

# An Effective Algorithm for Shadow Removal from Moving Vehicles

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**Abstract**— In automatic video monitoring, real-time detection and in particular shadow elimination are critical to the correct moving objects segmentation since they severely affect the surveillance process. In this paper, we put forward a rapid and flexible approach in which vehicles detection is based on the Gaussian Mixture Model and shadow elimination is based on morphology and edge detection. Experimental results show that the technique achieved promising accuracy.

**Keywords**— Shadow removal; Vehicle detection; Gaussian Mixture Model; Morphology

## I. INTRODUCTION

Among the work on moving object detection, including both vehicle detection and human detection, cast shadow removal is an important task to help improve detection accuracy and avoid analysis failure [1], [2]. Shadow detection is mainly used in video surveillance system as a pre-processing step to achieve better performance in applications such as object tracking[3] and automated driving[4]. Whereas in images depending on the type of input images such as indoor, outdoor or satellite; shadow detection and removal finds applications in object recognition [5] and scene interpretation [6]. For example, images are often analyzed, to infer the geometry of the objects causing the shadow, to obtain the 3D analysis of objects to extract geometry of object [6] or to find light source direction [7]. Other important applications include enhancing object localization and measurements, especially in the aerial image for recognizing buildings [5],[8],[9] for obtaining a 3D reconstruction of the scene [10], or detecting clouds and their shadows [11].

Shadows happen when objects block luminousness from an igniter source. Shadows give rich data about object condition and additionally light introductions. Then again, shadows may bring about humiliations for visual applications. For instance, object with their shadows structure mutilated figures and adjoining objects might be associated over shadows. Both can confound object acknowledgment frameworks. Portioning objects from shadows can be a nontrivial undertaking. An efficient shadow removal technique is, therefore, required for precise extraction of moving objects for further handling. Alluding to Fig. 1, shadows can be

extensively separated into cast and self-shadows. As uncovered in the Fig.1, the self-shadow is a part of the object, which is not lit up by the light-source. The cast shadow lying adjacent to the object belongs to background and self-shadow belongs to the foregrounds. Cast shadows are undesired for moving object detection and numerous different application and should be removed, while self-shadows belongs to the moving objects and ought to be saved. Cast and self-shadows are close in intensity, recognizing them as a cast and self-shadows is very difficult. Also, if objects have intensities like those of shadows, shadow evacuation could turn out to be to a great degree troublesome. Despite the fact that objects and shadows can be isolated, object shapes are frequently inadequate.

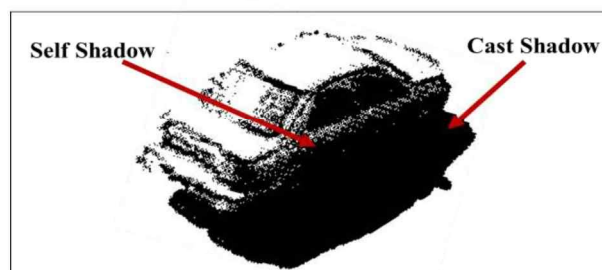


Fig. 1. An example of a shadow

Many works have been accomplished for shadow identification. In [12] foreground is detected with the normalized cross-correlation(NCC), and candidate shadow pixels are obtained A refinement procedure is then used to facilitate enhance shadow extraction

This article put forward a method for the automobile automatic detection and shadow removal of the vehicles which can be used in an application like make and model recognition [13].

The rest of the paper is organized as follows: Section 2 presents the proposed method for moving object detection and shadow removal, Section 3 demonstrates the experimental results and conclusions are drawn in Section 4.

## II. PROPOSED METHOD

Fig. 2 depicts a flowchart for the proposed process which has three major components of foreground detection which is based on Gaussian Mixture Model (GMM), and shadow removal based on morphology.

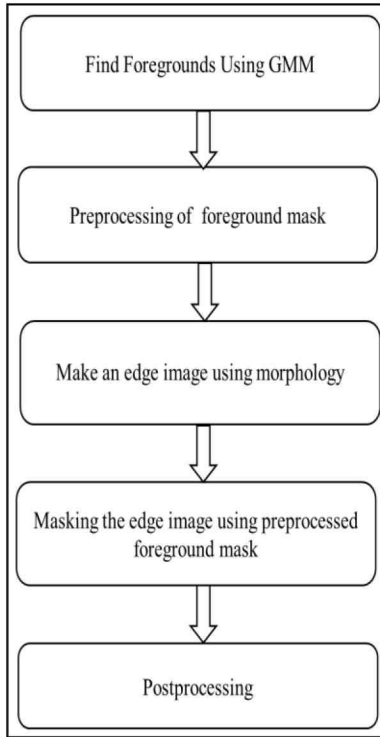


Fig. 2. Recommended method design

### A. Vehicle Detection

Moving object detection is an ordinarily utilized class of techniques for extracting out objects of interest in a scene for applications such as video surveillance and monitoring systems. It involves comparing an observed image with an estimate of the image if it contained no objects of interest. The regions of the image where there is a huge distinction between the observed and estimated images demonstrate the area of the objects of interest.

Firstly, pre-processing is the process of changing the raw data which is the input video sequences into a format that can be read for the next phase then  $3 \times 3$  kernel Gaussian filter is applied for smoothness and for removal of noise.

In background modeling, makes use of the new video frame in order to compute and update the background model. The main purpose of developing a background model is that it should be robust against environmental changes in the background, but sensitive enough to determine all moving objects of interest.

In foreground detection, it recognizes the pixels in the frame. Foreground detection compares the video frame with the background model and identifies candidate foreground pixels from the frame. To check whether the pixel is

significantly different from the corresponding background estimate is a widely-used approach for foreground detection.

Finally, this step removed any pixels which are not relevant to the image. It involves the process of improving the foreground mask based on the information obtained from the outside background model.

Our framework adjusts to deals vigorously with lighting changes, redundant movements of scene components, tracking through disordered areas, tardy moving objects, and presenting or expelling objects from the scene. Gradually moving objects take more time to be merged into the background since their shading has a bigger change than the background. Likewise, repetitive differences are learned, and a model for the background distribution is usually sustained even if it is in the short term replaced by another distribution which leads to more rapidly recovery when objects are removed. Our background modeling method holds two important factors -  $\alpha$  learning constant and  $T$ , the proportion of the data that should be accounted for, by the background.

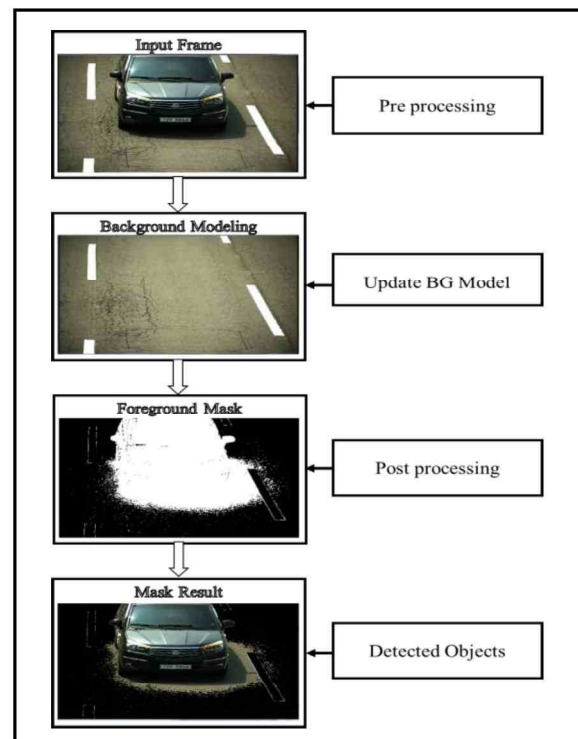


Fig. 3. Architecture for foreground detection

### B. Shadow Removal

The GMM can't distinguish a moving object and its shadow. As a result, if 2 cars are connected by its shadow, the GMM considers the 2 cars as one object as shown in Fig 4. This problem is due to the shadow so for solving this problem we use morphology method to remove the shadow from the frames of video.

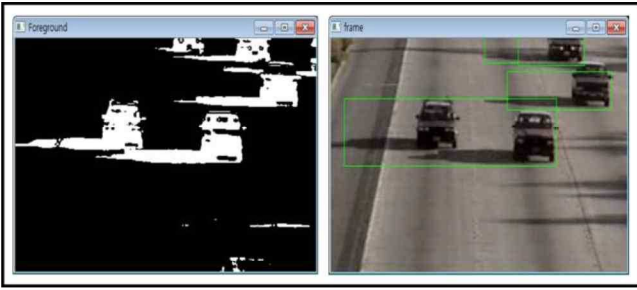


Fig. 4. Shadow problem

In this paper, we present a method for shadow removal as shown in Fig.5.

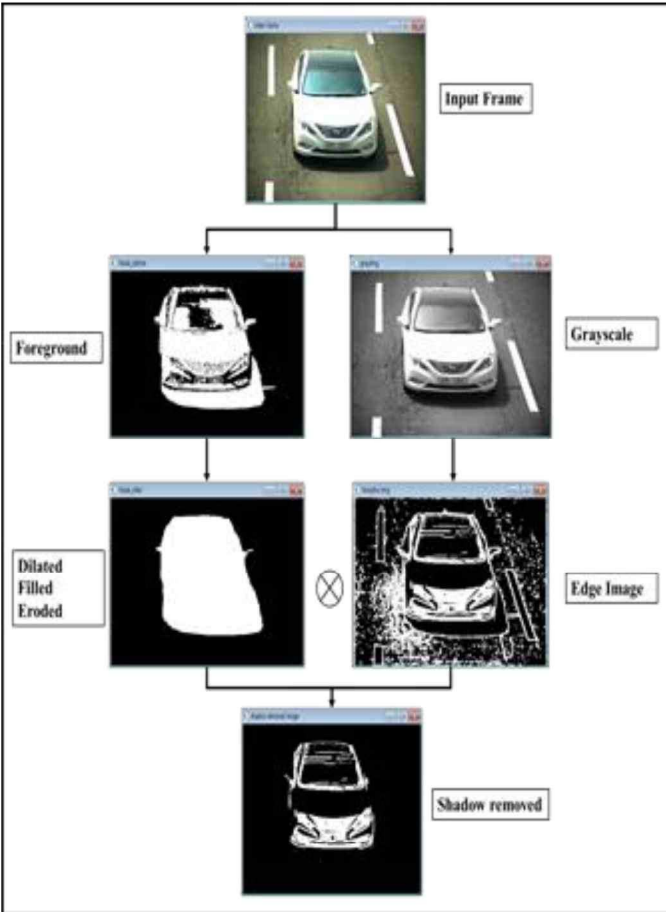


Fig. 5. Method for Shadow Removal

First the foreground is find using GMM which also contain shadow as shown in the Fig.3 then the images is dilated to connect the lines which have some spaces in between, after dilating the detected foreground if some blank spaces remains that is filled with the OpenCV API, then the image is eroded, so we will get the image as in the Fig.5. To make an edge image we converted the original image into grayscale and subtract the dilated image from the eroded image, to make a binary image we applied some threshold to subtracted image to make an edge image, after getting the edge image and preprocessed foreground image we masked the edge image

using preprocessed foreground mask in result we got shadow removed image as shown in the Fig. 5.

### III. RESULTS

The system used in this work is built with Intel Core i5 3.6GHz CPU, 8GB RAM. In the experiments, we use a video which contains 87 images of different vehicles. The experimental results outline that our framework is prepared to do precisely extricating 84 vehicles precisely indicating 96 % exactness regarding vehicles detection and 82 % exactness as far as shadow removal as appeared in the Tab. I.

However, sometimes the contour of the two or more objects are joint together which count different object as a single object which affects the accuracy of the system as shown in Fig.4, besides this shadow is also one of the great challenges that affects the moving object detection. Sometimes this algorithm has a problem to deal with the small size and low-resolution images because edges of vehicles are incorrect in some cases and we lose some useful information processing the image. However, the overall performance of the system is promising as shown in the Tab. I.

TABLE I. RESULTS

Method	Results		
	Total Images	Detected	Shadow removed
Morphology	87	84 (96%)	70 (82%)

TAB. I Results of the whole system.

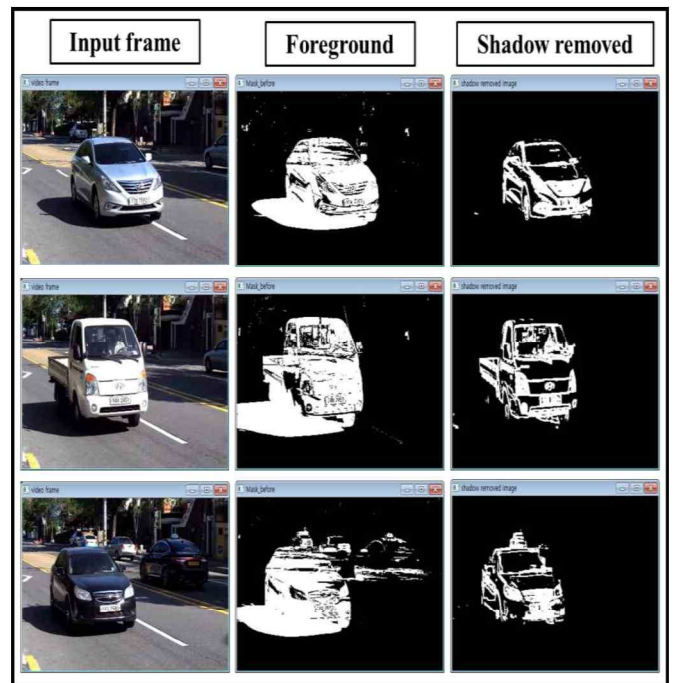


Fig. 6. Vehicle detection and Shadow removal

#### IV. CONCLUSION

This paper proposes a framework for the evaluation of object detection algorithms in surveillance applications using Mixture of Gaussian and shadow removal using edge detection and morphological method is proposed. From the experiment, we can see that the proposed technique performs well in video sequences, vehicles are detected accurately and the cast shadow is removed.

The framework can be used in real-time image processing due to the fact that this algorithm performs well for the open air environment along with its robustness and precision.

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#### REFERENCES

- [1] A. Prati, I. Mikic, M. M. Trivedi, and R. Cucchiara, "Detecting moving shadows: algorithms and evaluation," *IEEE transactions on pattern analysis and machine intelligence*, vol. 25, pp. 918-923, 2003.
- [2] K.-T. Song and J.-C. Tai, "Image-based traffic monitoring with shadow suppression," *Proceedings of the IEEE*, vol. 95, pp. 413-426, 2007.
- [3] B. Lei and L.-Q. Xu, "Real-time outdoor video surveillance with robust foreground extraction and object tracking via multi-state transition management," *Pattern Recognition Letters*, vol. 27, pp. 1816-1825, 2006.
- [4] Q. Wu, W. Zhang, and B. V. Kumar, "Strong shadow removal via patch-based shadow edge detection," in *Robotics and Automation (ICRA), 2012 IEEE International Conference on*, 2012, pp. 2177-2182.
- [5] B. Sirmacek and C. Unsalan, "Building detection from aerial images using invariant color features and shadow information," in *Computer and Information Sciences, 2008. ISCIS'08. 23rd International Symposium on*, 2008, pp. 1-5.
- [6] D. J. Kriegman and P. N. Belhumeur, "What shadows reveal about object structure," *JOSA A*, vol. 18, pp. 1804-1813, 2001.
- [7] M. Stamminger and G. Drettakis, "Perspective shadow maps," in *ACM Transactions on Graphics (TOG)*, 2002, pp. 557-562.
- [8] X. Jin and C. H. Davis, "Automated building extraction from high-resolution satellite imagery in urban areas using structural, contextual, and spectral information," *EURASIP Journal on Advances in Signal Processing*, vol. 2005, pp. 1-11, 2005.
- [9] B. Sirmacek and C. Unsalan, "A probabilistic framework to detect buildings in aerial and satellite images," *IEEE Transactions on Geoscience and Remote Sensing*, vol. 49, pp. 211-221, 2011.
- [10] M. Daum and G. Dudek, "On 3-d surface reconstruction using shape from shadows," in *Computer Vision and Pattern Recognition, 1998. Proceedings. 1998 IEEE Computer Society Conference on*, 1998, pp. 461-468.
- [11] P. M. Dare, "Shadow analysis in high-resolution satellite imagery of urban areas," *Photogrammetric Engineering & Remote Sensing*, vol. 71, pp. 169-177, 2005.
- [12] J. C. S. Jacques, C. R. Jung, and S. R. Musse, "Background subtraction and shadow detection in grayscale video sequences," in *XVIII Brazilian Symposium on Computer Graphics and Image Processing (SIBGRAPI'05)*, 2005, pp. 189-196.
- [13] Y. Gao and H. J. Lee, "Vehicle Make Recognition Based on Convolutional Neural Network," in *Information Science and Security (ICISS), 2015 2nd International Conference on*, 2015, pp. 1-4.