

A Novel User-Friendly Application for Foreground Detection with Post-Processing in Surveillance Video Analytics

Fancy Joy^{1*} and Dr. V Vijayakumar²

^{1,2}Sri Ramakrishna College of Arts and Science, Coimbatore

*Correspondence: Fancy Joy; fancyjoy1@gmail.com

ABSTRACT- Detection of the object in the video is a primary task of all video-processing-based applications. It is one of the challenging areas in computer vision. The paper presents a novel MATLAB-based object detection application based on an improved Gaussian Mixture Model. Gaussian Mixture Model with post-processing applied here for segmentation of foreground from background. The application is divided into three modules pre-processing, detection and post-processing. The morphological gradient filter uses here for segmenting the foreground objects from the background. The proposed method was tested for various video sequences with challenges and proved that the approach performs well for the majority video sequences.

Keywords: Object Detection, GMM, Post-processing.

ARTICLE INFORMATION

Author(s): Fancy Joy and Dr. V Vijayakumar;

Received: 19/10/2022; **Accepted:** 19/12/2022; **Published:** 25/12/2022;

e-ISSN: 2347-470X;

Paper Id: IJEER 1910-08;

Citation: 10.37391/IJEER.100477

Webpage-link:

www.ijeer.forexjournal.co.in/archive/volume-10/ijeer-100477.html



Publisher's Note: FOREX Publication stays neutral with regard to Jurisdictional claims in Published maps and institutional affiliations.

1. INTRODUCTION

In today's era of surveillance, video analytics plays a great role in various applications such as detection, tracking, street monitoring and intruder detection. Detection is the key task of all of these applications and this becomes complex due to various scenarios such as dynamic background, presence of shadow and occlusion etc. [5]. Many algorithms exist for object detection [2][3][11][17]. The main objective of this system is to provide the simplest benchmark method for foreground detection to be applicable in real-time. The proposed application used the Gaussian mixture model (GMM) with advanced filtering for object detection.

Nowadays people use surveillance cameras to ensure security. The proposed application can integrate with these cameras, which will help the users to detect objects rather than monitoring. The main objective of this application is to detect the object in surveillance video without human intervention. It will be useful in various applications such as security monitoring, street monitoring, traffic monitoring, and intruder detection. Since the application framework is simple and flexible, any user can handle the application without more effort.

The proposed method is a hybrid object detection approach. The hybrid method includes three modules: video denoising, object

detection and advanced filtering. Video denoising eliminates the noises in video frames. The background subtraction approach is used for detecting the object regions. Finally, an advanced filter filters the detected region that helps for effective segmentation of the foreground object from the background. The major contribution of this paper is to build a better application for object detection. The proposed method can be used as a MATLAB addon, without installing any software. The proposed work will be a convenient application for object detection in surveillance video. The remaining section of the paper is as follows *section 2* describes the proposed MATLAB application for object detection. *Section 3* presents the experimental results of object detection application and *section 4* concludes.

2. REVIEW OF LITERATURE

GMM is a statistical probabilistic background subtraction method which segments the foreground from the background. Stauffer and Grimson proposed the GMM in 1999[17]. GMM is one of the most used background subtraction methods and some researchers contribute modifications to it to handle complexities in the surveillance system. Researchers mainly focus on the ways such as pre-processing, parameter tuning and post-processing to improve the GMM algorithm. Some of the contributions to GMM are Bian & Dong [11], and Yi-Bing et al. [12], Y Song et al. [9], Yang et al. [13] and Prasad et al. [4].

Chen et al. [15] presented an improvement in GMM through a background updating period using different learning rates for the estimated background and foreground pixels. The result shows the method works better than the typical gaussian mixture model. Zhu et al. [14] improved the GMM based on motion estimation. They used an adaptive learning rate for better performance in moving object detection. Bian and Dong [11] also improved the gaussian mixture model. They used the edge gaussian mixture model with an improved neighbourhood-based difference to improve detection accuracy. But it still

requires enhancement to integrate moving objects. Yi-Bing et al. [12] improved the GMM for adapting the background and moving the object's integrity. The authors used an adaptive learning rate for fast-updating backgrounds. Results proved that adaptive background leads to exact detection. Y Song et al. [9] modified GMM for fast detection of objects. They enhanced the method by varying the number of Gaussians, according to the environment. The method reduced the computational complexity, which leads to fast execution. A combination of GMM, three frame differences and cropped frame techniques for object detection were introduced by Yang et al. [13]. The approach shows rapid detection and also obtained satisfying performance for practical application. Prasad et al. [4] applied GMM with erosion for object action detection. The authors tested the approach in railway station cameras and showed that the method successfully detects the object action. Still, research is going on in this background subtraction GMM approach.

Neagoe et al. [7] combined the K means clustering and gaussian mixture model with expected maximization. The proposed combined clustering approach shows significant performance over GMM. Han et al. [8] combined GMM with particle swarm optimization (PSO). The proposed method enhanced the convergence speed and classification performance. Zhao et al. [2] combined Principal Component Analysis (PCA) with the GMM for target detection. They proved that the method identified the targets with high accuracy and high efficiency. Zhang and Zhu [3] applied Local Image Flow (LIF), L-recent Windows (LrW) algorithm for parameter initialization and updating of parameters respectively to effectively detect objects under dynamic background. From the literature studies, it is clear that efficient post-processing is required to detect foreground objects accurately.

3. RESEARCH METHODS

The application framework is depicted in figure 1.

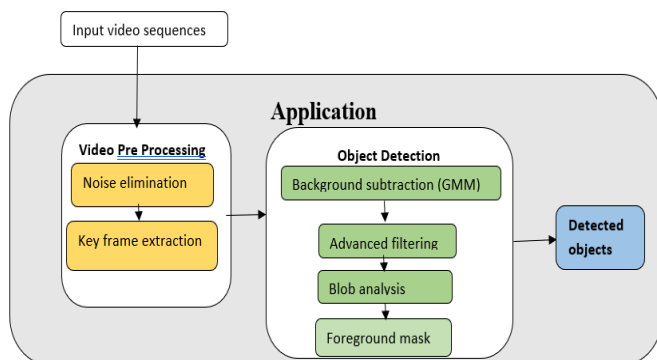


Figure 1: The framework of the proposed object detection application

The developed application architecture consists of video preprocessing, detection of objects and advanced filtering.

3.1 Video Pre-processing

Input video sequences were captured by surveillance cameras and transmitted into the application. Analyses the received video frames and eliminates the noises present in the video

using either TDBLMS algorithm or bilateral filter depending on user choice. TDBLMS is the two-dimensional block-based least mean square algorithm [1] that can be applied frame by frame of video. Each video frame divides into blocks and performs block by block from left to right and top to bottom using an LMS filter. An adaptive filter changes the parameters according to the image's least mean square error matrix to achieve fast convergence. A bilateral filter is a smoothing filter, which eliminates the noises with preserving edges [16]. Application users can choose either TDBLMS or bilateral filter for noise Extracting. Extracting the keyframes of video using the color histogram approach enables fast object detection [10]. A bilateral filter is a non-linear image filter that filters the image by eliminating noise and fine details. It converts video frames to smoother ones by preserving edges without blurring. Let S be the input image and the bilateral filter output image S_{filtered} .

$$S_{\text{filtered}}(p) = \frac{1}{w_t} \sum_{p_i \in \rho} I(p_i) r_k (\|I(p_i) - I(p)\|) s_k (\|p_i - p\|) \quad (1)$$

Where p is the coordinates of the current pixel, ρ is the window centred in q , and r_k indicates the range kernel and spatial kernel s_k . The intensity values of each pixel in the input image are replaced with a weighted average (w_t) of the intensity values of the adjacent pixel.

$$w_t = \sum_{q_i \in \rho} r_k (\|I(q_i) - I(q)\|) s_k (\|q_i - q\|) \quad (2)$$

3.2 Object Detection

Here proposed approach detects the object by background subtraction using GMM [17]. Gaussian Mixture Model used the gaussian probability density function to represent the video frame. An initial background model was calculated and initialized. Then compare the proceeding frames from the initialized background model and the difference is taken as the object. Background subtraction using the gaussian mixture model applies in keyframes to detect the foreground object. GMM is a parametric probability density function and each frame can be denoted as the weighted sum of gaussian probability density functions.

Let X_s be the pixel value and w be the mixture of weights for $i=1$ to n . Then Gaussian density function of the pixels of the frame can be represented as:

$$P(X_s) = \sum_{i=1}^K \omega_i * \eta(X_s, \mu_{i,s}, \Sigma_{i,s}) \quad (3)$$

Where μ_i, Σ_i are the mean and variance respectively.

K - number of gaussian distribution

ω_i - weight of i^{th} gaussian in the mixture.

μ_i - mean of pixel intensities

Σ_i - covariance matrix of pixel intensities.

η refers to the Gaussian probability density function which is defined by

$$\eta(X, \mu_i, \Sigma) = \frac{1}{\frac{m}{2\pi|\Sigma|^{\frac{1}{2}}}} e^{-\frac{1}{2(X-\mu)^T \Sigma^{-1} (X-\mu)}} \quad (4)$$

Here $w_{i,s}$ can be defined as

$$\omega_i = (1 - \alpha) \omega_i + \alpha(\mu_i) \quad (5)$$

Where α is the learning rate and $\mu_{i,s}$ is the mean value.

Every new pixel X_{i+1} compared against the previous K gaussian distribution of the pixel until a match is found. Mean μ is set to 1 if the background model matches otherwise μ assigned to 0.

$$\mu_i = \begin{cases} 1, & \text{If the background model matches} \\ 0, & \text{otherwise} \end{cases} \quad (6)$$

If the distribution found unmatched then the μ and σ_s^2 parameters remain the same. If the distribution found a match, then the parameters μ_s and σ_s^2 were updated based on previous distribution values.

$$\mu_s = (1 - \rho)\mu_{s-1} + \rho(X_s) \quad (7)$$

$$\sigma_s^2 = (1 - \rho)\sigma_{s-1}^2 + \rho(X_s - \mu_s)^T (X_s - \mu_s) \quad (8)$$

Where ρ is the second learning rate. It can be represented as

$$\rho = \alpha \eta\left(\frac{X_s}{\mu_i}, \sigma_i\right) \quad (9)$$

The key step in every background subtraction model is background modelling. This step compares the current frame to the background frame, and then classifies the pixels as foreground and background. Here the first 'M' distribution uses for background modelling. 'M' can be defined as

$$M = \operatorname{argmin}_m \left(\sum_{i=1}^m w_i > T \right) \quad (10)$$

Where T is the threshold value, which is the measure of the minimum portion of data that should be considered as background.

Gradient filters of morphological erosion and dilation were used as an advanced filter. Morphological dilation adds the pixel to the image boundary whereas erosion removes the pixel from the image boundary. The gradient filter is the difference between erosion and dilation. BLOB (Binary Large Object) analysis is one of the significant processes in the proposed application, which recognize the consistent image (*i.e.*, object) regions in the frame and result in a binary mask of corresponding frames. The foreground mask using GMM returns a binary mask, which represents foreground pixels as 1 and 0, as background pixel. Advanced filter using a gradient of morphological operations helps to better segmentation of foreground objects from the background.

The fundamental principle of morphological operation is to quantify each pixel in a binary image using a predetermined structural element. When a structural element's center falls on a specific pixel, the intersection of that structural element and the image is subjected to a logical operation. The four basic operations in morphological filtering are expansion, erosion, closed, and open operations. Dilation is the process of expansion of connected areas based on structuring elements. Dilation scans each pixel in the binary picture, using 0 or 1, and gets the maximum of the sum of the image pixel and the structural element, that is, the structural element and the image coincidence area. Let I be the image and S be the structuring element. Dilation operation can be defined as follows

$$I \oplus S = \max_{(i,j)} [I(x - i, y - j) + S(i, j)] \quad (11)$$

Erosion is the opposite operation of dilation. It scans each pixel in the binary image and take the minimum of the difference between the structural element and image pixel. Erosion is the shrinking of connected areas based on structuring element.

$$I \ominus S = \min_{(i,j)} [I(x + i, y + j) - S(i, j)] \quad (12)$$

4. SIMULATION RESULT

In this section, the detection result of frames of various video sequences is shown. Video sequences were chosen from the change detection dataset [18] and PETS 2009[19]. The proposed application was implemented in MATLAB 2019a. Figure 2 shows the screenshots of proposed applications. Input video sequences passed to the application and checked for histogram analysis. The proposed application uses 2 filters 1) TDBLMS and 2) Bilateral filter. GMM is applied to the video frames followed by a morphological gradient operation performed to get better detection results.

To evaluate the performance, the proposed approach compares the recent detection method Nguyen [6] using precision and F - measure. The proposed method also compares foreground mask with GMM. The detection result and foreground mask of some of the video frames from change detection shown in table 1. In table 1 row 1 indicates the resultant frame, row 2 indicates the dataset name with challenges, and row 3 shows the foreground mask of the resultant frame. Challenging frames are chosen here and the results show that the proposed application performs the good majority of cases.

Figure 3 compares proposed application result with Nguyen [6] method using precision. Precision measures the ratio of the number detected objects to the total number object that is present. The results prove that precision value of the proposed method is more than the Nguyen method. F-measure both proposed method and Nguyen's method depicted in figure 4. According to figure 4, the proposed approach shows good performance than Nguyen's method. But fast high motion value in some highway video frames degrades the detection performance.

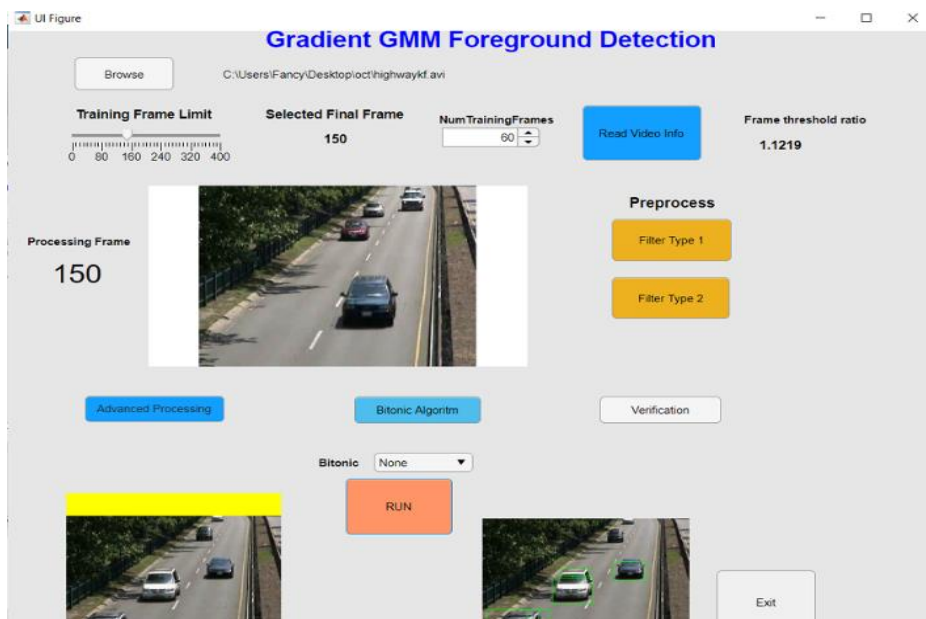


Figure 2: Screenshot of the proposed application

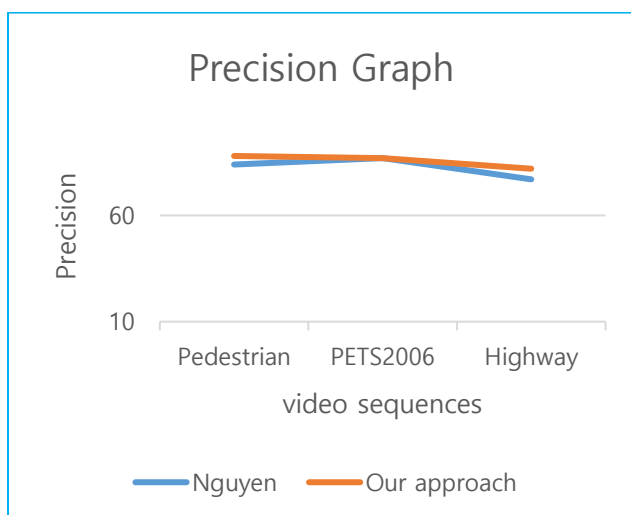


Figure 3: Comparison of proposed method with Nguyen [4] using precision

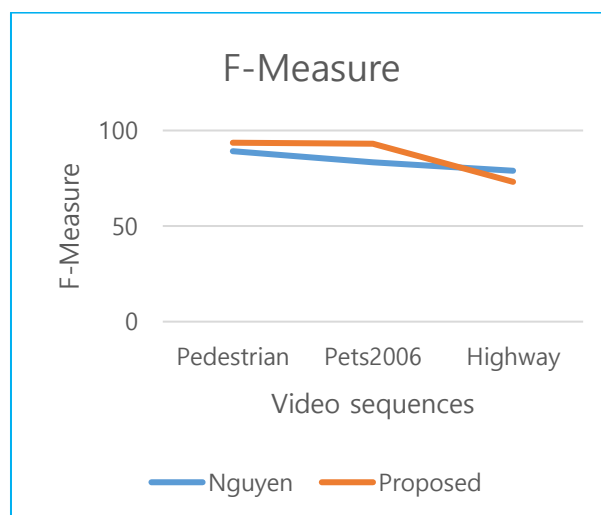


Figure 4: Comparison of proposed method with Nguyen [4] using F-Measure

Table 1: Result of application

Pedestrian (Illumination variation)	PETS 2009 (Dynamic background, occlusion)	PETS 2006 (Dynamic background, shadow)

Table 2: Comparison of GMM with the proposed application



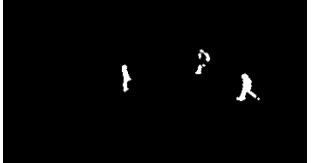







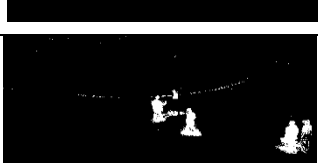

Frame no		GMM [17]	Proposed application
5			
10			
15			
20			

Table 2 indicates the comparison of the GMM [17] object detection method and proposed application in the PETS 2009 dataset. Column 1 indicates the frame number, column 2 shows the original frame, column 3, and column 4 represents the foreground mask of GMM and proposed application respectively. From table 2 it is clear that the proposed application performs better than GMM.

5. CONCLUSION

MATLAB applications for object detection were proposed in this paper. GMM with post-processing is used here for object detection. The approach includes preprocessing of video frames, object detection, and morphological gradient as an advanced filter. The proposed application shows good performance over GMM. The developed application will be convenient for users for practical implementation. Further enhancements need to handle object detection in the dynamic background, where motions are very fast.

REFERENCES

- Joy F., Vijayakumar V., "A State of Art Methodology for Real-Time Surveillance Video Denoising", In: Smys S., Tavares J., Balas V., Iliyasu A. (eds) Computational Vision and Bio-Inspired Computing. ICCVBIC 2019. Advances in Intelligent Systems and Computing, 2020, vol 1108, pp.894-901.Springer, Cham.
- Juan Zhao, Guihui Xie, Dongming Li and Mailing Song, "Improved GMM-based method for target detection", The Institution of Engineering and Technology, 2020, Vol.9, Issue.1, pp. 7-11.
- Caixia Zhang and Qingyang Xu, "An Improved GMM based Video Foreground Separation", The 31th Chinese Control and Decision Conference (2019 CCDC), 2019, pp.1371-1374.
- Venkata Prasad.Va, Chandra Sekhar Rayia, Cheggoju Naveena., Vishal R. satpute, "Object's Action Detection using GMM Algorithm for Smart Visual Surveillance System", International Conference on Robotics and Smart Manufacturing (RoSMa2018), Procedia Computer Science 133, 2018, pp. 276-283.
- Fancy Joy and V. Vijayakumar., "A Review on Multiple Object Detection and Tracking in Smart City Video Analytics", International Journal of Innovative Technology and Exploring Engineering (IJITEE), 2018, Volume-8 Issue-2S2 December.
- M.H Nguyen, T.L. Vuong, D.N. Nguyen, D.V. Nguyen, H. Le and T. Nguyen, "Moving object detection in compressed domain for high-resolution videos", Proceedings of the Eighth International Symposium on Information and Communication Technology, 2017.
- Victor-Emil Neagoe, Vlad Chirila-Berbentea, "Improved Gaussian mixture model with expectation-maximization for clustering of remote sensing imagery." 2016 IEEE International Geoscience and Remote Sensing Symposium (IGARSS), 2016, pp.3063-3065.
- Han, G, "An Improved Gaussian Mixture Model and Its Application", In: Wong, W. (eds) Proceedings of the 4th International Conference on Computer Engineering and Networks, Lecture Notes in Electrical Engineering, 2015, vol 355. Springer, Cham.
- Y. Song, N. Fu, X. Li and Q. Liu, "Fast moving object detection using improved Gaussian mixture models," 2014 International Conference on Audio, Language and Image Processing, 2014, pp. 501-505.
- Kumthekar, A. V., and J. K. Patil, "Key frame extraction using color histogram method." International Journal of Scientific Research Engineering & Technology, 2013, pp. 207-214.
- Zhiguo Bian and Xiaoshu, "Moving object detection based on improved gaussian mixture model" 2012 5th international congress on image and signal processing (CISP 2012), 2012.
- LI-Yi Bing, JIA He-jiang, and LI Ao, "A moving object detection method based on improved GMM", Advanced materials research, 2012, vol.225-226, pp. 637-641.

- [13] Jinfu Yang, Wanlu Yang and Mingai Li," An efficient moving object detection algorithm based on improved GMM and cropped frame technique", Proceedings of 2012 IEEE International Conference on Mechatronics and Automation August 5 - 8, Chengdu, China,2012.
- [14] Yingying Zhu, Ye Liang and Yanyan Zhu," The improved gaussian mixture model based on motion estimation",2011 third international conference on multimedia information networking and security, IEEE,2011.
- [15] Chen, G., Yu, Z., Wen, Q., & Yu, Y., "Improved Gaussian Mixture Model for Moving Object Detection". Lecture Notes in Computer Science,2011, pp. 179–186.
- [16] S.Paris, P. Kornprobst, J Tumblin and F. Durand, "Bilateral filtering: Theory and applications", Foundations and trends in Computer graphics and Vision, 2008, Vol.4, Issue.1, pp.1-73.
- [17] Chris Stauffer and W. Eric L. Grimson," Adaptive background mixture models for real-time tracking," Proceedings of the 1999 IEEE computer society conference on computer vision and pattern recognition, IEEE.Comput.Soc, 1999.Part.Vol.2.
- [18] <http://www.changedetection.net/>
- [19] <http://cs.binghamton.edu/~mrldata/pets2009>



© 2022 by Fancy Joy and Dr. V Vijayakumar.
Submitted for possible open access
publication under the terms and conditions of
the Creative Commons Attribution (CC BY) license
(<http://creativecommons.org/licenses/by/4.0/>).