Middle-East Journal of Scientific Research
24 (Special Issue on Innovations in Information, Embedded and Communication Systems): 51-57, 2016
ISSN 1990-9233; © IDOSI Publications, 2016
DOI: 10.5829/idosi.mejsr.2016.24.IIECS.23139

Foreground Object Detection Using Expectation Maximization Based Effective Gaussian Mixture Model

S. Kanagamalliga, S. Vasuki and M. Shanmugapriya

Department of Electronics & Communication Engineering,
Velammal College of Engineering & Technology, Madurai Tamil Nadu, India

Abstract: While numerous algorithm has been proposed for object detection with demonstrated success, but a crucial problem is to improve the performance of appearance variation, illumination changes and occlusion. Gaussian Mixture Model (GMM) has been widely used for moving object detection due to its huge applicability. However, the Gaussian Mixture Model cannot properly model noisy or non stationary background modes. We have proposed a foreground object detection scheme, i.e., Gaussian mixture model is fused with the expectation maximization algorithm for improving the segmentation quality of moving objects. EM-EGMM is used to discard the noises and fill the holes for getting complete background region. Our approach is to demonstrate the accuracy under different conditions. Experimental results demonstrate that our method runs fast, robust and accurate, as compared to the several state-of-the-art detection methods.

Key words: Background Model · Gaussian Mixture Model (GMM) · EM (Expectation Maximization) based EGMM (Effective Gaussian Mixture Model) · Foreground object detection

INTRODUCTION

Moving object detection is an important task within the field of computer vision and multimedia fields, including video surveillance and editing, motion and action recognition, human-computer interfaces (HCI), content based video compression and automatic traffic monitoring [1, 2]. It is still a very challenging task in dynamic backgrounds, illumination changes, appearance variation & object occlusion, etc. [3]. A typical detection algorithm depends on foreground object detection, which divides the observed image into two complementary sets of pixels that cover the entire image [4]. Background subtraction (BS) is used to detect the moving or static objects and it involves the comparison of an observed image with an estimated image that does not include any object of interest; this technique is known as background model (or background image).

This method is widely used approach for foreground object detection, such as Gaussian Mixture Model (GMM) usually compares the current frame with an existing background model to obtain foreground method [5]. The background subtraction method is to benefit of difference method of the current image and background image to detect moving objects, with clear algorithm, but very sensitive to the changes in the external environment and has poor anti- interference ability. However, it can contribute the most complete object information in the case of the background is known. Any motion detection system based on background subtraction needs to handle a number of critical situations such as:

- Sudden changes in the light conditions, (e.g. sudden raining), or the existence of a light switch (the change from daylight to non-natural lights in the evening),
- Movements of objects in the background that leave parts of it different from the background model and
- Multiple objects moving in the scenery for both long and short periods.

The moving object detection can be broadly classified into change detection based approaches and modeling based approaches [6]. The major contribution of this paper includes the following: EM (Expectation-maximization) based EGMM (Effective Gaussian Mixture Model) method is proposed to improve the segmentation

Corresponding Author: S. Kanagamalliga, Department of Electronics & Communication Engineering, Velammal College of Engineering & Technology, Madurai Tamil Nadu- India.

quality of the moving objects. EM based EGMM is the method of modeling the background by using image sequences.

This algorithm provides a feasible option to measure the parameters in GMM models. It is an iterative model that can be used to make a maximum likelihood estimation of parameters based on the imperfect data set. The EGMM algorithm has the better effect on the stability, sensitivity and quick convergence. In EGMM method, the extracted objects are detected by the EM algorithm.

The remainder of this paper is standardized as follows. Section II reviews the related works in our analysis. In Section III, elaborates the proposed method, including EM based EGMM algorithm to improve the quality of moving object. Section IV gives the experimental result analysis. The conclusion is drawn in Section V.

Related Work: Various kinds of methods are proposed for improving the quality of video-based tracking method. The literatures dealing with the object detection are revised as follows.

Object Detection: Moving object detection is used to locate objects in the frame of the video sequences. It is used in various background subtraction techniques. In Olivier *et al.* [4], background subtraction technique must adapt to gradual or fast illumination changes (changing time of day, clouds etc), changing motion (camera oscillations), changes in the background geometry (e.g., parked cars) and bootstrapping. Some application requires background subtraction algorithms to be embedded in the camera, so that the computational load comes as the major concern. Pixel based background subtraction techniques satisfied for the lack of spatial consistency by a constant updating of their model parameters.

In Zhou Liu *et al*. [7], the background modeling is to improve the accuracy and to deal with highly dynamic scenes, the spatial information is reflected at the feature level.

Proposed Method: The proposed method of detection model includes Gaussian mixture model to introduce the derive model of expectation maximization algorithm. In this paper, it deals with the new technique Expectation Maximization (EM) - Effective Gaussian Mixture Model (EGMM) is revised as follows.

Gaussian Mixture Model: Gaussian mixture model is used to implement the background model to detect the moving objects. For detecting moving objects in video surveillance scheme uses the Gaussian mixture model, is essential this model has the color values of a specific pixel as a mixture of Gaussians. But the pixel values that don't ?t the background distributions are considered as foreground. The parameters of a mixture of Gaussians for which each node of a sensor network had di?erent mixing coe?cients could be predicted using a distributed version of the well-known expectation-maximization (EM) algorithm.

The probability of observing a given pixel value p_t at time t is given by

$$p(p_t) = \sum_{j=1}^{k} w_{j,t}\, \sigma(p_t, \mu_{j,t}, \textstyle\sum j, t) \quad (1)$$

Where k is the number of Gaussian Mixture and that is used.

The number of k varies depending on the memory allocated for simulations. Then the normalized Gaussian σ is a function of $(p_t, \mu_{j,t}, \sum j, t)$ which represents the weight, mean and co-variance matrix of the ith Gaussian at time respectively. The value of background model is determined by the

$$B = argmin_b(\textstyle\sum_{i=1}^{b} \omega_t > T) \quad (2)$$

Where T is the threshold value.

If a pixel does not match with any one of the back-ground component, then the pixel is marked as foreground. The noise in the foreground binary mask is removed through proper connected component labeling. Gaussian model is highly sensitive, low memory requirements and it does not cope with multimodal background.

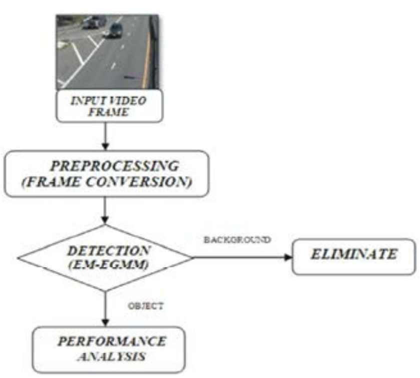


Fig 1: Flow Diagram of Proposed Method

In fig (1), the input frame in the video surveillance is given to the frame conversion. In the preprocessing phase, the ?rst step of the moving object detection process is capturing the image information using a video camera. The background object is eliminated and the object become as original color.

EM algorithm for Gaussian Mixture Model: EM algorithm provides a beneficial option to estimate the parameters in GMM models. It is an iterative method can be used to create a maximum likelihood estimation of parameters based on the imperfect set. The EM algorithm is capable for fitting the given data and the result in a fuzzy cluster, i.e., the possible of each sample is belongs to the distribution. EM algorithm is one of the benefits effects of its scability, quick convergence and manageability of computation. In the EM algorithm method, the weight assigned to background pixels is large due to the higher frequency of occurrence.

The EM algorithm can be started by either initializing the algorithm with a set of initial parameters and then conducting an E-step, or by starting with a set of initial weights and then doing a first M-step. We define the EM (Expectation-Maximization) algorithm for Gaussian mixtures as follows. The algorithm is an iterative algorithm that starts from some initial estimate of Θ(e.g., random) and then proceeds to iteratively update Θ until convergence is detected. Every iteration consists of an E-step and an M-step.

E (Estimation)-Step: For given parameter value, we compute the expected value of the latent variable. Denote the current parameters value of Θ. Compute ω_{ik} for all data points $x_i, 1 < i < N$ and all mixture components $1 < k < K$.

Note that for each data points x_i, the membership weights are defined such that $\sum_{k=1}^{K} \omega_{ik} = 1$. This yields an N×K matrix of membership weights, where each of the rows sums to 1.

M (Maximization)-Step: It updates the parameter model based on the latent variable calculated using ML method. Now use the membership weights and the data to calculate new parameter values.

Let $N_k = \sum_{i=1}^{N} \omega_{ik}$, i.e., the sum of the membership weights for the kth component. This is the effective number of data points assigned to component K.

Specially,

$$\beta_k^{new} = \frac{N_k}{N}, 1 < k < K \tag{3}$$

These are new mixture weights

$$\mu_k^{new} = \frac{1}{N_k} \sum_{i=1}^{N} \omega_{ik} . x_i , 1 < k < K \tag{4}$$

The updated mean is calculated in a manner similar to how we could compute a standard empirical average, except that the ith data vector x_i has a fractional weight ω_{ik}. Note that this is a vector equation since μ_k^{new} and x_i are both d-dimensional value.

$$\gamma_k^{new} = \left(\frac{1}{N_k}\right) \sum_{i=1}^{N} \omega_{ik} . (x_i - \mu_k^{new})(x_i - \mu_k^{new})^t \; 1 < k < K \tag{5}$$

Again we get an equation that is similar in form to how we would normally compute an empirical covariance matrix, except that the contribution of each data point is weighted by ω_{ik}. Note that this is a matrix equation $d \times d$ of dimensionality on each side.

The equation in the M- step 1<k<K, need to be computed in this order, ie., first compute the k new β*'s*, then the k new μ_k^{new} and finally the k new $\gamma_k^{'} s$. After we have computed all of the new parameters, the M-step is complete and we can now go back and recompute the membership weights in the E-step, then recompute the parameters again in the E-step and continue updating the parameters in this manner.

EM based EGMM: The Effective Gaussian Mixture Model (EGMM) is one of the simpler and faster converging approaches of the moving object detection. It is a model based method often tries to maintain a balance between the accuracy and implementation complexity. The conventional EGMM based methods values of each pixel over time, using the mixture of distributions.

$$\{X_1 \ldots \ldots , X_t\} with \; X_i = I(u, v, i) \tag{6}$$

Here, the region gray or color value is denoted by $I(u,v,i)$ at time i. The EM based EGMM (Expectation maximization based Effective Gaussian Mixture Model) is the method of modeling the background by using image sequences. In traditional EGMM, the frame is directly used as the initial data of all single Gaussian Models at the basics of modeling and the model will be continuous updated with small weights.

(a)

(b)

(c)

Fig. 2: (a) original video frame, (b) vehicle obtained with GMM, (c) vehicle obtained with EM based EGMM.

However, there are usually two or more vehicles rather than one vehicle in the first frame, but it difficult to make the accurate parameters for each single Gaussian model. The EM based EGMM algorithm provides a feasible option to estimate the parameters in GMM models.

It is an iterative model that can be used to make a maximum likelihood estimation of parameters based on the data sets. In our method, any one of the input video frames to be detected is selected. The selected target of the background object will be black in color and that object will be in original color using EM-EGMM method as shown in fig (5). The shadow components also have larger weights when occlusion exists. The EGMM algorithm has the better effect on the stability, sensitivity and quick convergence.

Experimental Results: The proposed technique has been evaluated on video of many real scenes and provides superior results over existing methods. In this section, detection parts of experiments are given to demonstrate the performance of our method. First, the influence of foreground detection is illustrated by changing the input objects as original color. The detection is of equal logical path 288*352 of size.

The background becomes black as shown in Fig (4). In this part, the method includes GMM (2) and their improved versions (EM-EGMM) are based on modeling the background.

(a)

(b)

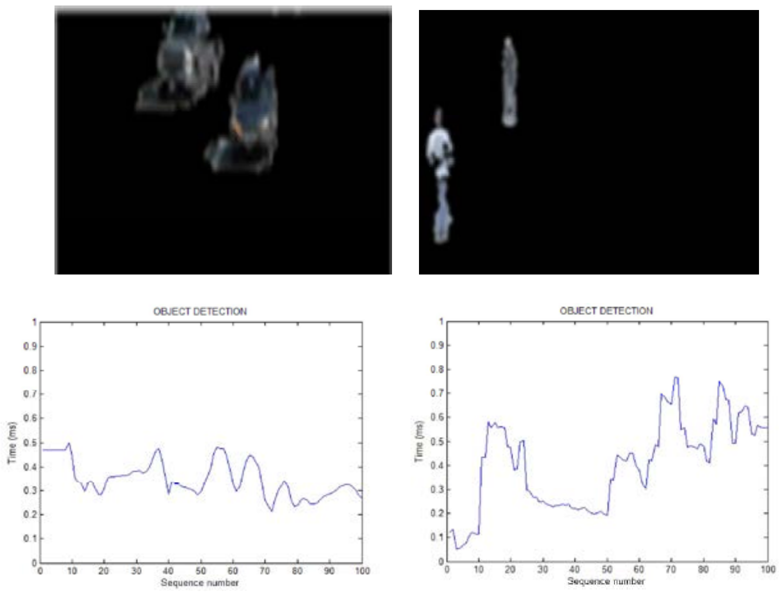
Fig. 3: (a & b) Input Video Frame

Effectiveness: In this work, the EM based EGMM modeling method is utilized to improve the background generated. As shown in Fig. 4, the extracted vehicle field with GMM is presented as the left images. As a result, the EM based EGMM modeling method makes it possible to obtain the whole region linked to the vehicles. The processing result shows the shape of region as the original frame in Fig. 4 (b).

Accuracy: In order to test the accuracy of the proposed method using EM-EGMM, the region is detected by without occluded cases. The accuracy is very high while it is compared to other parameters as shown in Table (1).

(a) (b)

Fig. 4(a & b): Foreground Detection output



(a) (b)

Fig. 5: Object detection output and Average Time Plot

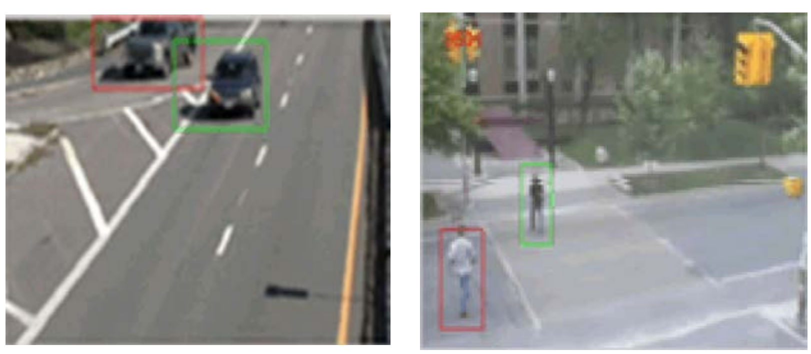


Fig. 6: Object Tracking

Table 1: Quantitative comparison of tracking results

PERFORMANCE MEASURES	CAR	PERSON	VAN-CAR
DETECTION RATE (DR)	48.307	49.82	47.321
FALSE ALARM RATE (FAR)	48.134	42.23	41.3102
ACCURACY (ACC)	93.874	99.39	97.121
JACCARD COEFFICIENT (JC)	46.8366	49.69	45.432
MATTHEW'S CORRELATION COEFFICIENT (MCC)	3.0731e-12	7.3511e-12	5.4318e-12
PERCENTAGE OFCORRECT CLASSIFICATION (PCC)	48.5257	49.87	47.6317

Quantitative Analysis: The performance of the process is measured by the following parameters: detection rate (DR), false alarm rate (FAR), accuracy (ACC), jaccard coefficient (JC), Matthew's correlation coefficient (MCC) and Percentage of correct classification (PCC).

$$DR = \frac{TP}{TP+FN}, FAR = \frac{FP}{FP+TN} \tag{7}$$

$$ACC = \frac{TP+FN}{TP+FN+TN+FP}, JC = \frac{TP}{TP+FP+FN} \tag{8}$$

$$MCC = \frac{TP\times TN-FP\times FN}{(TP+FP)(TP+FN)(TN+FP)(TN+FN)} \tag{9}$$

$$PCC = \frac{TP+TN}{TP+TN+FP+FN} \tag{10}$$

Where TP, FP, TN and FN denote the number of true positives (foreground pixels correctly classified as foreground), false positives (background pixels wrongly classified as foreground), true negatives (background pixels correctly classified as background) and false negative (foreground pixels wrongly classified as background), respectively.

The accuracy (ACC) is high in the person input. Because this provides the background model which works well for relatively static backgrounds with low amount of motion. However, its performance drops in car and van-car sequences where the object image pixel is high as shown in Fig (5) and tracking result is shown in Fig (6).

Accuracy (ACC), JC and MCC are considered to be the best as shown in Table (1) and are used for the experiments. FAR is also used for the average results to highlights the misclassification. For lower FAR and higher ACC, JC and MCC represent better results. The difficulty of assessing background subtraction algorithms originates from the lack of a standardized evaluation framework, the frames are widely used in computer vision to assess the performance of a binary classifier is the percentage of correct classification (PCC). TPR is sensitivity or recall in machine learning. FPR is the fall-out and can be calculated as one minus the more well-known specificity.

The comparison between GMM and EM-EGMM is shown in the Figure (7). Thus the accuracy of our proposed method is 99.39 which is effective than the existing detection methods.

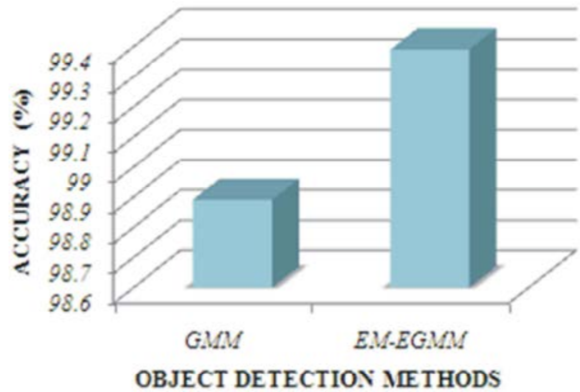


Fig 7: Comparison of GMM and EM-EGMM

CONCLUSION

In this paper, we proposed a foreground object detection scheme, i.e., GMM is fused via multi-view learning framework by using multiple with the expectation maximization algorithm for improving the segmentation quality of moving objects. In order to improve the accuracy the EM based EGMM algorithm is used to obtain preferable detection regions. The detection object becomes the original frame and the background become black in color. This method has also a very good effect on the removal of noise and shadow and be able to extract the complete and accurate picture of moving human body as well as in moving vehicle. The main advantage of this method is fast, simple and achieved with high accuracy. The experimental results demonstrate that our method is more accurate under various conditions.

REFERENCES

1. Yingjie Xia, Xingmin Shi, Guanghua Song, Qiaolei Geng and Yuncai Liu, 2014. Towards Improving Quality of Video-Based Vehicle Counting Method for Traffic Flow Estimation, Elsevier B.V.
2. Gil-jin Jang and Minholee, 2015. A Genetic algorithm based moving object detection for real-time traffic surveillance, IEEE signal processing letters, Vol.22, No.10.
3. Shanshan Zhang, Christian Bauckhage and Armin B.Cremers, 2015. Efficient Pedestrian Detection via Rectangular Features Based on a Statistical Shape Model, IEEE Transactions on Intelligent Transportation Systems, Vol. 16, No. 2.

4. Olivier Barnich and Marc Van Droogenbroeck, 2011. ViBe: A Universal Background Subtraction Algorithm for Video Sequences, IEEE Transactions on Image Processing, Vol. 20, No. 6.
5. Tengfei Long, Weili Jiao, Guojin He and Wei Wang, 2014. Automatic Line Segment Registration Using Gaussian Mixture Model and Expectation-Maximization Algorithm, IEEE Journal Of Selected Topics In Applied Earth Observations And Remote Sensing, Vol. 7, No. 5.
6. Dibyendu Mukherjee, Q.M. Jonathan Wu and Thanh Minh Nguyen, 2014. Gaussian Mixture Model with Advanced Distance Measure Based on Support Weights and Histogram of Gradients for Background Suppression," IEEE Trans. on Industrial Informatics, Vol. 10, No. 2.
7. Zhou Liu, Kaiqi Huang and Tieniu Tan, Fellow, 2012. Foreground Object Detection Using Top-Down Information Based on EM Framework, IEEE Trans. on Image Processing, Vol. 21, No. 9.