A Review on the Detection and Removal of Shadows in Daytime Traffic Images

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Abstract. Segmentation of moving objects in a video sequence is a challenging issue when the images are acquired in an outdoor scene at daytime. Shadows are often detected along with their respective moving objects that make them more difficult to separate in subsequent processes. But, when shadows are detected and removed from moving blocks, the computer vision algorithms can be applied more accurately. We present and compare the most suitable approaches for detecting shadows in an outdoor traffic scene at daytime.

Keywords: Shadow detection, Traffic images, Segmentation.

1 Introduction

A common problem in traffic applications is that shadows are detected along with their respective moving objects. Shadows can affect the shape and color of the objects and they can even merge areas, therefore the presence of shadows has a negative effect on scene analysis and interpretation systems [1]. In the other hand, with a shadow-free image better outcomes can be achieved during object segmentation, tracking, recognition, understanding scene, etc. Then, it is more desirable to separate objects from its shadings areas during the first processing step. During the past decades many attention was paid to the area of shadow detection and removal applied to specific application such as traffic surveillance [2] [3], face recognition [4] and image segmentation [5].

1.1 Shadows

Shadows are important phenomena when a vision-based computer system works with day-time images. According to the classification reported in [6], shadows are composed of two parts: self-shadows and cast shadows. The first is the section of the

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© C. Delgado, C. Gutiérrez, R. Velázquez, H. Sossa (Eds.) *Received 23/01/11*
Advances in Computer Science and Electronic Systems *Accepted 20/02/11*
Research in Computing Science 52, 2011, pp. 347-354 *Final version 07/03/11*

object that is not illuminated by the light source, and the last is the area projected on the scene by the object. And cast shadows can be classified in umbra y penumbra, this is the totally and partially blocked area, respectively. In Fig. 1 a typical car is presented with shadows. In outdoor scenes, the movement of the sun and passing clouds are responsible of changing light conditions. The sun causes a slow, systematic, variation in the intensity and the direction of the received illumination, and, finally, it defines the shape, size and directions of shadows. In Fig. 2 a vehicular scene with shadows is presented during a day long.

Fig. 1 Shadows on a vehicle. The self shadow is denoted with a dashed white line (…). The cast shadow is located under and beside the car. The umbra is denoted with type 2 line (.-.-) .

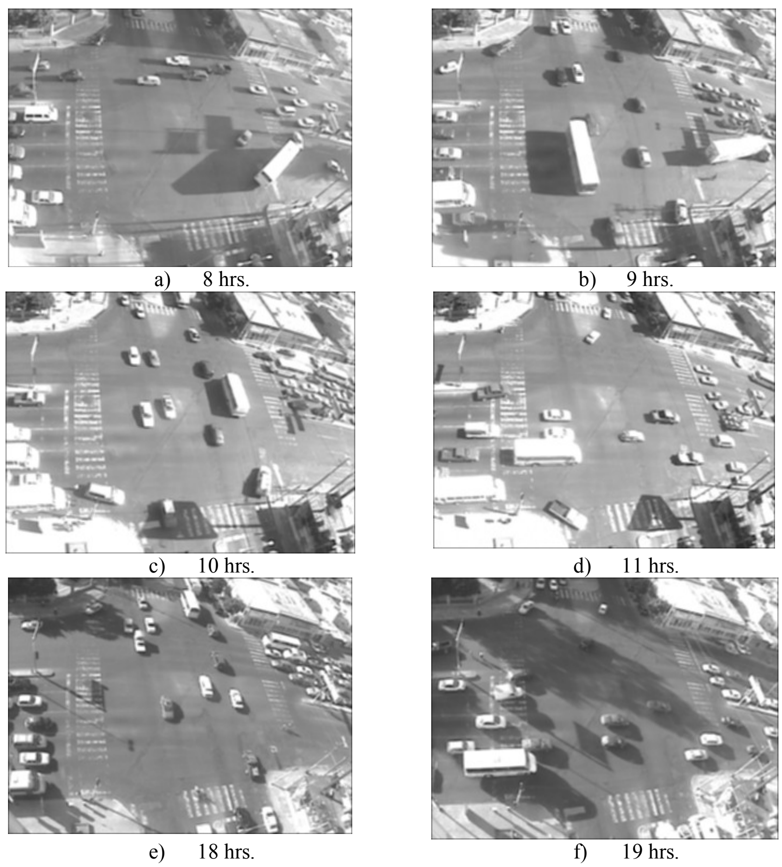


Fig. 2. Vehicular scene with shadows generated by illumination conditions during a day long.

1.2 Traffic applications

In the context of Intelligent Transportation System (ITS), vision-based systems for traffic analysis are developed to help traffic flow management, some examples include speed measurement [7] [8], classifying and counting vehicles [9] [10], etc. The analysis of the events taking place in a crossroads offers the opportunity to avoid harmful situations and the potential to increase security. Then, the challenge is developing an automatic visual system that reasons about the moving vehicles being observed and extracts high-level information [11], useful for traffic monitoring and detection of unusual activity. Unfortunately, computer vision is not massively applied in traffic monitoring applications because existing systems still suffer from poor reliability, high cost and unbalanced accuracy[12]. Their accuracy partially depends on weather conditions: fog, snow, rain; but also by illumination conditions in the scene. Then, to achieve a reliable high level understanding of a traffic scene, the image acquired has to be pre-processed in order to get moving objects segmented as the first stage of processing. In Fig. 3 an example of a traffic image with shadow is shown.

a) b)

Fig. 3. Problems generated in day-time images with shadows. a) Some vehicles are merged; b) Shadows change the color of the vehicles.

2 Shadow detection algorithms

Recognizing shadows in an image is generally a hard task. In vision systems, cast shadow detection is important part of the preprocessing. In this section we present algorithms suitable to apply in traffic scenes.

2.1 Gray-scale video sequences

2.1.1 Multi-gradient shadow identification (MGSI)

In [3] a shadow identification algorithm is presented. First, the ratio between the image and its background is computed, this is,

$$D(i,j) = \frac{B(i,j)}{I(i,j)}k \quad (1)$$

where $B(i,j)$ is the value of the background, $I(i,j)$ is the current image and k is a prefixed factor. Later, a threshold is computed for D.

$$R = Th_m^M(D) \quad (2)$$

where $m < M$ are the threshold values. Then, a multi-gradient analysis is calculated using convolution kernels for detection in three directions, Fig. 4. Finally, the shadow image is the threshold applied to the absolute addition of gradients.

$$\underset{G_{x_1}}{\begin{array}{|c|c|}\hline +1 & -1 \\ \hline 0 & 0 \\ \hline\end{array}} \quad \underset{G_{x_2}}{\begin{array}{|c|c|}\hline 0 & 0 \\ \hline -1 & +1 \\ \hline\end{array}} \quad \underset{G_{y_1}}{\begin{array}{|c|c|}\hline +1 & 0 \\ \hline -1 & 0 \\ \hline\end{array}} \quad \underset{G_{y_2}}{\begin{array}{|c|c|}\hline 0 & -1 \\ \hline 0 & +1 \\ \hline\end{array}} \quad \underset{G_{d_1}}{\begin{array}{|c|c|}\hline +1 & 0 \\ \hline 0 & -1 \\ \hline\end{array}} \quad \underset{G_{d_2}}{\begin{array}{|c|c|}\hline 0 & +1 \\ \hline -1 & 0 \\ \hline\end{array}}$$

a) b) c)

Fig. 4. Convolution kernels for a) vertical b) horizontal, and c) diagonal edge detection.

2.1.2 Normalized cross-correlation shadow identification (NCCSI)

The algorithm reported in [13] is based in the Normalized cross-correlation (NCC), that is calculated using:

$$NCC(i,j) = \frac{ER(i,j)}{E_B(i,j)E_T(i,j)} \quad (3)$$

where (i,j) is the pixel in this position, $ER(i,j)$ is the value of the pixel by its background value, $E_B(i,j)$ is the mean square root of the background, and $E_T(i,j)$ is the mean square root of the image, the neighborhood is considered for each value. Then, the classifier for shadow pixel is:

$$S(i,j) = \begin{cases} If\ \left((NCC(i,j) \geq \propto) \wedge \left(E_T(i,j) < E_B(i,j)\right)\right), & 1 \\ \qquad\qquad otherwise, & 0 \end{cases} \quad (4)$$

where $\propto$ is a threshold value. Finally, the shadow refinement is achieved by the analysis of the ration between the image and its background.

2.1.3 Adaptive shadow segmentation (ADSS)

A real-time traffic monitoring system is developed by [12]. Initially, the image differences (D) is obtained between current frame and the last background, then every pixel is classified using give formula,

$$U(i,j) = \begin{cases} If\ D(j,j) > T_b, & BRIGHT \\ If\ D(j,j) < T_d, & DARK \\ otherwise, & BACKGROUND \end{cases} \quad (5)$$

where T_b and T_d are the threshold value for pixel classification in bright and dark set, respectively. Then, shadows are identified a dark area connected to bright area that share same direction.

2.1.4 Edge-based moving shadow removal (EBMSR)

In [1] is presented an algorithm for removing moving shadows based on detection of edges when Sobel procedure has been applied. It is assumed that moving objects (C_t) (called foreground) and edges (E_t) were calculated previously. The initial seed region is acquired by:

$$IS_t = C_t - DB_t - IF_t \tag{6}$$

where t means the t-th frame, DB_t the dilated boundary of change mask and IF_t contains the interior regions of foregrounds. Finally, this seed region is analyzed to obtain the minimum rectangle that fits each group of foregrounds.

2.2 Color video sequence

2.2.1 Sakbot Shadow Detection

The Statistical and Knowledge-Based Object Tracker (Sakbot) [14] works in the HSV color space that corresponds closely to the human perception of color. It uses a classifier to define whether a pixel belongs to a shadow, that is,

$$SP_t(i,j) = \begin{cases} if \quad \left(\propto \leq \dfrac{I_t^V(i,j)}{B_t^V(i,j)} \leq \beta\right) & \\ \wedge\left((I_t^S(i,j) - B_t^S(i,j)) \leq \tau_S\right) & \\ \wedge(|I_t^H(i,j) - B_t^H(i,j)| \leq \tau_H), & 1 \\ \quad otherwise, & 0 \end{cases} \tag{7}$$

where $I_t^n(i,j)$ is the pixel corresponding to the n-th channel, $B_t^n(i,j)$ is the background pixel to the n-th channel given the t-th frame, and τ_S y τ_H are threshold value defined.

3. Performance results

For experimentation, we worked off-line with 282 images taken in a heavily transited crossroads in the city of Querétaro, México. The camera was placed on top of a tower, about 28 m above ground level. The computer had an AMD Turion processor running at 2.1GHz, 4GB of internal RAM, and a Matrox Corona II frame grabber. The computer programs were written in Matlab 2009 to process gray scale images with a resolution of 320 columns times 240 rows. Sakbot is the only method that could not be implemented, because it works with HSV color space images. The results are presented in Table 1. MGSI has the best performance, what makes especially suitable its implementation on-line.

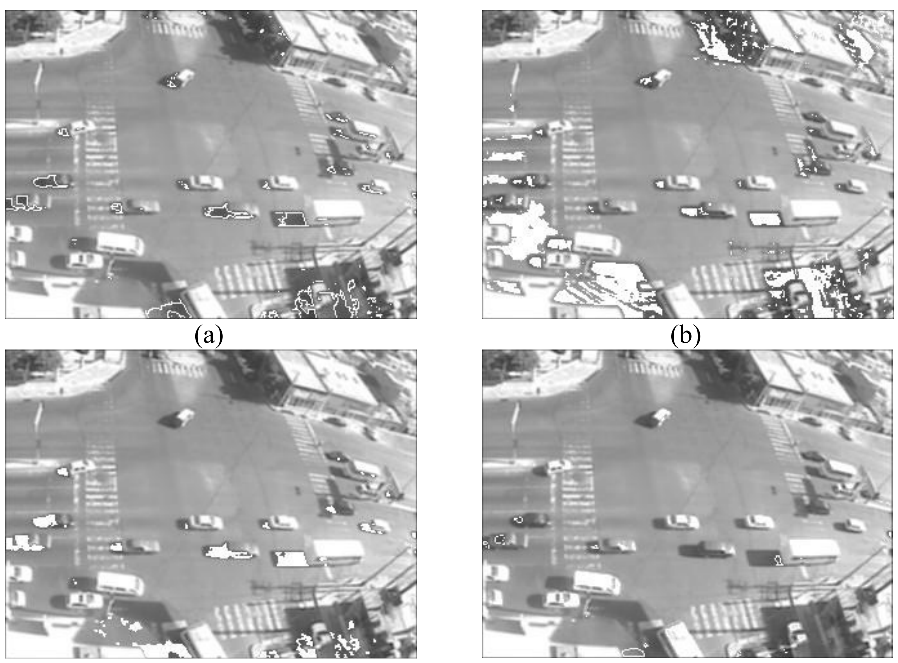
For implementation some values was fixed in every method. In MGSI we set $k = 1$, $m = 0$ and $M = 1.5$. In NCCSI $\propto = 0.9995$. In ADSS we had $T_b = 100$ and $T_d = -50$. Finally, in EDMSR we set $\lambda = 2$ for the structuring element in morphological operations.

4. Comparison

Surveillance traffic applications have strong constraints because they must work on real-time. Five different strategies suitable for this kind of systems have been presented in previous section; in Table 2 they are compared. It is remarkable that most of them exploit two aspects; the first is the relation between the n-th image and its background. And the second is edge information about the scene; based on the fact that the vehicle has significant edges, however cast shadows are edgeless [1]. We need to apply a robust shadow elimination method to improve performance of a vision-based traffic monitoring system. In the future, we will apply this present methods in real video sequences on real-time at daytime, and develop an exhaustive comparison between them. Obviously, a new method of shadow elimination and removal will be proposed.

Table 1. Performance of presented methods: a) time elapse to process 282 images b) mean time to process each image.

Method	a)	b)
MGSI	1 min 25 s.	0.2295 s.
NCCSI	8 min 56 s.	1.9017 s.
ADSS	4 min 17 s.	0.9135 s.
EDMSR	5 min 18 s.	1.1271 s.



(a) (b) (c) (d)

Fig. 5. Examples of images with detection of shadows applying: (a) MGSI (b) NCCSI (c) ADSS y (d) EDMSR. Shadows are denoted with white pixels.

Table 2. Comparison of presented methods: (a) relationship between current image and its background and (b) border information obtained by.

Method	(a)	(b)
MGSI	Ratio	Vertical, horizontal and diagonal edge detection
NCCSI	Ration and cross-correlation	Classification
ADSS	Difference	Proximity
EDMSR	None	Sobel, vertical, horizontal operation
SAKBOT	Ration and difference	Classification

Conclusion

In this paper a comparison between methods suitable to apply in surveillance vehicle systems was presented. In this kind of systems some aspect related to nature scene influence what is captured in images. Shadows specially are present in day-time images, because they are generated by illumination (sun, clouds, rain, etc.). Besides, a surveillance system has to work on-line with images acquired, and it makes more desirable that image processing is a fast process. In the present implementation, we showed that MGSI has the best performance and it is suitable to work on-line as a part of the pre-processing stage. We believe that one new method is feasible with an advised level of performance.

Acknowledgement

We want to acknowledge the financial support of this work through the PROMEP-SEP (UAQ-PTC-162) project.

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