Vehicle Shadow Removal For Intelligent Traffic System

Dae Geun Jang and Eui Jeong Kim, *Member, KIMICS*

Abstract**—**The limited number of roads and the increasing number of vehicles demand the automatic regulation of overspeed vehicles, illegal vehicles, and overloaded vehicles and the automatic charge calculation depending on the type of the vehicle. To meet such requirements, it is important to remove the shadow of the vehicle as processing and recognizing an image captured by a camera. The shadow of the vehicle is likely to cause misclassification of the vehicle type due to diverse errors and mistakes occurring when detecting geometrical properties of the vehicle. In case that shadows of two different vehicles are overlapped, not only the type of the vehicles may be misclassified but also it is difficult to accurately identify the type of the vehicles. In this paper, we propose a robust algorithm to remove the shadow of a vehicle by calculating the luminance, the chrominance, the gradient density of the cast shadow from information acquired using the image subtraction of the background, and to recognize the substantial vehicle figure. Even when it is hard to detect and split a target vehicle from its shadow as shadows of vehicles are attached to each other, our robust algorithm can detect the vehicle figure only. We implemented our system with a general camera and conducted experiments on various vehicles on general roads to find out our vehicle shade removal algorithm is efficient when detecting and recognizing vehicles.

I. INTRODUCTION

With the number of roads and vehicles increasing in recent years, several problems have arisen in relation to the regulation on overspeed vehicles, illegal vehicles, and overloaded freight vehicles, and the automatic toll system. To address the problems, unattended surveillance and management systems using cameras are installed on the roads. However, the speed limit for regulating the overspeed vehicles varies depending on the type of vehicles, and it is required to automatically classify the vehicle type for the sake of the accurate regulation of the overloaded freight vehicles and the automatic toll system In response to this, researches are made on a vision-base monitoring system using an image processing and recognition mechanism in the intelligent traffic system [1]. As the image captured by the camera contains more information, vision-based system is applicable to diverse fields and lowers the cost than the system using a magnetic loop detector or a RFID (Radio Frequency IDentification). Yet, since it is hard to split the image into the vehicle and the cast shadow, it is not easy to detect only the vehicle figure from the image and a variety of vehicle complicates the type classification. Researches are in progress to detect and classify vehicles but their outputs are insufficient to be adopted to the public transportation system.

The vehicles can be detected and classified using the breadth of vehicle [3], which requires a vehicle image from a side view. Otherwise, the vehicles can be classified based on only the breadth and height of the vehicle [4, 5], which is subject to the misrecognition owing to inaccurate properties including the size, the shape, and the location of the vehicle because the vehicle shadow from the rays of the sun is included in the region of a vehicle object.

While many researches are carried out on solutions to split the shadow from the input image for a long period of time, there are not a few restrictions to show the efficient performance in the actual circumstances [1]. To overcome these restrictions, a method was suggested to efficiently remove the shadow by use of properties of the shadow even in the external environment [2]. This method calculates a probability of which pixels correspond to the shadow in the image using shadow properties of the luminance, the chrominance, and the gradient density. By effectively separating the target vehicle and the shadow by use of the probability and edge information of the image, better performance can be obtained than using only the edge or the luminance information. Still, this method does not remove the shadow connecting several vehicles in motion. In case that different vehicles are connected by the cast shadow, this method is apt to misrecognize the shadow as a single full-size vehicle and is subject to the erroneous vehicle detection and classification.

This paper proposes the robust shadow removal algorithm capable of segmenting connected vehicles and recognizing the respective vehicles by removing not only the shadow created by a moving vehicle but also the shadow connecting several different vehicles. In the

Manuscript received August 18, 2006.

Dae Geun Jang, Korean Intellectual Property Office (E-mail: stealth66@naver.com)

Eui-jeong Kim(MR.) Ph.D Prof. Department of Computer Education, College of Education, Kongju National University, 182 ShinkwanDong, Kongju, Chungnam 314-701, South Korea (Tel : +82-41-850-8823, Fax : +82-41-850-8165, E-mail: ejkim @kongju.ac.kr)

following, Chapter 2 briefly provides our vehicle classification system using a block diagram. Chapter 3 deals with our method to detect the vehicle and to calculate the shadow probability, Chapter 4 details our shadow removal algorithm, and Chapter 5 analyzes and compares our method and a method using the shadow properties using images of the general road. Finally, Chapter 6 concludes this paper.

II. CONCEPT AND METHODOLOGY

Fig. 1 is a flowchart explaining our suggested method to detect and remove the entire shadow. The background image is generated from an input image sequence . Any background estimation algorithm can be used to generate a stationary background from image sequences. A fast and accurate scoreboard-based algorithm for estimating stationary background was discussed. This algorithm has been adopted for making stationary background image. To extract the moving blob from a traffic surveillance video, background subtraction was adopted with respect to color information and gradient information of the background and the input images. The morphological operation and the median filter were employed to generate a binary image mask which is the supplemented blob information. Since the extracted blob contains the vehicle and its shadow together, a composite shadow confidence probability is computed using shadow features in luminance, chrominance, and gradient density domains to remove the shadow. The shadow confidence probability is a probability that pixels of the extracted blob are classified to pixels of the shadow region not the object region. After only edge information of the vehicle is retained using the shadow confidence probability and the edge information of the input image, the shadow is separated from the cast shadow in a non-rigid form by bounding convex hull. This shadow removal method may result in error as recognizing several vehicles being occluded by the shadow as a single large vehicle. To address this problem, among the shadow-free blob obtained based on the shadow confidence probability computed at each pixel and the edge information of the input image, it is determined whether the several vehicles are attached due to the shadow by calculating the presence or absence of a shadow bar that is acquired

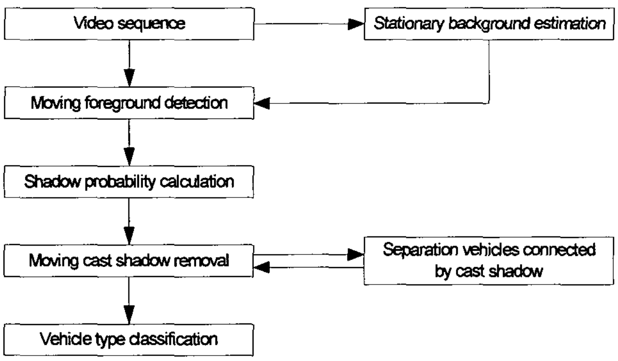


Fig. 1 Block diagram of the proposed system

by use of roadside width information and the shadow features. Upon determining the presence of the accompanied vehicles, a modified mask is generated using the shadow bar. The accompanied vehicles are segmented and identified respectively by repeating the shadow removal with respect to the modified mask.

III. VEHICLE DETECTION AND SHADOW CONFIDENCE PROBABILITY CALCULATION

3.1 Vehicle detection

The vehicle detection extracts the moving blob based on the background subtraction of the input image and the background. Given that RGB color channels of the input image are R_f, G_f, B_f, and RGB channels of the background are R_b, G_b, B_b, the maximum absolute value $Diff_c$ in the individual color channel is defined as follows.

$$Diff_c = \max\{|R_f - R_b|, |G_f - G_b|, |B_f - B_b|\} \quad (1)$$

We obtain a gradient density difference in the same manner as below:

$$Diff_g = \max\{|GD_{Rf} - GD_{Rb}|, |GD_{Gf} - GD_{Gb}|, |GD_{Bf} - GD_{Bb}|\} \quad (2)$$

where the gradient density is defined as

$$GD(x,y) = \frac{1}{(2w+1)^2} \sum_{i=m-w}^{i=m+w} \sum_{j=n-w}^{j=n+w} |G_x(i,j) + G_y(i,j)| \quad (3)$$

and, G_x and G_y are the horizontal and vertical edge magnitudes from pixel (i, j) using the laplacian gradient operator. 2w+1 is the size of an average window filter. The binary image can be attained in accordance with Equation (4) based on Equations (1) and (2).

$$F(x,y) = \begin{cases} 1, & if \quad Diff_c > T_1 \quad or \quad Diff_g > T_2 \\ 0, & otherwise \end{cases} \quad (4)$$

The calculated binary image based on Equation (4) contains noise due to the error in the background which may cause errors in next procedure. Thus, the modified mask(Mask(x,y)) is generated using the transformation morphology and the median filter.

$$Mask(x,y) = medianfilter\{morph\{F(x,y)\}\} \quad (5)$$

More accurate initial mask is generated by removing a hole in the mask and small blobs outside the mask based on the determination that the small blobs are not the object.

3.2 Shadow probability calculation

First, the input image and the background are converted from the RGB channel to the YCbCr channel. The YCbCr channel is the most effective channel for the shadow removing among plural color channels [4]. Each shadow confidence probability is calculated using the subtraction of the input image and the background, and the shadow features in the luminance, chrominance, and gradient density domains. The obtained shadow confidence probability denotes that pixels of the extracted blob may be pixels of the shadow region not the object region.

3.2.1 Luminance probability

The calculation of luminance probability is based on a property that the luminance of the shadow is lower than that of the background. Let the luminance of the input image be L_{fore} and the luminance of the background be L_{back}. The luminance difference L_{diff} between the input image and the background is expressed as the following Equation (6).

$$L_{diff}(x,y) = L_{fore}(x,y) - L_{back}(x,y) \tag{6}$$

The luminance probability S_L is computed from L_{diff} as given by

$$S_L = \begin{cases} 1 & , \quad L_{diff}(x,y) \le 0 \\ (T_L - L_{diff}(x,y))/T_L, & 0 < L_{diff}(x,y) < T_L \\ 0 & , \quad L_{diff}(x,y) \ge T_L \end{cases} \tag{7}$$

For the negative L_{diff}, it is most likely to be the shadow and S_L is set to 1. If the L_{diff} is higher than the threshold T_L, it is the object and S_L is set to zero. The luminance probability between 0 and T_L is calculated to provide a smooth transition by choosing a linear mapping.

3.2.2 Chrominance probability

The calculation of the chrominance probability is based on a property that the difference between the chrominance of the shadow and that of the background is very little. Given that CbCr components of the input image are Cb_{fore} and Cr_{fore}, respectively, and that CbCr components of the background are Cb_{back} and Cr_{back}, respectively, the chrominance difference C_{diff} is calculated as the following Equation (8).

$$C_{diff} = \left|Cb_{fore}(x,y) - Cb_{back}(x,y)\right| + \left|Cr_{fore}(x,y) - Cr_{back}(x,y)\right| \tag{8}$$

The chrominance probability S_C is calculated in accordance with Equation (9).

$$S_C = \begin{cases} 1 & , \quad C_{diff}(x,y) \le T_{C1} \\ (T_{C2} - C_{diff}(x,y))/(T_{C2} - T_{C1}), & T_{C1} < C_{diff}(x,y) < T_{C2} \\ 0 & , \quad C_{diff}(x,y) \ge T_{C2} \end{cases} \tag{9}$$

If C_{diff} is less than threshold T_{C1}, the region is most likely to be the shadow and S_C is set to 1. If C_{diff} is greater than threshold T_{C2}, the region is most likely to be the object and S_C is set to zero. As for C_{diff} between T_{C1} and T_{C2}, S_C is calculated to give a smooth linear transition. Note that T_{C2} is determined twice as large as T_{C1}.

3.2.3 Gradient density probability

The calculation of the gradient density probability take advantage of a property that the difference between gradient densities of the shadow and the background is less than the difference between gradient densities of the object and the background. Let the gradient density of the background be GD_{back} and that of the object be GD_{object} The gradient density difference GD_{diff} between the input image and the background is given as Equation (10).

$$GD_{diff}(x,y) = GD_{fore}(x,y) - GD_{back}(x,y) \tag{10}$$

The gradient density probability S_G is calculated from GD_{diff} based on Equation (11).

$$S_G = \begin{cases} 1 & , \quad GD_{diff}(x,y) \le T_{G1} \\ (T_{G2} - GD_{diff}(x,y))/(T_{G2} - T_{G1}), & T_{G1} < GD_{diff}(x,y) < T_{G2} \\ 0 & , \quad GD_{diff}(x,y) \ge T_{G2} \end{cases} \tag{11}$$

As for GD_{diff} less than the threshold T_{G1}, the region is most likely to be the shadow an S_G is set to 1. As for GD_{diff} greater than T_{G2}, the region is likely to be the object and S_G is set to zero. For GD_{diff} between T_{G1} and T_{G2}, S_G is calculated to give a smooth transition. Note that T_{C2} is determined twice as large as T_{C1}.

3.2.4 Total shadow probability

$$S_{total}(x,y) = S_L(x,y) \times S_C(x,y) \times S_G(x,y) \tag{12}$$

Edges of the object and the background have severe changes of the luminance and the color and especially the high gradient density comparing with the inside of the edges. That is why a relatively high value having noise characteristic is generated at edges and such a high value results in erroneous shadow calculation. In this respect, the erroneous edge region is removed by changing S_L, S_C, and S_G of coordinates corresponding to adjacent nine pixels based on the edge pixels of the initial mask, to 1. Next, the total shadow probability S_{total} is computed to determine whether the pixels are shadows by multiplying the luminance probability, the chrominance probability, and the gradient density probability. S_{total} denotes a probability to classify the extracted pixels as the shadow pixels, not the object pixels.

IV. THE PROPOSED SHADOW REMOVAL ALGORITHM

4.1 Shadow bar detection

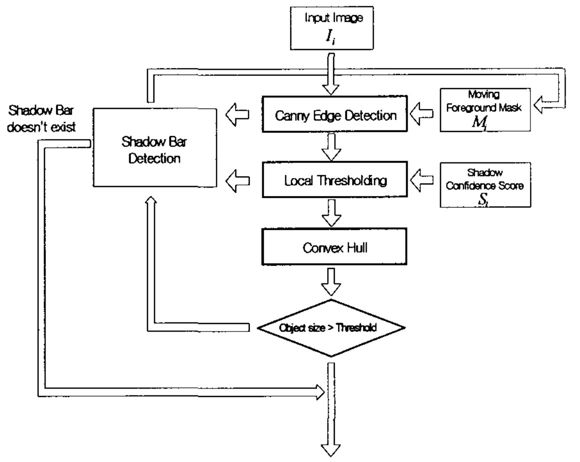


Fig. 2 Proposed moving cast shadow removal algorithm

Fig. 2 is a flowchart of our proposed shadow removal algorithm. Vehicles connected by the shadow are liable to be recognized as a single vehicle and induce error in the shadow removal and the vehicle type classification. To overcome these problems, the shadow-connecting vehicles should be separated from each other, for which the shadow bar is adopted. First, a threshold T_{width} for determining whether vehicles are connected by the shadow is determined using roadside width information in the vehicle surveillance area. As a typical bus or truck is not wider in width than a road lane, it is assumed that several vehicles are connected by the shadow upon detecting a large vehicle exceeding T_{width}, and the presence or the absence of the shadow bar is determined. It is to be understood that the detection of the vehicle having the width higher than T_{width} does not necessarily denote the shadow-connecting vehicles. For example, a very large vehicle having a width exceeding the road lane may be detected, or a long vehicle like a bus may change its road lane. In this situation, the absence of the shadow bar aids to recognize as the single vehicle. If T_{width} is set to too low, calculations increase due to the determination whether the shadow is connecting vehicles with respect to most of vehicles. Too high T_{width} is liable to miss small vehicles connected by the shadow. Therefore, this paper defines $T_{width} = lane\ width \times \frac{2}{3}$

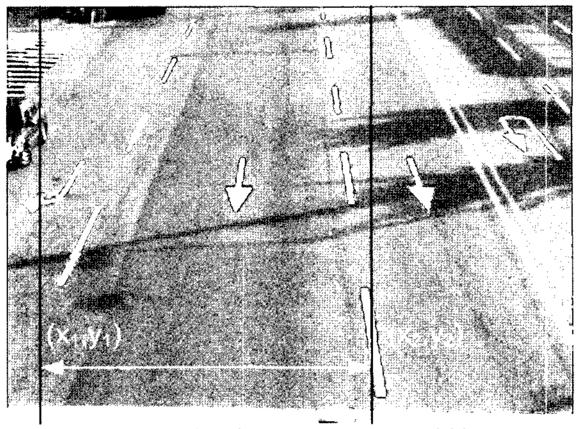


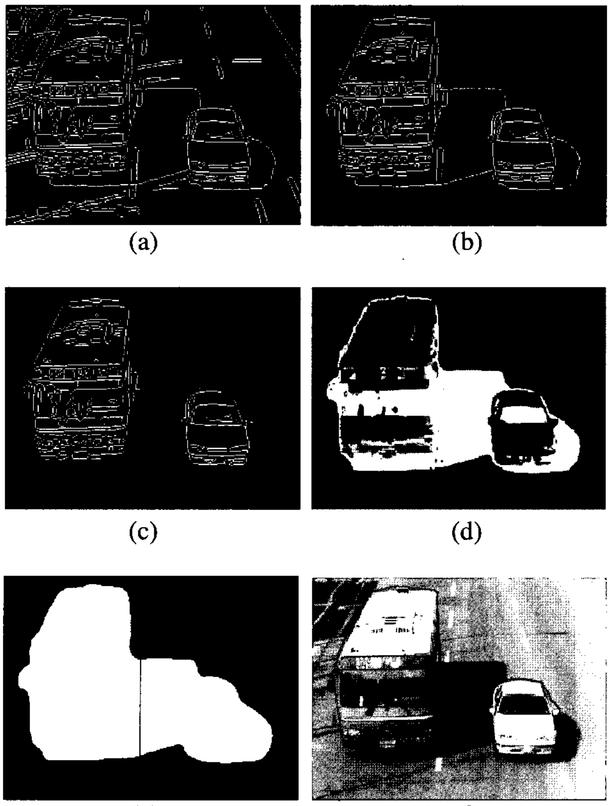
Fig. 3 Threshold using lane width

The shadow bar is a vertically or horizontally connected straight line that is assumed to consist of only cast shadow pixels in the foreground mask. In more detail, the shadow bar is a vertical or horizontal shadow set consisting of only shadow pixels that connect two vehicles but are not part of the two vehicles. Let a virtual point at which extended lanes cross be a focus point in Fig. 3. The vertical shadow bar passes the focus point in parallel with the lane. A large mask is separated from the region where the shadow bar is detected, and the separated mask is changed to two smaller masks. The shadow removal is conducted to the changed masks. Two properties are used to detect the shadow bar:

Property 1 : The difference in the gradient density between the cast shadow and the background is lower than the difference in gradient density between the object and the background.

Property 2 : shadow confidence score of pixel in cast shadow region is higher than that in the object region.

The edge information is acquired by applying a canny edge operator to the input image as shown in Fig. 4(a). Fig. 4(b) depicts only the border inside the mask. By removing the edge information of the outer border region of the mask, and the edge information generated by the road lane based on the edge information of the background, it can be seen that the edge information of the shadow connecting the vehicles are eliminated as shown in Fig. 4(c). The vertical shadow bar can be generated between the vehicles of Fig. 4(c) based on Property 1. The shadow bar is searched from the center of the mask in order to reduce the calculations. Meanwhile, if the shadow bar is generated at weak edges within a large object, totally different problem arise comparing with the case when the shadow connects the vehicles. As a single object is segmented into several parts, errors affect the object recognition and classification, and the feature detection. To address these errors, Property 2 is used. As for the total shadow probability of the input video in Fig. 4(d), S_{total} of pixels estimated to be the shadow has a light value close to 1 and that of pixels estimated to be the object has a dark value close to zero. By retrieving the vertical shadow bar consisting of the pixels estimated as the shadow from the center of the mask that is generated to reduce the calculations while



(a) (b) (c) (d) (e) (f)

Fig. 4 Shadow bar finding procedure

satisfying Property 1 and Property 2, the first shadow bar is detected as shown in Fig. 4(e). The generated mask is separated based on the shadow bar and the convex hull is performed to the separated masks, to thus detect the shadow-free objects in Fig. 4(f).

4.2 *Cast shadow removal*

Only edges in the mask are generated by detecting the edge of the input video by aid of the canny edge operator and multiplying the initial mask. The more the shadow pixels are estimated, the higher the luminance probability, the chrominance probability, and the gradient density probability become. In result, the total shadow probability S_{total} is higher than the object pixel value, and conversely the vehicle region becomes lower.

$$E_{edge}(x,y)=\begin{cases}0, & S_{total}\geq T_S\\ 1, & S_{total}<T_S\end{cases} \tag{13}$$

Therefore, when the total shadow probability of the edge pixels in the mask is higher than the threshold T_S as in Equation 13, the pixels are estimated as the edge of the shadow and are discarded. Otherwise, only the edge pixels of the shadow are removed through the local thresholding that retains pixels based on the estimation as the edge of the vehicle. Subsequently, the shadow is removed from the mask and the vehicle object alone is detected by performing the convex hull only to the edge of the remaining object. The cast shadow can be identified as the moving foreground excluding the object.

V. EXPERIMENTAL RESULTS AND ANALYSIS

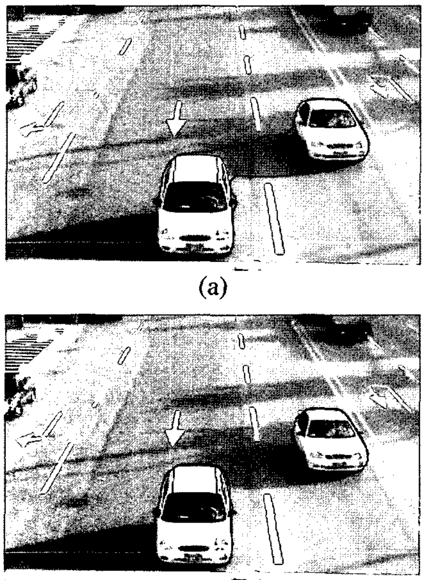
To test the performance of our proposed shadow removal algorithm, the vehicle type classification tests were conducted to the real input video and the background image captured on the road. Our algorithm proved its effectiveness through the performance analysis and the comparison of the accuracy of the vehicle type classification between the proposed shadow removal algorithm and the existing method. The image sequences of the road were captured for 63 minutes in MPEG using cameras, and the size of the image is 320 × 240. As the time passes by, the passive shadow increases due to trees by the roadside. Table 1 shows results of the vehicle type classification of the proposed algorithm and the existing method. In Table 1, "missed detection" represents a case when the algorithm cannot detect the presence of the vehicle in the surveillance area, and "false classification" represents the false classification of the vehicle type in the surveillance area. The "miss detection" may happen to a dark-colored vehicle or vehicles connected by the shadow. In case of the dark-colored vehicle, the "miss detection" is liable to occur because the luminance level of the vehicle is similar to the chrominance level and the edge information of the vehicle is obscure. The "false detection" may occur when the size of the vehicle is not accurately measured due to the incomplete shadow removal from the vehicle, or when multiple vehicles connected by the shadow is classified as a single large vehicle.

Table 1 Comparison of performance

	Missed detection rate	False classification rate	Correct Classification rate
Effective method	6.5 %	13.9 %	86.1%
Proposed method	0 %	0.9 %	99.1%

Fig. 6 depicts results of the shadow removal and the vehicle type classified using the existing algorithm and the proposed algorithm. In Fig. 5, the blue outline indicates the vehicle object calculated by the computer, and the estimated vehicle types are set forth below the corresponding images.

The shadow of the moving vehicle greatly affects the accuracy of the type classification and the vehicle detection. Fig. 5(a) shows two vehicles connected by the cast shadow and the existing method cannot detect one vehicle due to the false recognition as a single large vehicle. Fig. 5(b) shows that the proposed algorithm recognizes each vehicle and correctly classifies the vehicle type. The red vehicle on the left, which is stationary, was detected as the background. Features for the type



(a)

(b)

Fig. 5 Shadow removal procedure(image size: 320 x 240 pixels): (a) Effective method (large vehicle, misse d detection) (b) Proposed method (small vehicle, small vehicle)

classification are the width, the lateral length, the size, and the girth of the vehicle. In the following, Fig. 6 shows the results of the counted number of vehicles and the vehicle classification compared between the effective method, the proposed algorithm, and the manual work in relation to the 63-minuite video taken over the roadside. In Fig. 6, the counted vehicles are classified into three categories: small, medium, and large. The vertical axis of the graph indicates the number of vehicles in each category.

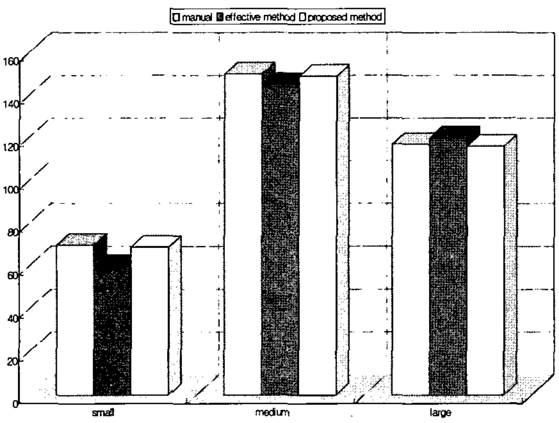


Fig. 6 Results of vehicle classification and vehicle count in 63 minutes

The above experimental results were attained by removing the shadow from vehicles, counting and classifying the vehicles on the roadside under the relatively light traffic. Conversely, the proposed method is subject to the false classification in the heavy traffic because of the occlusion that makes it look like different vehicles being connected in part in view of the camera. To reduce the effects of the occlusion, the angel of the camera over the roadside was set as high as possible enough to detect and classify the moving vehicles at the lowest end on the screen. In specific, the camera was installed to look down the roadside, and the occlusion occurred much less as comparing with the camera being installed in the direction of the road. Furthermore, it is expected that better performance could be acquired with respect to the errors by combining with the analysis algorithm for consecutive frames.

VI. CONCLUSION

We presented the robust algorithm for effectively removing the cast shadow in the vehicle surveillance and classification system. Even when multiple vehicles are connected by the shadow to make it hard to segment and detect the individual vehicle, our robust algorithm can recognize each vehicle. The chrominance information subtraction and the gradient density subtraction of the background and input images were used to extract the moving blob from the traffic surveillance video. The total shadow probability was computed using the information relating to the luminance, the chrominance, and the gradient density to remove the shadow in the non-rigid form. The shadow-connecting vehicles were identified by calculating the presence or the absence of the shadow bar which was detected based on the width information of the roadside and the shadow features. Upon identifying the vehicles connected by the cast shadow, the modified mask is generated using the shadow bar and the shadow removal is repeated for the modified mask. Then, the connected vehicles are segmented and recognized respectively. The experimental results of the proposed algorithm proved its effectiveness and facility in the vehicle classification and the vehicle count as well as the vehicle speed measurement and the vehicle tracing.

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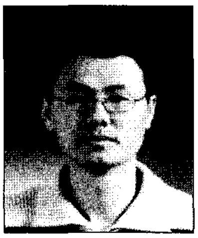

Dae-geun, Jang Career Ph.D. of electronics, 2003. Senior researcher, ETRI, 1996 ~ 2005. Patent examiner, KIPO, 2005 ~.Major parts Document image processing, Computer vision & recognition, Mpeg4.

Eui-jeong, Kim Career Ph.D. of computer science, 1997. Researcher, SERI 1997 ~ 1998. Professor of Kongju National University, 1998 ~. Major parts Computer vision, Pattern recognition, Virtual reality.