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To cite this article: Moch. Arief Soeleman *et al* 2020 *J. Phys.: Conf. Ser.* **1430** 012032

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# An Improvement for Background Modelling using a Mixture of Gaussian and Region Growing in Moving Objects Detection

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**Abstract.** Most of the research on object detection that uses discussing background is only necessary for the decision of the background model by assuming all statistical objects are part of the background. This caused a debate called "foreground aperture," where statistical purposes that represent moving backgrounds, the position of the initial object will be detected as false detection. Related to the new background modeling is needed to overcome this problem. This paper proposes how to obtain an efficient background model that meets real requirements. As a background model, the Mixed-of-Gaussian Model (MOG) was adopted and refined with some improvements with the Region Growing method. Evaluation to measure the performance of the MOG algorithm and Region Growing by using a detection rate to calculate the number of right and wrong in the detection of moving objects.

## 1. Introduction

Moving object tracking on video or commonly called video tracking [1] is a very challenging problem to be investigated because every environmental condition that is tracked is different and has its uniqueness. Common issues in video tracking that pose challenges such as loss of information due to projection of 3D objects into 2D, changes in the pose of objects as they move, changing lighting, disturbing backgrounds, or closed or invisible objects partially or wholly due to other purposes become a research topic that is still being developed [2], [3]. Lots of video tracking development that can be used to help the needs of the community from entertainment to security.

Each tracking method requires an object detection mechanism to be tracked. The most common approach for object detection is to use information in a single frame. There are several methods used to determine the object in the tracking video, such as point detectors, background subtraction, segmentation, and supervised learning [4]. Generally, the background subtraction (BGS) method is widely used in tracking systems. Because background modeling significantly influences system performance, a reliable BGS method is necessary in this case. However, many challenges are related to background modeling [4].

Although this method is very sensitive to dynamic scene changes, many adaptive modeling methods have been developed to deal with this problem. One approach is the method proposed by Stauffer and Grimson [5], the Mixture of Gaussian (MOG) method. This method is applied to vehicle tracking on the highway, but MOG parameters such as the number of gaussian models and variances must be chosen manually.

Many frames need to be collected before estimating the background model, and this causes computational complexity and memory space requirements to be large [6], [7]. MOG model also has



some weaknesses, and the learning process will be slow when the initial introduction, especially in busy environmental conditions, and the model can not distinguish between shadows and objects.

Previous research has been done to improve the model by KaewTraKulPong et al. [8] using the Adaptive Gaussian Mixture method, and the learning process is faster than MOG and also successfully handles shadows. The method developed by KaewTraKulPong et al. succeeded in improving the Grimson et al. method by speeding up the learning process when object detection runs at the start of a working system, and the problem of shadows on detected objects was detected to be eliminated.

Both the methods of Grimson et al. [5] and also KaewTraKulPong et al. [8] when the learning process occurs, the system will update the background model that has been created. The KaewTraKulPong et al. [8] has been proven successful in overcoming problems in the previous method, but the foreground produced by this method is still incomplete when compared to ground truth or manual segmentation. Although the KaewTraKulPong et al. method is adaptive enough to be used in all kinds of moving object detection environments, it still requires manually determining the appropriate parameter values.

This paper aims to develop a method of detection of moving objects based on foreground modeling developed by KaewTraKulPong et al. The hope of the results of this study includes the improvement of previous algorithms by adding the Region Growing algorithm to get more accurate.

## 2. Related Work

Grimson et al. [5], proposed an improvement in the method of background modeling on this standard MOG on which to base this research. The Gaussians method approach is used to update the background model, then the distribution of a mixture of several Gaussian models is adaptively evaluated to determine which is the most likely part of the background. The result is a stable model for building background, can be used in real-time video captured with the possibility of many problems that will arise such as lighting changes and this method successfully overcome them, and can overcome repetitive object movements

KaewTraKulPong et al. [8], many background models have been introduced to deal with a variety of different problems. One successful solution to the problem of background modeling is to use the adaptive background method proposed by Grimson et al. However, this method has the disadvantage that the system is slow when learning at the beginning of the system is used, especially in environments that are quite a lot of disturbances such as the movement of objects that should be part of the background. In addition, it cannot distinguish between shadows and moving objects. This method improves the previous method by re-evaluating the equation used, and the research uses different equations at different phases. When combining with shadow detection, the method results in segmentation far better than the previous method. However, this method still has problems with foreground aperture, where background pixels that move in the next frame are not considered part of the foreground, causing "holes" in the foreground detection that results.

Utasi et al. [9], using a separate foreground model using a single Gaussian distribution to represent a broad homogeneous foreground area. This model is updated in the same way as the original MOG background model. In overcoming the foreground aperture challenge, foreground pixels are investigated at pixels around a similar foreground. If the pixel has a variation of the foreground component in the range of pixels understudy, then the deviation (deviation) in the neighboring pixel will be increased.

Schindler et al. [10], proposed a method for overcoming problems in background subtraction. However, this study can be concluded successfully overcoming the foreground aperture problem compared to other methods. This study combines MOG to produce a background model using Markov Random Field (MRF) to refine the foreground. The contribution of this research is not to maintain the background model but to determine pixels as the background or foreground.

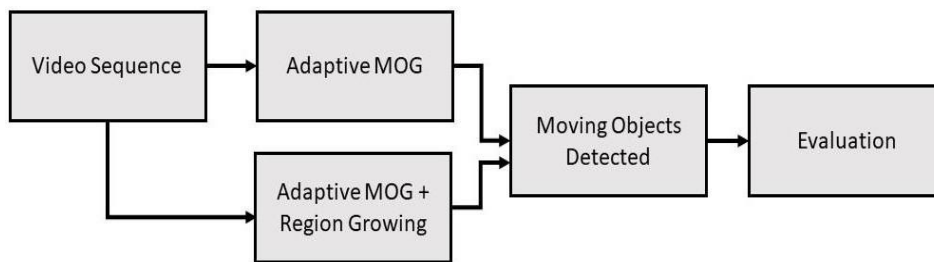
## 3. Methodology

In this section, the following steps are carried out for the experiment can show in figure 1:

1. The image sequence for each video frame is included in the original Gaussian Mixture Model algorithm.
2. Then the image sequence is entered in the modified Gaussian Mixture

Model algorithm to get the latest foreground value. The proposed method is by adding background analysis.

3. Then the results of the foreground above will be compared using the provided ground truth.
4. Foreground results will be evaluated using the precision rate and false alarm rate



**Figure 1.** Proposed Method MOG+Region Growing

### 3.1 Mixture of Gaussian

The Gaussian mixture model is a probabilistic model that assumes all data points are generated from a mixture of a limited number of Gaussian distributions with unknown parameters. It can be assumed that the mixed model is a generalization of k-means clustering to include information about the data covariance structure and also the Gaussian centers. For foreground detection, each pixel is compared to each Gaussian and then classified also using Gaussian. Maintenance models are created using multilevel EM algorithms intended to provide real-time consideration. Stauffer and Grimson [5] generalized this idea by modeling the history of color features of each pixel using a mixture of K Gaussians. Grimson et al. proposed a K value of 3 to 5. The equation of the mixture of gaussian can be described as follows:

$$P(X_t) = \sum_{i=1}^K \omega_{it} \eta(X_t, \mu_{i,t}, \Sigma_{i,t}) \quad (1)$$

$$\eta(X_t, \mu_{i,t}, \Sigma_{i,t}) = \frac{1}{(2\pi)^{\frac{n}{2}} \Sigma_{i,t}^{1/2}} \exp\left\{-\frac{1}{2}(x_t - \mu_{i,t})^T \Sigma_{i,t}^{-1} (x_t - \mu_{i,t})\right\} \quad (2)$$

$$\omega_{i,t} = (1 - \alpha)\omega_{i,t-1} + \alpha M_{(i,t)} \quad (3)$$

$$\mu_{i,t} = (1 - \rho)\mu_{i,t-1} + \rho X_{i,t} \quad (4)$$

$$\sigma_{i,t}^2 = (1 - \rho)\sigma_{i,t-1}^2 + \rho(X_{i,t} - \mu_{i,t})^2 \quad (5)$$

$$\rho = \alpha\eta(X_t, \mu_{i,t}, \sigma_{i,t}) \quad (6)$$

$$Z = \arg \min_b (\sum_{k=1}^b w_k > c_f) \quad (7)$$

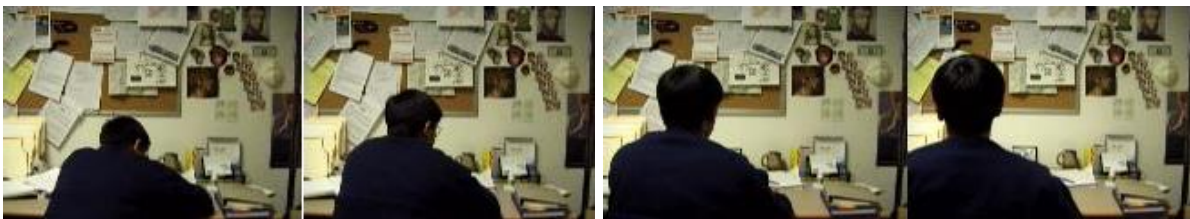
### 3.2 Region Growing

Region Growing [11] is an approach method for image segmentation, starting with a few pixels (seeds) that represent different image regions and grow so that they form wider regions of the image. To use this method, rules are needed that explain the mechanism of growth and the rules of homogeneity of each region after growth. However, in this study, growing regions did not start from seeds but from initial initialization of regions obtained from binary segmentation. By using initial initialization, the region growing region process becomes faster in time complexity. The first step in how this method works is to determine the initial initialization. Then the region will develop into an actual region by detecting whether the outer pixels of the region have criteria for membership of the region.

### 4. Experimental Result

This part provide the experimental results of the algorithms implemented for discover moving object using Mixture of Gaussian and Region Growing. These experiments are conducted on a series of real video. All video processing is used for moving objects where the objective of the system is to improve performance of Mixture of Gaussian using Region Growing. We used MATLAB 2016b and ran on PC with processor i5, 3.40GHz, RAM 4 GB.

The dataset used in this experiment uses the Wallflower dataset for the Moved Object, Foreground Aperture & Waving Tree problems. All three datasets are used to adequately represent the issues raised. In the Moved Object dataset, it has a path where the initial frame shows a static background which in the next frame there is a human object or a moving object coming inside the frame. Foreground Aperture has a reverse path with the previous dataset, and this dataset has a path of people or stationary objects in and in the next frame the object moves. And the Waving Tree dataset has a challenge where there are tree branches that are always moving regularly and then there are moving objects in the frame.

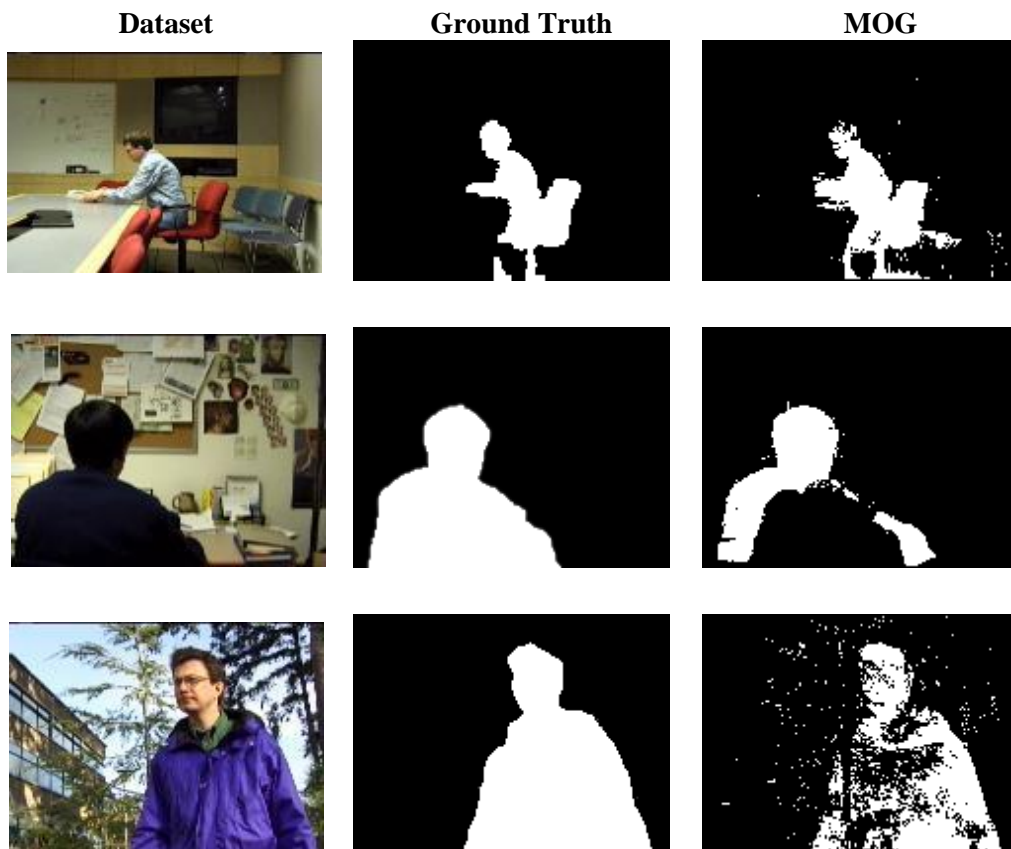




**Figure 2.** The dataset from Wall Flower, from Top to Bottom is Moved Object, Foreground Aperture and Waving Tree dataset

#### 4.1 Experiments with Original MOG

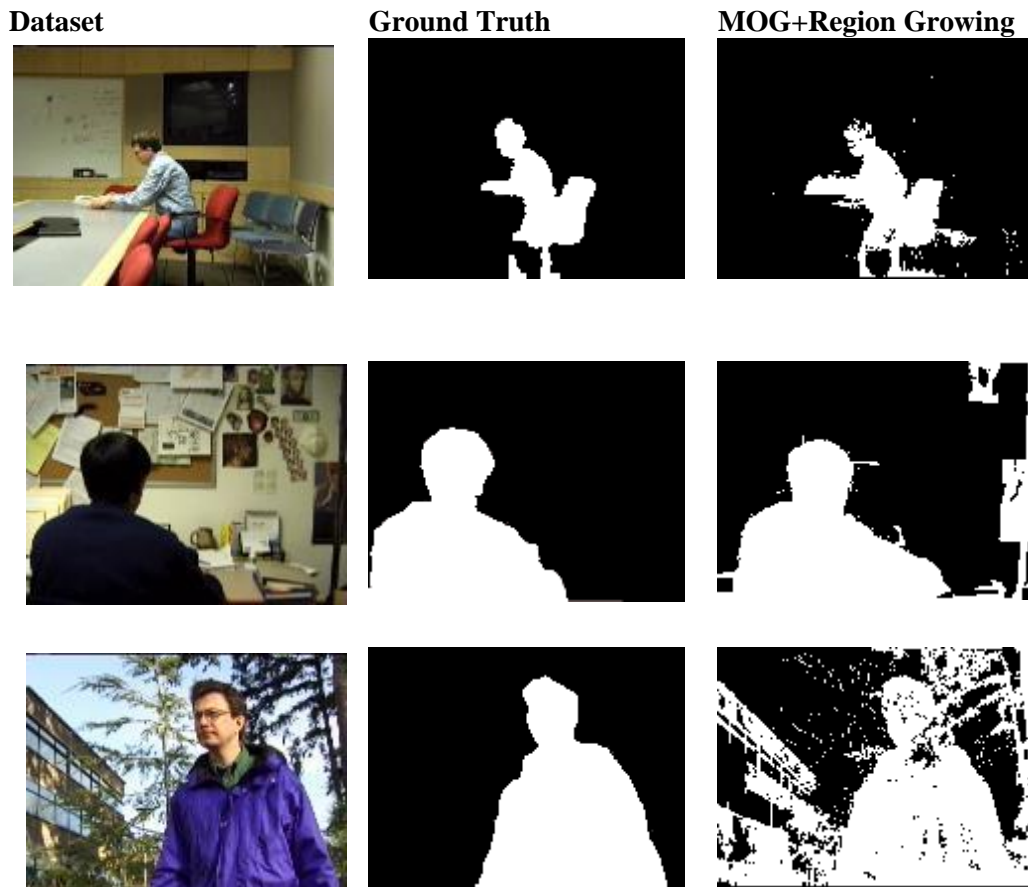
In the original MOG method, parameters are determined manually at the beginning of detection. Each dataset uses parameter values as below to be able to get foreground detection results that are close to ground truth. The values used can be seen in figure 3 as follows:



**Figure 3.** Result of Detection using MOG

#### 4.2 Experiments using MOG and Region Growing

Then the MOG results are analyzed to get an initial seed that is useful to correct the foreground that is not detected. Using the Region Growing method used, the seed specified above. The data used are datasets from Wellflower, among others, Moved Object, Foreground Aperture & Waving Tree. The experimental results can be shown in Figure 4 as follows:



**Figure 4.** Result of Moving Object Detection using MOG + Region Growing

#### 4.3 Evaluation

The algorithm evaluation process uses two parameters, namely detection rate, and false alarm rate. These metric metrics are obtained based on the following parameters

1. True Positive (TP): detected region that there is a moving object.
2. False Positive (FP): a detected region in which there is no moving object.
3. False Negative (FN): a moving object is not detected.
4. Detection rate or Precision rate:

$$DetRate = \left( \frac{TP}{TP + FN} \right) \times 100\% \quad (7)$$

$$Det_{Rate} \equiv \left( \frac{TP}{TP+FN} \right) \times 100\% \quad (8)$$

**Table 1.** Performance Result of MOG and MOG+Region Growing in Moving Object Detection

Dataset	Method	TP	FP	TN	FN
<b>Moved Object</b>	MOG	1676	455	16915	154
	MOG+RG	1677	557	16813	153
<b>Foreground Aperture</b>	MOG	2229	898	16915	154
	MOG +RG	4669	1728	12530	271
<b>Waving Tree</b>	MOG	3585	451	12873	2281
	MOG+RG	5359	5113	8211	517

## 5. Conclusion

Improved object detection accuracy with different problem characteristics can be done by using the algorithm used and the appropriate foreground modeling method. Tests with MAE calculations show high True Positive values on all three datasets, which means that the MOG + Region Growing method produces the right object detection. Even so, the value of False Positive also increased, which can be interpreted as there are regions that are not included in the detected object.

## Acknowledgments

Authors wishing to acknowledge to Kemenristek Dikti for financing the 2019 PTUPT Skim Research.

## References

- [1] L. A. and S. R., "Dealing Background Issues in Object Detection using GMM: A Survey," *Int. J. Comput. Appl.*, vol. 150, no. 5, pp. 50–55, 2016.
- [2] E. M. and A. Cavallaro, *Video tracking: theory and practice*. United Kingdom: John Wiley & Sons, Ltd Registered, 2011.
- [3] and Z. S. H. Yang, L. Shao, F. Zheng, L. Wang, "Recent advances and trends in visual tracking: A review," *Neurocomputing*, vol. 74, no. 18, pp. 3823–3831, 2011.
- [4] J. L. and M. Park, "An Adaptive Background Subtraction Method Based on Kernel Density Estimation," *Sensors*, vol. 12, pp. 12279–12300, 2012.
- [5] C. S. and W. E. L. Grimson, "Adaptive background mixture models for real-time tracking," *Proc. 1999 IEEE Comput. Soc. Conf. Comput. Vis. Pattern Recognit.*, vol. 2, pp. 246–252, 1999.
- [6] T. Bouwmans, "Recent Advanced Statistical Background Modeling for Foreground Detection - A Systematic Survey," *Recent Patents Comput. Sci.*, vol. 4, no. 33, pp. 147–176, 2011.
- [7] Z. Zivkovic, "Improved adaptive Gaussian mixture model for background subtraction," *Proc. 17th Int. Conf. Pattern Recognit.*, vol. 2, no. 2, 2004.
- [8] P. K. and R. Bowden, "An Improved Adaptive Background Mixture Model for Real-time Tracking with Shadow Detection," in *Adv. Video Based Surveill. Syst.*, 2001, pp. 1–5.
- [9] A. U. and L. Czuni, "Reducing the Foreground Aperture Problem in Mixture of Gaussians Based Motion Detection," *14th Int. Work. Syst. Signals Image Process. 6th EURASIP Conf. Focus. Speech Image Process. Multimed. Commun. Serv.*, vol. 5, pp. 157–160, 2007.



- [10] K. S. and H. Wang, "Smooth foreground-background segmentation for video processing," *Lect. Notes Comput. Sci. (including Subser. Lect. Notes Artif. Intell. Lect. Notes Bioinformatics)*, vol. 3852, pp. 581–590, 2006.
- [11] A. M. Mahaman Sai C, Karim Kalti, Basel Solaiman, "A Combined Approach Based on Fuzzy Classification and Contextual Region Growing to Image Segmentation," in *13th International Conference on Computer Graphics, Imaging and Visualization (CGiV)*, 2016.