, Computer Vision, and Pattern Recognition國際研討會參加之學者專家來自全球超過兩千人，台灣參加人

數亦不少，包含本校、北科大、高應大、師大、大同大學等校之教授與學生。本次研討會大會安排了4場Keynote Speech 及3場invited talk。均由國際知名學者教授主講，受益良多。10 場oral presentation session，論文品質相當不錯。

三、攜回資料名稱及內容

會議論文光碟及論文集一冊。

備註：請於會議結束後一個月備妥報告電子檔寄 yaling@mail.ntpu.edu.tw，送研究發展處備查。

1. 本人同意將此報告內容授權刊載於臺北大學網路或有關刊物內。

報告人簽章：林道通

日期：100 年 8 月 12 日

Pedestrian and Vehicle Classification Surveillance System for Street-Crossing Safety

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Abstract— *This paper presents a framework for automatic pedestrian and motor vehicle classification in a street-crossing safety surveillance system. The proposed method is a coarse to fine classification approach divided into two branches. The moving objects are detected, tracked and clustered into fast moving and slow moving categories according to a motion speed estimation method. This approach is applicable to identify motor vehicles and further differentiate cars from scooters using width and shape features. The second part identifies slow moving objects. We improved the Recurrent Motion Image (RMI) algorithm to sort out the pedestrians due to their high RMI value. Haar-like features and the Adaboost algorithm are then employed to distinguish between pedestrians and scooters. Cars and scooters are identified using the object aspect ratio (AR) and area feature. The experimental results show that the recognition rate for 320 objects achieved 92.5%. The proposed system is promising for application to the traffic monitoring surveillance system.*

Keywords: Automatic pedestrian and vehicle classification, road safety surveillance, distance estimation, recurrent motion image, Haar-like feature

1. Introduction

With economic development the number of various traffic vehicles has grown rapidly. Therefore, the demands on the traffic safety surveillance system has dramatically increased. According to government statistics, we found that traffic violation is the main cause of traffic accidents. To reduce traffic violation situations, human based manual monitoring is not possible due to limited police man-power. A sensor based monitoring system is not helpful because it is not cost effective to construct a huge sensor network in a metropolitan area [1] [2]. Several researches have been reported in this field. Zheng and Liang [3] presented various types of lines and arcs with edge-like and ridge-like strip patterns and detected cars in multi-view real-world scenes using the Adaboost algorithm. Javed et al. [4] proposed a co-training method to improve a boosted classifier for moving object classification. Wen et al. [5] used the Support Vector Machine (SVM) and wavelet feature for motorcycle recognition. Jazayeri et al. [6] applied the Hidden Markov Model (HMM) to recognize cars by vehicle shape, color and type. Tabb and Davey et al. [7] utilized the Active Contour Model to identify moving objects into human or non-human. Bertozzi et al. [8] relied on the specific characteristics of pedestrians such as vertical symmetry and strong presence of edges for pedestrian classification. Zang and Klette [9] employed the height/width ratio and the corners to classify traffic objects. Broggi et al. [10] proposed a human shape localization method for pedestrian detection based on symmetry, size, ratio and shape. Javed and Shah invented the Recurrent Motion Image (RMI) [11] algorithm to recognize pedestrians by observing periodic pedestrian motion. Ern and Joo [12] presented a new RMI framework able to identify four-legged animals. Johnsen and Tews [13] improved RMI for outdoor people and vehicle classification. In this work, we propose a pedestrian and vehicle classification method for lane-crossing detection surveillance. This approach is a computer vision based surveillance system that can classify moving objects on roads, detect lanes automatically and issue a warning for lane-crossing moving objects. Our system is aimed at reducing traffic accidents and improving traffic safety.

General computer vision based surveillance systems can be divided into three important components: motion segmentation, object tracking, and object analysis [14] [13]. In the motion segmentation part, moving objects are detected and extracted. If the object is completely segmented we may obtain good features for further analysis. Therefore, the segmentation quality will affect the object feature soundness and object analysis accuracy. Background subtraction is a common method used to extract moving objects by creating an initial background image. The foreground of the moving object image is obtained by computing the difference between the current image and background image. Stauffer and Grimson [15] proposed a Gaussian Mixture Model(GMM) for background modeling which is a reliable and widely used background model. GMM can create a dynamic background and update the background image. Haque et al. [16] applied

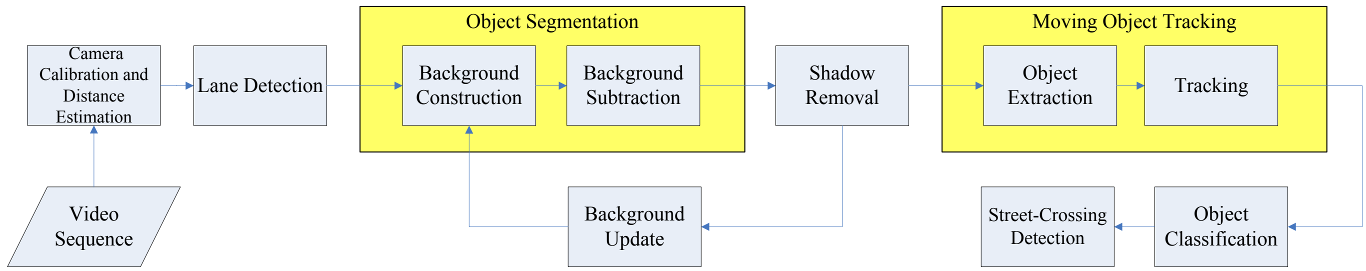

Fig. 1: Figure 1. Flowchart of the proposed automatic pedestrian and vehicle classification surveillance system for street-crossing safety.

GMM to detect multiple objects. Zhang et al. [17] improved GMM to detect targets of interest in videos. Codebook [18] is another popular background model which has a better updating effect for light changes and noisy backgrounds such as trees and shaking leaves. Zhang et al. [19] proposed an efficient combination of codebook models for motion detection. However, the Codebook produces a side effect with redundant object shadows. We employed the Gaussian Mixture Model to perform background image construction and foreground image extraction in this study. Object tracking is another key issue in an automatic surveillance system. Tracking is often achieved using object features such as the object center, edge, speed, etc. Johnsen and Tews [13] applied the Kalman filter to perform linear position prediction. Gao et al. [20] employed an automatic particle filtering algorithm to track a vehicle. Ern and Joo. [12] used central point, bounding box, size, velocity and the change in size of each blob for tracking correspondence. In this work we adopted the RGB color histogram and object center as the object feature for tracking purposes. Object classification approaches can be divided into three main categories: (1) learning based algorithm using a large number of training databases, (2) feature based methods and (3) motion information based schemes. Abd-Almageed and Hussein et al. [21] implemented a fast and accurate human detector based on the histogram of oriented gradients. Viola and Jones [22] introduced cascade Adaboost selectors for face detection. This algorithm has becoming a popular and practical object detection method when the strong and weak classifiers are well trained from an extensive number of examples. This paper modified the RMI algorithm [11] and combined it with the Adaboost algorithm [22] to improve the classification accuracy. The rest of this paper is organized as follows. Section 2 introduces the formal components of the proposed system. Section 3 elucidates the detailed classification methodology. Section 4 reports the experimental results and Section 5 draws conclusions and presents recommendations for future improvement for this work.

2. System Architecture

Figure 1 presents the flowchart of the proposed automatic pedestrian and vehicle classification and street-crossing safety surveillance system. The proposed system is comprises of the following main procedures: camera calibration and distance estimation, lane detection, object segmentation, shadow removal, moving object tracking, object classification and street-crossing detection. The detailed descriptions of these procedures are illustrated as follows.

2.1 Camera Calibration and Longitudinal Distance Estimation

Generally, the movement speeds of pedestrians and vehicles are different. We coarsely divide moving objects according to speed and further ensure the object type using detailed features. The longitudinal distance between the object and camera and the object lateral width are important. In order to calculate the accurate distance, speed and width of moving objects, we need to calibrate the camera and obtain the correspondence between the camera Field of View (FOV) and scene distance [23]. Figure 2 illustrates the longitudinal distance estimation concept for moving objects. In Fig. 2, the longitudinal distance D is calculated as follows:

$$D = H(tan\theta_1 - tan\theta_2) \tag{1}$$

$$\theta_1 = \theta - \frac{FOV_v}{2} + n_1\frac{FOV_v}{I_h} \tag{2}$$

$$\theta_2 = \theta - \frac{FOV_v}{2} + n_2\frac{FOV_v}{I_h} \tag{3}$$

where θ denotes the angle between the camera axis L(plotted in blue line in Fig. 2) and the perpendicular axis to the ground, θ_1 is the angle between the highest pixel of object (n_1) in FOV_v and the perpendicular axis to the ground. θ_2 is the angle between the lowest pixel of object (n_2) in FOV_v and the perpendicular axis to the ground. FOV_v is the height of the camera image, I_h is the horizontal width of the image, H is the height from the physical camera to the ground.

Figure 3 interprets the lateral distance estimation concept. The lateral width distance D_w is calculated as follows.

$$D_w = L[tan(n_2\frac{FOV_h}{I_v}) - tan(n_1\frac{FOV_h}{I_v})] \tag{4}$$

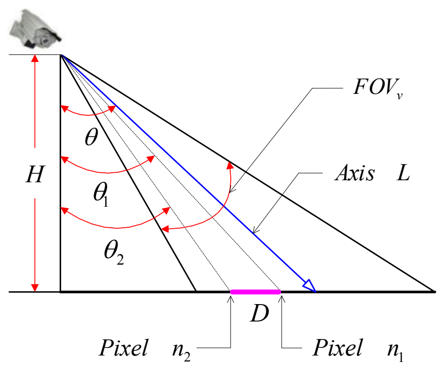

Fig. 2: The illustration of object longitudinal distance estimation [23].

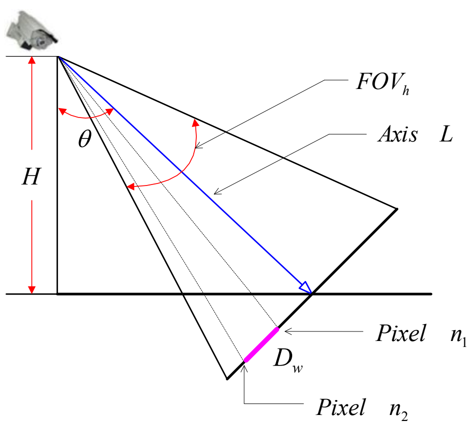

Fig. 3: The lateral distance estimation concept [23].

where $L = \frac{H}{\cos\theta}$, FOV_h is the horizontal width of the camera FOV, I_v is vertical height of the image.

2.2 Lane Detection

We employed the Hough transform to detect all straight lines in the FOV. Afterward the lane is filtered through a RGB color information filter and the white lines are retained. The Hough transform computes each pixel at location (x, y) in the image and obtains (a, b) which satisfies a linear equation as Eq. (5). That is, it transfers the parameter space from (x, y) to the parameter space (a, b).

$$y = ax + b \tag{5}$$

The Hough transform uses the accumulator array which records the number of pixels whose coordinate (x, y) fits Eq. (5) for each parameter set (a, b). The maximum in accumulator array with row and column index (a, b) is the most representative straight line in image. However, the Hough transform method is unable to detect the vertical lines. Therefore, the Cartesian coordinate (a, b) is transformed into the polar coordinate (r, θ) as follows.

$$r = x\mathbf{cos}\theta + y\mathbf{sin}\theta \tag{6}$$

The indices r and θ of accumulator array are in a range (r_{min}, r_{max}) and $(\theta_{min}, \theta_{max})$, and $0 \leq r \leq i$, $0° \leq \theta \leq 360°$.

2.3 Object Segmentation

Object segmentation is one of the most important preprocessing tasks for video surveillance systems. The segmented foreground object quality will affect the object feature extraction soundness and the object recognition accuracy in the later analysis. The background subtraction method is a popular approach for foreground object extraction. A background model needs to be established first. The foreground object is then obtained by subtracting the background from the current image. Usually, noise exists in the resultant foreground image. We need to remove the noise utilizing morphological dilation and erosion operations. We apply the Gaussian mixture model (GMM) [15] to generate a background model image. GMM is an adaptive update statistical model. GMM is able to overcome the variation in pixel values caused by the light source. GMM is a very robust background model. Time t, the most recent history of each pixel $\{x_0, y_0\}$ in images can be expressed as:

$$\{X_1, \cdots, X_t\} = \{I(x_0, y_0, i) : 1 \leq i \leq t\} \tag{7}$$

where I is the image sequence. The recent history of each pixel $\{X_1, \cdots, X_t\}$ is built using K Gaussian distributions. The Gaussian mixture model pixel value X_t is as follows:

$$P(X_t) = \sum_{i=1}^{K} w_{i,t} \cdot \eta(X_t, \mu_{i,t}, \sum_{i,t}) \tag{8}$$

where $w_{i,t}$ is the ith GMM weight estimated at time t. $\mu_{i,t}$ is the ith average value of GMM at time t. $\sum_{i,t}$ is the ith covariance matrix of GMM at time t. K is the amount of Gaussian distributions.

2.4 Shadow Removal

Light source may have a great effect upon foreground objects extracted from the background model. The foreground object will probably contain shadow and the shadow is generally connected with the object. As a result erroneous feature information is extracted from the excess foreground region and incorrect object shape. In brief, shadow removal is a significant issue in these systems. We utilized an approach proposed by Cucchiara et al. [24] to remove the shadow on the HSV color space. The formula is as follows:

$$Shawdow = \begin{cases} 1 & \alpha \leq \frac{I_t}{B_t^t} \leq \beta, \left|I_t^H - B_t^H\right| \leq \tau^H, \\ & \left|I_t^S - B_t^S\right| \leq \tau^S \\ 0 & otherwise \end{cases} \tag{9}$$

Where I_t and B_t are foreground and background images respectively at time t. H is Hue, S is Saturation and V is value in HSV color space.

2.5 Object Extraction and Tracking

The foreground object can be obtained from the above mentioned procedures. We perform the connected component operation on the foreground to obtain a more solid and complete region. An object with a small area is discarded. The object is tracked using the similarity of its central location area and R, G, and B color histograms. The similarity is measured using the following equation:

$$\rho_{XY} = E\left[(\tfrac{X-\mu_X}{\sigma_X})(\tfrac{Y-\mu_Y}{\sigma_Y})\right] = \frac{\sigma_{XY}}{\sigma_X \sigma_Y} \qquad (10)$$

where μ_X and μ_Y are the average of random variable X and Y, respectively. σ_X and σ_Y are the standard deviation of random variable X and Y, respectively. $\sigma_X Y$ denotes the covariance of X and Y.

The correlation coefficient value is $-1 \leq \sigma_X Y \leq 1$ where 1 represents a perfect positive correlation. On the other hand -1 represents a perfect negative correlation and 0 means no correlation. As a result, the closer the value of $\sigma_X Y$ approximates 1, the more probable the objects are the same.

3. Pedestrian and Vehicle Classification

The proposed approach is a coarse to fine classification method divided into two stages. Moving objects are detected first, tracked and classified into fast moving and slow moving categories according to the object motion speed estimation. This approach is applicable in identifying motor vehicles and further differentiates them into cars or scooters using the width feature. The second part identifies slow moving objects based on the improved Recurrent Motion Image (RMI) algorithm, Adaboost algorithm, object aspect ratio (AR) and area feature. Figure 4 shows the flowchart for the proposed classification approach. The detailed method is illustrated as follows.

3.1 Low-speed Vehicles Category Classification

Objects with low motion speeds, they could be either pedestrians, scooters, or cars. More discrimination criteria are needed to for further identification as follows.

3.1.1 Pedestrian Classification

This section presents a modified Recurrent Motion Image (RMI) algorithm to improve pedestrian classification accuracy. Javed [11] proposed the RMI method which measures the periodic difference in a moving object image. Generally, the leg motions of walking pedestrians are significant, while the motion changes in the lower part of a moving vehicle is relatively low. The original RMI is computed as follows.

$$D_A(x,y,t) = I_A(x,y,t-1) \oplus I_A(x,y,t) \qquad (11)$$

where $I_A(x,y,t)$ is the binary silhouette image sequence of object A. $D_A(x,y,t)$ represents the differences between two consecutive image frames for object A (time t and $t-1$) with an exclusive-or operation.

The RMI sums up the different images $D_A(x,y,t)$ for a period of time τ to indicate the features of the moving object. The RMI was defined as follows:

$$RMI_A = \sum_{k=0}^{\tau} D_A(x,y,t-k) \qquad (12)$$

When pedestrians walk toward or forward in a longitudinal direction toward the camera, the leg motion is not obvious and will result in an error decision. To solve this problem we present a modified RMI version. The new RMI is calculated as follows. We redefine the difference image as $D_A^{new}(x,y,t)$:

$$D_A^{new}(x,y,t) = G_A(x,y,t-1) \oplus G_A(x,y,t) \qquad (13)$$

where $D_A(x,y,t)$ is the gray silhouette image sequence for object A. $D_A^n ew(x,y,t)$ is the difference between two gray image object motion frames at time t and $t-1$ with exclusive-or operation. The modified Recurrent Motion Image(RMI_A^{new}) is defined as follows.

$$RMI_A^{new} = \sum_{k=0}^{\tau} bin(D_A(x,y,t-k)) \qquad (14)$$

where bin represents the binary operation.

The original RMI was computed using the difference between two binary silhouette images. However, the RMI becomes very small when the pedestrian walks slowly due to the small amount of binary silhouette pixels. We overcome this drawback and propose a new RMI formula using the differences between two gray images. The new RMI is able to induce obvious motion variance and achieve a voting mechanism for identification accuracy improvement. The voting mechanism is designed by defining two accumulators Acc_1 and Acc_2 for each object. If the RMI_A is greater than a threshold T_o, the Acc_1 increases by 1, otherwise the Acc_2 increases by 1. If the RMI_A^{new} is greater than a threshold T_n , the Acc_1 increases by 1, otherwise the Acc_2 increases by 1. Finally, if Acc_1 is larger than Acc_2, the object is classified as a pedestrian. If the Acc_1 is smaller than Acc_2, the object is undefined. If Acc_1 is equal to Acc_2, the classification result remains as the previous output.

If the pedestrian stands still or moves slightly, the RMI value will be too low and the pedestrian will be incorrectly regarded as a vehicle. In this work, we adopted the Adaboost classifier algorithm [22] to further discriminate low-speed moving objects. Consequently, the proposed system performance has accomplished great progress in pedestrian recognition.

As we know, the lower parts of the pedestrian and scooter are different. We applied MIT CBCL database [25] for training and obtained the Adaboost classifiers.The MIT CBCL data consists of 924 pedestrians with image resolution

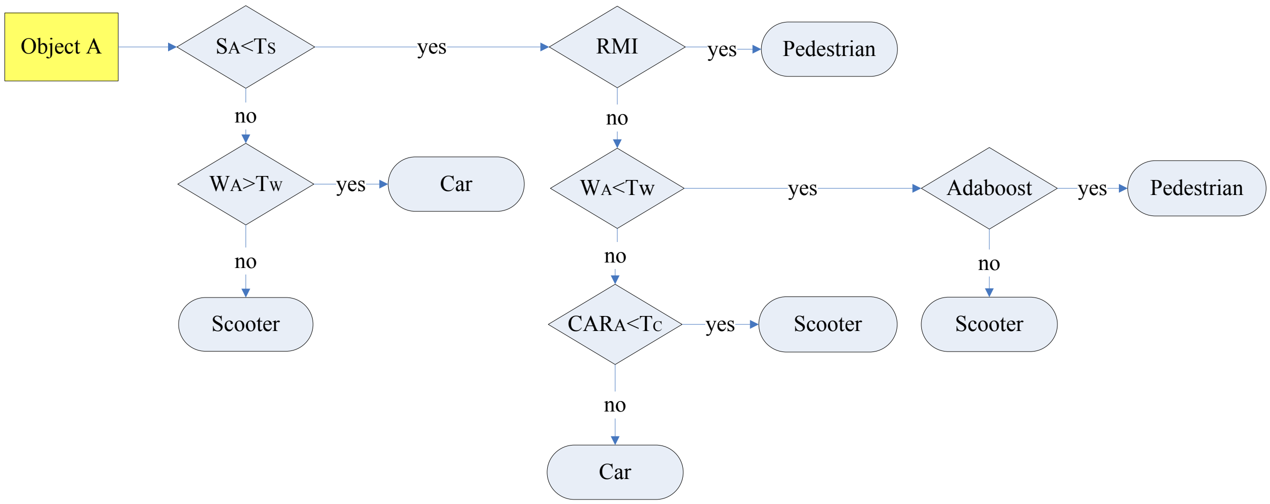

Fig. 4: The flowchart of the proposed object classification approach.

Fig. 5: Training examples of MIT CBCL [25].

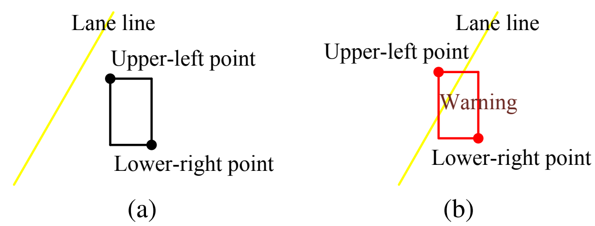

Fig. 6: (a)No warning signal is issued if the upper-left point and the lower-right point are on the same side of the street middle lane.(b) Lane-crossing violation is detected.

128×64. The lower body resolution was scaled to 23×19. The number of positive examples was 924 The number of negative examples was 2000. Some of the training examples are shown in Fig. 5. The number of Adaboost classifier stages was 27. The minimum hit rate was 0.9950 and the maximum false alarm rate was 0.5000 [26].

3.1.2 Cars and Scooters Classification

As illustrated in Section 3.1.1 we employed the Adaboost algorithm to screen out the pedestrians from slow motion or still objects. The remaining objects may be different types of vehicles. For the low-speed vehicles with low RMI values, the object width and area features are used to distinguish between cars and scooters. Yet, because scooters always turn to exchange lanes, the widths of the car and scooter may be similar. The Contour Area Rate(CAR) was adopted to perform finer discrimination using the following formula:

$$\begin{cases} Scooter & CAR_A > T_C \\ Car & CAR_A \leq T_C \end{cases} \tag{15}$$

where $CAR_A = C^2/A$ and C is the object contour length, and A is the object area, T_C is the threshold. When all objects are scaled to the same size the scooter contour length is higher than that of the car, while the scooter area is lower than that of the car. Hence, if the CAR_A value is larger than T_C , the object is viewed as a scooter. Otherwise, the object is regarded as a car.

4. Experimental Results

The proposed system was implemented using the Microsoft Visual studio C++ 2005 on the Intel i5 computer platform. In this system, street lanes are detected automatically and the moving objects are classified and justified if they are crossing the road by checking whether four corners of object bounding box cross-over the street middle lane. If the end-points of the bounding box diagonal line is located on two sides of the lane, the system will indicate the object is crossing over the road and issue a warning, as shown in Fig. 7 According to our simulation statistics the proposed system achieves 100% correct alarm accuracy.

The proposed system classified the moving objects into cars, scooters and pedestrians. We tested the system using three videos containing 154 cars, 123 scooters and 43 pedestrians. Table 1 presents the classification performance. The overall classification performance achieved 92.50%. The

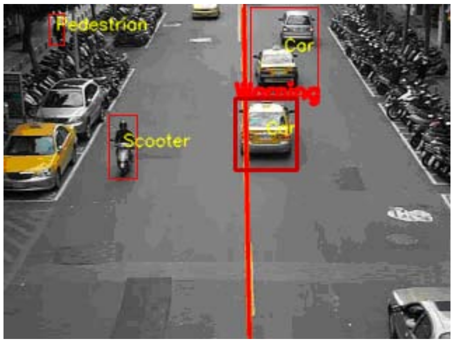

Fig. 7: Example of detection results.

Table 1: The resultant classification performance.

Category	# of Objects	True	False	Accuracy
Car	154	146	8	94.00%
Scooter	123	114	9	92.68%
Pedestrian	43	36	7	83.72%
Overall	320	296	24	92.50%

car identification accuracy was up to 94.80%. The scooter accuracy was 92.68%. The pedestrian classification accuracy was 83.72%. Most of the recognition errors were due to incomplete features for broken object segmentation and incorrect tracking for occlusion objects.Table 1 presents the results.

5. Conclusions

We presented a reliable traffic surveillance system capable of providing lane-crossing monitoring. This paper presented a framework for automatic classification for pedestrians and motor vehicles for a street-crossing safety surveillance system. The proposed method is a coarse to fine classification approach divided into two branches. The moving objects are detected first, tracked and clustered into fast moving and slow moving categories according to a motion speed estimation method. This approach is applicable for identifying motor vehicles and further differentiates vehicles into cars or scooters using width and shape features. The second part identifies slow moving objects. We improved the Recurrent Motion Image (RMI) algorithm to sort out pedestrians due to its high RMI value. Haar-like features and the Adaboost algorithm were employed to distinguish between pedestrians and scooters. Finally, cars and scooters were identified using the object aspect ratio (AR) and area features. The experimental results show that the recognition rate for 320 objects achieved 92.50%. The proposed system is promising for application to traffic monitoring surveillance systems. Several issues need to be enhanced to improve the classification accuracy including more complete object segmentation and a better tracking method.

Acknowledgement

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