

# Low Complexity Background Subtraction and Adaptive Noise Elimination for Moving Object Segmentation

Nuwan Sanjeewa and Won Ho Kim\*

*Division of Electrical, Electronic & Control Engineering,  
Kongju National University, Republic of Korea*

*\*Corresponding Author*

## Abstract

In this paper, we present a moving object segmentation algorithm based on low complexity background modeling and adaptive noise elimination for real-time CCTV surveillance system. In the proposed algorithm, firstly, the moving candidate objects were extracted by using simplified Gaussian model based background subtraction which has low complexity compared with conventional methods, and then adaptive noise elimination operation is applied to difference image in order to get refined moving objects. For the performance verification, the proposed algorithm has simulated using outdoor surveillance video stream, and the simulation result has showed that the proposed background modeling and adaptive noise elimination have good performance although it has less computational load compared with conventional methods. Also, it has confirmed the practicality which can be applicable for real-time CCTV surveillance system.

**Keywords:** Image signal processing, Moving object segmentation, Computer vision, Video surveillance system.

## INTRODUCTION

The moving object segmentation methods are divided into mainly two types in the processing of surveillance video sequence. There are frame difference method and background subtraction method. Frame difference method is very fast and easy for implementation since it has very low complexity. But it cannot be used for object tracking and object's shape detection in direct [1]-[3]. On the other hand, background subtraction method is considerable for moving object segmentation since it gives details of object's shape. However, it has required efficient processing method for background modeling and updating having high complexity in real-time moving object detection of CCTV surveillance system. Thus, it should have low complexity since the background modeling and updating processing already occupied considerable amount of time of overall object detection processing [4]-[8]. Also, in the processing of above moving object segmentation methods, additional processing is required to refine moving object's shape. which is noise elimination processing of difference image by using a certain noise threshold value.

The noise elements of difference image are changed due to various surveillance field environments and surveillance camera types.

To improve computational complexity and performance of moving object segmentation algorithm, this paper proposes the simplified Gaussian model based background subtraction method and field environments-independent adaptive noise elimination method. The paper is organized as follows. Section 2 presents low complexity background modeling and subtraction method based on simplified Gaussian model. Section 3 illustrates improved adaptive noise elimination method. Section 4 we present results of computer simulation. And finally, in section 5, we present our conclusions.

## LOW COMPLEXITY BACKGROUND MODELING AND SUBTRACTION

Typical approach of background modeling is to model each pixel in a video frame with a Gaussian distribution. This is basic model for many background subtraction algorithms. Additionally, most of the methods use the color values of pixel consisted of three R-G-B elements. On the other hand, this paper presents background modeling method using simplified Gaussian model based on probability of a pixel sequence over certain time-period. Also, this algorithm uses gray-level value to reduce the computational complexity of background modeling and updating. This algorithm applied pixel based processing, and processing steps of the background modeling and updating method are as follows.

1) At first, it quantizes the gray-level image having pixel values varying 0-255 into 26 linear levels as listed in table 1. It is assumed that any pixel value may be changed in range of 0~10 due to the noise.

**Table 1.** Quantization table

Bin Number	1	2	...	25	26
Pixel Value	0-9	10-19	...	240-249	250-255

2) And then, it starts to fill those bins by putting current frame's pixel values to the proper bins and repeat filling

until n-th frame. After processing of n-th frame, replace the average value of bin ( $\mu_{MWR}$ ) having the most number of pixel to pixel value of background image ( $PV_B$ ).

$$PV_B(x, y) = \mu_{MWR}(x, y) \quad (1)$$

The processing steps described above are done for each pixel in the input image sequence over a certain period and finally background can be obtained by taking the average of most weighted bin since the value of the most weighted bin means the most repeated value over the certain period. Therefore, the average of those most repeated values is updated as background pixel value of the certain coordinate. As above description, the proposed simplified background modeling has low complexity by using time-average of gray-level values of the most weighted quantization bin among 26 bins compared with previous methods using three R-G-B elements with range of 0~255 and basic Gaussian model approach.

Once the background image is generated, background subtraction operation is done in order to extract the moving object areas. The resulted image obtained by background subtraction has not only real moving regions, but also the noise regions due to system noise, shadow, texture etc. Therefore, further processing is required, and next step is to remove noise pixels from the difference image.

### ADAPTIVE NOISE ELIMINATION

Most of the conventional methods used fixed threshold to remove noises of difference image obtained by background subtraction. But it can be deleted considerable number of pixels of real objects in the difference image obtained from various surveillance environments. Therefore, it needs adaptive threshold approach to remove only noise pixels related the various video surveillance environments and systems.

The popular adaptive threshold approach uses the standard deviation and mean of the background subtracted difference image. The conventional noise threshold  $TH_{noise}$  is obtained by combining the standard deviation ( $\sigma$ ) and mean ( $\mu$ ) of the background subtracted difference image as equation (2). The  $\lambda$  is user defined parameter and  $N$  is the total number of processed frames.

$$TH_{noise} = \mu + \lambda\sigma \quad (2)$$

$$\sigma = \sqrt{\frac{1}{N} \sum_{i=1}^N (x_i - \mu)^2} \quad (3)$$

$$\mu = \frac{1}{N} \sum_{i=1}^N x_i \quad (4)$$

The noise threshold value is calculated for each frame though, it is totally depended on the user defined value of  $\lambda$ . Therefore, this method has disadvantage of setting some user defined constant. In addition, the  $\sigma$  and  $\mu$  have lower values because the number of zero pixel is

increased, and it cause to decrease the noise threshold value and the noise pixels those have comparatively high value will be remained as foreground. Therefore, this method is mainly able to remove the noises having white Gaussian distribution because the Gaussian noise generally has low values. Of course, they can be eliminated by increasing the value of  $\lambda$ , but the problem is the value of  $\lambda$  is pre-defined and it cannot be changed according to the real-time situations. Also, this method has disadvantage of high computational load since the mean and standard deviation have to be calculated.

Thus, this paper proposes a method which is fully adaptive to the real-time situations in the surveillance fields and there is no any parameter that should be set by user. All the parameters and constant will be calculated automatically and the proposed method is explained in bellows.

The proposed adaptive noise threshold ( $TH$ ) is obtained as a combination of mean of difference image ( $\mu$ ) and number of zero valued pixels ( $N_{zero}$ ) as equation (5).

$$TH = \frac{N}{N_{zero}} \times \frac{\mu}{(N - N_{zero})} \quad (5)$$

The  $\mu$  is calculated according to the equation (4) and number of zero pixels in the difference image is counted by scanning the background subtracted difference image.

The behavior of the threshold depending on the introduced parameters can be described as follows. If all pixel values of the difference image are zero when there are no moving objects, then the system is the best condition it does not need a threshold for noise elimination. If the number of zero pixels decrease, the reason could be either there are many moving objects or system has considerable amount of noise. Therefore, the value of threshold should be increased. If the number of zero pixels increase, the reason could be either there few moving object or system noise is comparatively low. Therefore, the value of threshold should be decreased.

As using proposed adaptive threshold, the noises are effectively eliminated depending on variable field environments of system. The higher value of pixel than the adaptive threshold is decided to be moving pixel and the lower value of pixel than adaptive threshold is decided to noise pixel as equation (6). The  $BSI(x, y)$  is background subtracted difference image and  $TH$  is adaptive threshold, the  $IMG(x, y)$  is binary moving object image.

$$IMG(x, y) = \begin{cases} 1, & \text{if } BSI(x, y) \geq TH \\ 0, & \text{else} \end{cases} \quad (6)$$

The binary moving object image has usually a number of closely spaced scattered small regions. It needs further processing for segmenting those disorder pixels in order to obtain the final moving objects. Generally, the eight-connected component labeling [9] is applied to the resulted image after processing of background subtraction and adaptive noise elimination. The labels those have small number of pixels is removed by considering as scatters and noises.

**SIMULATION RESULTS**

The computer simulation was performed using  $720 \times 480$  size of color video sequence as shown in figure 1. Test video was acquired by using digital camcorder to test algorithm.



**Figure 1.** Test video frames for computer simulation

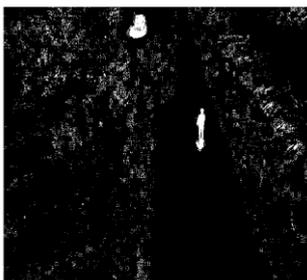
At first, background image was generated by using proposed low complexity background modeling method. And then, background image was subtracted from current image to get difference image. Finally, adaptive noise threshold is used to remove noises and to get binary moving object image.



**Figure 2.** Generated background image by the proposed method

The figure 2 shows the generated background image by using proposed simplified background modeling method. It has low computational complexity compared with previous methods using R-G-B color elements and basic Gaussian model approach in theoretically as described previous section.

For performance comparison of conventional and proposed adaptive noise threshold, two adaptive thresholds were simulated with same condition. The figure 3 shows simulation result images using the conventional noise threshold and the proposed noise threshold.



(a) Conventional method



(b) Proposed method

**Figure 3.** Simulation result images using two adaptive thresholds for noise elimination

Figure 3-(a) shows result image after background subtraction and conventional adaptive noise elimination by using equation (2) with  $\lambda=2$ , and figure 3-(b) shows result image after background subtraction and proposed adaptive noise elimination by using equation (5).

As shown in figure 3-(b), The number of remained noise pixels is very small compared with the conventional adaptive noise elimination shown in the figure 3-(a). it shows that the proposed adaptive noise elimination method has better performance to remove unwanted pixels such as shadow, system noise, scatters, etc. Therefore, the proposed noise elimination method using equation (5) is capable of adapting to the various real-time situations in the surveillance field without any user pre-defined parameter. As a result, it was confirmed that the proposed adaptive threshold method has better performance of noise elimination although it has less computational load since the standard deviation value is not required.

Finally, the eight-connected component labeling is applied to the binary moving object image. The final result image of simulation is shown in figure 4 and two moving objects (moving car and moving man) are well segmented as marked in rectangles.

In conclusion, it is verified that the proposed moving object segmentation algorithm based on simplified background modeling and improved adaptive noise elimination has good performance although they have less computational load as shown in the final simulation result.



**Figure 4.** Final result image of computer simulation

## CONCLUSIONS

This paper presented a method to segment moving objects based on low complexity background subtraction and adaptive noise elimination. The proposed algorithm consisted of two main functions. At first, it is low complexity background subtraction based on simplified Gaussian model to extract moving objects, and secondly, adaptive threshold processing effectively to remove noises of the background subtracted difference image. The proposed background modeling has low computational complexity compared with previous methods using R-G-B color elements and original Gaussian model approach theoretically, and the applied adaptive threshold method has low computational load than other conventional method using mean and standard deviation values.

Finally, the simulation result showed that the proposed background modeling and adaptive noise elimination have good performance although it has less computational load. Therefore, it will be able to perform well in real-time video surveillance system comparatively to the conventional moving object segmentation methods.

## ACKNOWLEDGMENTS

This work was supported by the research grant of the Kongju National University. (Project No. 2014-0638)

## REFERENCES

- [1] Zhan Chaohui, Duan Xiaohui, Xu Shuoyu, Song Zheng, Luo Min, 2007, "An Improved Moving Object Detection Algorithm Based on Frame Difference and Edge Detection," *IEEE Conference on Image and Graphics*, pp.519-523.
- [2] W.H.Kim, Nuwan Sanjeewa, 2013, "A Moving Human-Object Detection for Video Access Monitoring," *WASET International Journal of Computer, Information and Control Engineering*, Volume 7, Number 9, pp.588-590.
- [3] Cucchiara, Grana, Piccardi, Prati, 2013, "Detecting moving objects, ghosts, and shadows in video streams," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, Volume 28, pp.1337-1342.
- [4] Z. Zivkovic, 2004, "Improved Adaptive Gaussian Mixture Model for Background Subtraction," *Proc. Int'l Conf. Pattern Recognition*, vol. 2, pp. 28-31.
- [5] Sen, Das, Chowdhury, 2009, "Saving Electrical Power in a Surveillance Environment", *Seventh IEEE International Conference on Advances in Pattern Recognition*, pp.274-277.
- [6] Heikkila, Pietikainen, 2006, "A texture-based method for modeling the background and detecting moving objects," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, Volume 28, pp.657-662.
- [7] P. Kaew TraKul Pong and R. Bowden, 2001, "An Improved Adaptive Background Mixture Model for Real-Time Tracking with Shadow Detection," *Proc. of European Workshop Advanced Video Based Surveillance Systems*.
- [8] C. R. Wren, A. Azarbayejani, T. Darrell, and A. Pentland, 1997, "Pfinder: Real-time tracking of the human body," *IEEE Trans. on PAMI*, vol. 19, no. 7, pp. 780-785.
- [9] Rafael C. Gonzalez and Richard E. Woods. 2002, *Digital Image Processing*. Prentice Hall, New Jersey, 2nd edition, USA.
- [10] McAndrew, Wang, Tseng, 2007, *Introduction to digital image processing with Matlab*, Cengage Learning Press, USA.