Dealing Background Issues in Object Detection using GMM: A Survey

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ABSTRACT
Moving object detection is critical task in video analytics. Gaussian Mixture Model (GMM) based background subtraction is widely popular technique for moving object detection due to its robustness to multimodality and lighting changes. This paper presents the critical survey about various GMM based approaches for handling critical background situations. This survey describes various challenges faced by background subtraction such as shadow, sudden and slow light changes, multimodal background, bootstrap, camouflage, foreground aperture, camera jitter etc. and study of various modifications or extensions of GMM to handle these issues. This study helps researcher to select appropriate GMM version based on critical background condition.

General Terms
Pattern Recognition, Computer Vision, video surveillance

Keywords
Object Detection, Background Subtraction, Gaussian Mixture Model, Background challenges

1. INTRODUCTION
Moving object detection is important task in video analytics. Accuracy at object detection level significantly affects the high level image sequence analysis [1].Lots of research has been carried out to improve the performance of object detection. However, accurate object detection is still challenging due to critical dynamic background conditions [3]. These critical background situations may include flickering monitor, snow, rain, waving tree, shadow, sudden illumination change due to light on/off, slower illumination change during sunrise and sunset, foreground aperture, busy background, object with color same as background, camera jitter etc. Efficient moving object detection system must cope up with these conditions and extract region of interest accurately. Various basic techniques have been defined to detect object such as background subtraction, optical flow, frame differencing [2].Among these, background subtraction is commonly used method due its low memory requirement, simplicity and easiness in implementation [3].

First step in Background subtraction is background modelling. Mean filter, Approximate Median, Kernel Density estimation, single Gaussian, Gaussian mixtures are few background modelling techniques [4]. Among these, Gaussian mixture modelling (GMM) defined by Stauffer and Grimson[5] is widely popular due to its robustness in handling multimodal background and lighting changes. However, scientist still exploring and innovating the established research for performance improvement of object detection.

The aim of this paper is to summarize all the study about GMM based object detection according to different background situations which they can handle. This survey will help researcher to select appropriate GMM version according to their application. The paper is divided in four subsections. Second section describes original GMM in brief along with its challenging background situations. Third section summarizes the study of various GMM versions w.r.t. different background situations. Paper is concluded in section four.

2. GMM BASED BACKGROUND SUBTRACTION
GMM is probabilistic approach for background modelling. Each pixel in the scene is modeled by a mixture of K Gaussian distributions [5]. The probability that a certain pixel has a value of $\boldsymbol{X_t}$ at time t can be written as

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

Where $\omega_{i,t}$ is the weight, $\mu_{i,t}$ is the mean value, and $\Sigma_{i,t}$ is the covariance matrix for the i^{th} Gaussian distribution at time t. where η is a Gaussian probability density function.

$$\eta(X_t, \mu, \Sigma) = \frac{1}{(2\pi)^{n/2}|\Sigma|^{1/2}} e^{-\frac{1}{2}(X_t-\mu_t)^T\Sigma^{-1}(X_t-\mu_t)} \quad (2)$$

The K distributions are ordered based on ratio w/σ and the first B distributions are used as a model of the background of the scene.[5] Where B is estimated as

$$B = argmin_b\left(\sum_{k=1}^{b} \omega_k > T\right) \quad (3)$$

The threshold T is the minimum fraction of the background model. Background subtraction is performed by marking a foreground pixel any pixel that is more than 2.5 standard deviations away from any of the B distributions [5]. The first Gaussian component that matches the test value will be updated by the following update equations, The prior weights of the K distributions at time t, $\omega_{(k,t)}$, are adjusted as follows[5].

$$\omega_{k,t} = (1-\alpha)\omega_{k,t-1} + \alpha(M_{k,t}) \quad (4)$$

Where α is the learning rate and $M_{k,t}$ is 1 for the model which matched and 0 for the remaining models. After this approximation, the weights are renormalized. 1/α defines the time constant which determines the speed at which the distribution's parameters change. The μ and σ parameters for unmatched distributions remain the same. The parameters of the distribution which matches the new observation are updated as follows.

$$\mu_t = (1-\rho)\mu_{t-1} + \rho X_t \quad (5)$$

$$\sigma_t^2 = (1-\rho)\sigma_{t-1}^2 + \rho(X_t-\mu_t)^T(X_t-\mu_t) \quad (6)$$

Where, $\rho = \alpha\eta(X_t|\mu_k, \sigma_k)$

Performance of this system to be satisfactory the appropriate initial tuning of parameters α and T is important [5, 26]. Two main facts about GMM which helps to effectively deals with some background situations are as follows. First, learning rate determines the speed of adaptation to illumination changes which permits to handle the gradual illumination change in the background [3, 5]. Second, use of mixture model allows more than one color to be included in to background model, which is big advantage when background situation is multimodal [3, 5]. Despite these issues, there are many more issues arises in real background scene and that couldn't be handled by original GMM. These issues include shadow, sudden illumination change, camera jitter, foreground aperture, camouflage, bootstrap etc. [3]. Next section includes extensive survey about various GMM versions which is established to deal with these challenges along with multimodality and illumination change.

3. BACKGROUND CHALLENGES AND GMM VERSIONS

Background can be static or dynamic. Object detection in static background is simple. It requires less memory and computational time. Implementation is easy for such system. In the case of dynamic background, required object detection system is complex. Object detection system has to adapt with dynamic background and perform satisfactorily in real time. Various background situations and solution to handle these situations using GMM based object detection system are discussed in next subsections.

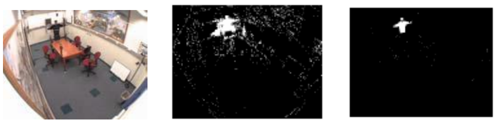
3.1 Shadow

Shadow is mostly explored background challenge, since this is common issue in indoor and outdoor scene. It arises certainly if foreground object is present in the scene. Incorrect labeling to shadows as foreground pixels may cause failure in applications such as tracking, video surveillance, motion segmentation, etc.

Wang et al[6] used mixed color space to suppress shadow. The color space adopted as **(r, g, I)** while **r, g** are normalized chromaticity coordinates and **I** is the intensity coordinates. The shadow is suppressed using criteria $\beta \leq I_t/\mu_i \leq \gamma$. Where (r_t, g_t, I_t) is observed value at the pixel in frame t. μ_i, σ_i is mean and standard variance of the ith Gaussian distribution. During low intensity r, g components are noisy. This may affect the performance. Hence the solution for this problem is mixed color space

$$x = \begin{Bmatrix} (r,g,I) & if\ I > Itd \\ (R,G,I) & if\ I < Itd \end{Bmatrix} \quad (7)$$

Where Itd is a threshold and R, G are red and green color component. This modification improves the results, especially for video sequences including dark scenes, of background modeling.



(a) (b) (c)

Fig. 1. (a) Image of a person and shadows;(b) Detection result using RGB; (c) using (*r, g, I*).

Porikili et al[7], assumes that shadow effects on luminance and saturation while maintaining hue constant. Their method adapted luminance difference and saturation difference. Additionally, authors defined shadow color range as a conic cylinder around the background color vector. This approach improves the detection accuracy.

Kristensen et al[8] studied seven different color space to observe the behavior of shadow covered pixel. In the case of YCbCr color space, Y will always be smaller when shaded and that Cb and Cr will go towards 128, i.e. the origin. With this information and considering noise three rules are developed. All three assume that a negative change in Y has already been detected. Rules are shown in Fig.1

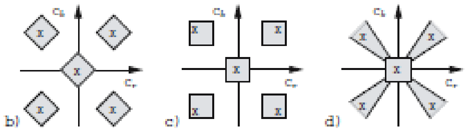


Fig.2. Three different shadow detection rules. The gray areas represent the part of the CbCr plane where a new pixel is ruled to be a potential shadow. The area location is based on the stored mean of Cb and Cr (Cb Cr)

Tian et al[9] improved the original GMM for shadow removal by integrating the intensity information. The normalized cross-correlation (NCC) of the intensities is calculated at each pixel of the foreground region between the current frame and the background image. The pixel is detected as shadow if NCC is greater than predefined threshold T_s and intensity of pixel is greater than predefined threshold T_i. This approach allows shadow detection in bright areas only.

Mazeed et al[10], described a statistical disturbance technique for shadow detection. The algorithm initially uses N frames to form the background model. From these frames, the mean and the variance is computed for each color band (RGB) in each pixel. The brightness distortion, β, is computed between the background model and a new pixel. If this distortion is negative then new pixel is considered as shadow and classified as background.

3.2 Sudden and Slower Illumination Change

Sudden and slower illumination change is quite common issue in indoor and outdoor scene respectively. Learning rate parameter in original GMM determines the adaptation rate. Therefore, it's proper tuning helps GMM to deal with slow illumination change in the background. Whereas, GMM performance degrades in the sudden light change due to selected learning rate value is insufficient to adapt with sudden change. If learning rate is kept high for such background case, then foreground object will merge in background. Various modification and extension for GMM is defined in order to improve the performance in slow and sudden light change.

Teixeira et al [11] proposed cascade of change detection tests including noise-induced, illumination variation and structural changes. Pixels are removed from set of candidate foreground pixel if they pass one of these tests. Illumination variation change detection is carried out by simple co-linearity test. The test consists evaluation of the angle between the current pixel color vector v^c and the reference color vector v^r.

$$\cos\theta = \frac{v^c . v^r}{\|v^c\|\ \|v^r\|} \quad (8)$$

If cos(θ) is greater than a predefined threshold T_I , vectors are considered to be collinear and the test is validated. Such pixels are marked as background pixel and removed from candidate foreground pixel set. This approach deals effectively with illumination changes as shown in fig 3.

Fig.3 Test sequences and detection outputs for GMM based on cascaded change detection

Porikily et al.[7] applied learning rate adaptation based illumination change score. In this approach, the reference image is updated if only a lighting change occurs in the scene. Gaussian models with low variance (high confidence) are not updated in this case. For this propose, an illumination change score λ(t)is computed for a set of randomly selected pixels that do not correspond to an object in the previous frame. If illumination change score λ (t) is larger than a threshold τ the learning parameter is adjusted as

$$\alpha = 0.01 + \frac{\lambda\,(t)}{c} \qquad \tau < \lambda\,(t) \tag{9}$$

Where, c is the number of pixels in the pixel set Q. The value of τ is determined empirically, and it controls the agility of the update mechanism. This method improved the adaptation performance of the original GMM by observing the amount of illumination change in the background and updating a second learning coefficient accordingly. This improvement significantly reduces the computational load by minimizing unnecessary model updates.

Javed et al. [12] developed a hierarchical approach that combines color and gradient information to solve the problem about rapid intensity changes. Javed et al. [12] adopted the k^{th}, highest weighted Gaussian component of GMM at each pixel to obtain the gradient information to build the gradient-based background model. However, choosing the highest weighted Gaussian component of GMM leads to the loss of the short term tendencies of background changes. Whenever a new Gaussian distribution is added into the background model, it is not selected owing to its low weighting value for a long period of time. Consequently, the accuracy of the gradient-based background model is reduced for that the gradient information is not suitable for representing the current gradient information.

To solve this problem Hu at al[13], selected the value of k using Short Term Color Background Model(STCBM) and Long Term Color Background Model(LTCBM). It helps to develop a more robust gradient-based background model and maintain the sensitivity to short-term changes.

Wang et al [6], adjusted the learning rate to deal with sudden illumination change. In this case, If the pixel number of detected foreground pixels is larger than a threshold (e.g., 70% of the whole image pixels as in Wallflower), learning rate adjusted to a high value; otherwise, it sets to a low value.

3.3 Multimodal Background

Multimodal situation arises when motion is present in the background. For e.g. if scene contains one or more of situations like waving tree, flickering monitors, rippling water, snow or rain; then scene is called as multimodal scene.

Original GMM robustly handles multimodal background. However, parameter K is fixed experimentally and constant over time which is not optimal in terms of detection and computational time [5].

Zivkovic [14] uses recursive equation with dirichlet prior for appropriate selection of number of component for each pixel. GMM initialization start with one component centered on the first sample and new components are added based on following condition.

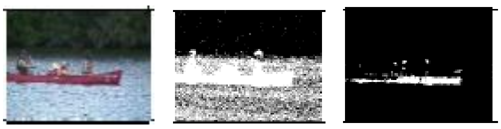
$$B = arg\,\min_b \left(\sum_{m=1}^{b} \omega_m \quad > (1 - c_f) \right) \tag{9}$$

Where, c_f is a measure of the maximum portion of the data that can belong to foreground objects without influencing the background model. The Dirichlet prior with negative weights will suppress the components that are not supported by the data and component will be discarded if its weight becomes negative. This improved GMM reduces the processing time.

In the same way, Lee [15] presented an online EM learning algorithm for training adaptive Gaussian mixtures. Set of recursive parameter update equations is derived based on short term sufficient statistics. These parameters are computed without additional storage of auxiliary variables. Experimental result showed superior efficiency and robustness on large simulations as well as real video data.

Chen and yang et al [16] proposed an approach to construct background models directly from compressed video. It utilizes the information from DCT coefficients at block level to construct accurate background models at pixel level. In this case, algorithm models DCT coefficients of each block in DCT domain as a mixture of Gaussians. Each pixel block is processed using Euclidian distance as matching function. A threshold is associated with it to determine if the current block matches a Gaussian, and the threshold will be updated. This approach has much lower computational cost, compact model storage without affecting the performance of original GMM.

In terms of improved detection accuracy, Zhao et al [17] proposed a novel background modeling Method based on Type-2 Fuzzy Gaussian Mixture Model (T2-FGMM) and Markov Random Field (MRF), for motion detection in dynamic scene. Spatial-temporal constraints are introduced into the T2-FGMM by a Bayesian framework. The evaluation results show that this approach performs better than the sound Gaussian Mixture Model (GMM) in typical dynamic backgrounds such as waving trees and water rippling.



(a) (b) (c)

Fig. 4 (a) Test sequence containing rippling water (b) GMM (b) T2-FGMM foreground mask.

3.4 Camera Jitter

Camera shake is called as camera jitter. It results in specific frequent change in background scene. The original GMM is initialized using a training sequence. If this sequence is noisy and/or insufficient to model background correctly, then it generates false classification in the foreground detection mask due to the related uncertainty.

Bouwmans et at [18] proposed Type-2 Fuzzy Mixture of Gaussians Model (T2FMGM) to account for the uncertainty in the background. Uncertain mean vector or covariance matrix is used to produce the T2 FMGM with uncertain mean vector (T2 FMGM-UM) or uncertain variance (T2 FMGM-UV).

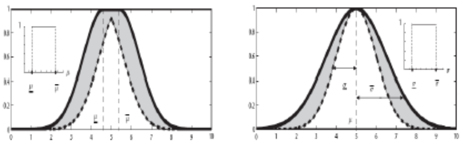


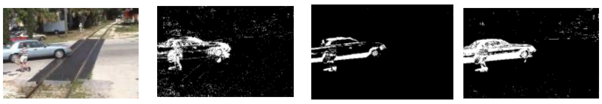
Fig. 5(a) the Gaussian primary MF with uncertain mean. b): At the right, the Gaussian primary MF with uncertain std having uniform possibilities. The shaded region is the footprint of uncertainty. The thick solid and dashed lines denote the lower and upper MFs.

Uncertainty mean is $\mu \in [\underline{\mu}, \overline{\mu}]$ .and uncertainty in variance is $\sigma \in [\underline{\sigma}, \overline{\sigma}]$. The factor k_m and k_v control the intervals in which the parameter vary as follows:

$$\underline{\mu} = \mu - k_m \sigma, \quad \overline{\mu} = \mu + k_m \sigma, \quad k_m \in [0,3] \tag{10}$$

$$\underline{\sigma} = k_v \sigma, \quad \overline{\sigma} = \frac{1}{k_v} \sigma, \quad k_v \in [0.3,1] \tag{11}$$

This approach works better for camera jitter as compared to original GMM as can be seen from Fig 6



(a) (b) (c) (d)

Fig.6 (a) Test sequence (b) original GMM (c) T2 FMGM-UM (d) T2 FMGM-UV Foreground Mask.

Huijun Di et al. [19] said that original GMM assumes the correspondence among the pixels in concurrent frames, therefore cannot handle the case which contains camera jitter. They developed a new background model by introducing correspondence into it. Based on this model, they formulated the foreground segmentation and correspondence estimation as a labeling problem. Spatial context is enforced to every pixel based on tree structure. This allows using dynamic programming (DP) technique to compute global optima efficiently. Finally, background model is updated based on estimated optimal correspondence. This method reduces parallax effect and registration errors significantly refer fig 7

(a) (b)

Fig. 7 (a) Test Sequence (b) detection output

Achkar [20] uses hysteresis based component matching to improve the object blob quality at object detection stage. Camera perturbation is addressed at frame level depending on percentage of pixels classified as foreground.

3.5 Bootstrap

This condition arises if background is continuously busy with foreground objects. Two cases are possible in such scene. First case, Background is too busy and no single frame will available without object. Second case, background is busy still some initial frames without objects are available.

Amintoosi et al [21], handled first case using QR decomposition method. Here, Background is identified using QR decomposition. R-values are taken from QR Decomposition and then applied to decompose a given system to indicate the degree of the significance of the decomposed parts. Then image is split into small blocks and background blocks are selected based on weakest contribution, according to the assigned R values. This improves object detection accuracy significantly in busy environment.

Harville et al [22] proposed adaptive Gaussian mixture per pixel in the combined input space of depth and luminance invariant color. This model is further improved for bootstrap challenge by adapting the learning rate based on scene activity. Proposed method robustly handles second kind of bootstrap challenge. It is also suited for real time environment.

3.6 Camouflage

This kind of scenario may contain foreground object with color similar to background. It causes ambiguity during detection process about decision with foreground or background. Original GMM requires fine tuning of important parameters but still it tends to increase in false alarm.

Cristani et al [23] proposed joint pixel-region analysis which is called as adaptive spatio-temporal neighborhood analysis (ASTNA). In this method, each pixel went through BGPP (Background per Pixel) test. If this test becomes true for given pixel then it is classified as background else considered as not background. Pixels those are marked as 'not background' in this test need to carry BGPR (Background Per region) test. If this test is validate for given pixel then it will classify as background otherwise marked as foreground.

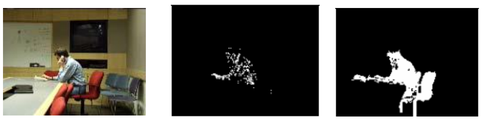
Harville et al [22] proposed adaptive Gaussian mixture per pixel in the combined input space of depth and luminance invariant color. This model is improved for camouflage by making color based segmentation criteria dependent on depth observations. This modification significantly reduces the misclassification caused due to camouflage.

Darell et al [24] proposed the multidimensional clustering based on range and color at image pixel. Range based segmentation is largely independent of color, and hence not affected by problems of shadows and camouflage. However, range alone is also not sufficient for the good segmentation: depth measurements are rarely available at all pixels in the scene, and foreground objects may be indistinguishable in depth when they are close to the background. Color segmentation is complementary in these cases. Their combinational clustering robustly deals with camouflage situation.

3.7 Foreground Aperture

It is the phenomena in which parts of large moving homogenous regions become part of the background instead of being selected as moving pixels. Very less research has been taken place for this challenge. However, it must carry more attention as one of the important common issue in background.

Utasi et al [25] uses separate foreground model with single Gaussian distribution to represent large homogenous foreground areas. This model is updated in same way as background model in original GMM. Foreground pixels are investigated for similar foreground neighbor, to deal with foreground aperture challenge. If the pixel has foreground component variance within a range of the investigated pixel then neighbor’s deviation is increased. It is known as deviance flooding. It is checked for pixels within fix radius and marked as foreground pixel.



(a) (b) (c)

Fig 8 (a) Test sequence (b) original GMM(C) Utasi model Foreground Mask

Table 1 summarizes all GMM approaches based on background challenges.

Table 1 Summary of GMM approaches corresponds to background challenges

Sr. No.	*Background Challenges*	*GMM Modifications/Extensions*	*Authors*
1	Shadow	1. Mixed Color Space 2. Adaptation of luminance and saturation difference 3. YCbCr color space with shadow detection rules 4. Normalized cross correlation 5. Statistical Disturbance Technique	1. Wang et al [6] 2. Porikilly et al [7] 3. Kristensen et al [8] 4. Tian et al [9] 5. Mazeed et al [10]
2	Sudden and Slower Illumination change	1. Cascaded GMM 2. Learning rate adaptation based on illumination change score 3. Combination of color and gradient information 4. Long term and short term tendencies of change 5. Learning rate adjustment if sudden change	1. Teixeira et al [11] 2. Porikily et al [7] 3. Javed et al [12] 4. Hu et al [13] 5. Wang et al [6]
3	Mutimodality	1. Dirichlet Prior 2. Online EM algorithm 3. Background construction using DCT 4. Type-2 Fuzzy Gaussian Mixture Model (T2-FGMM) and Markov Random Field (MRF)	1. Zivcovic[14] 2. Lee at al [15] 3. Chen et al [16] 4. Zhao et al [17]
4	Camera Jitter	1. T2 FMGM-UM and T2 FMGM-UV 2. Background model with correspondence 3. Hysteresis based component matching	1. Bouwmans et at [18] 2. Huijun Di et al.[19] 3. Achkar [20]
5	Bootstrap	1. QR decomposition 2. Learning rate adaptation based scene activity	1. Amintoosi et al [21] 2. Harville et al [22]
6	Camouflage	1. Adaptive Spatio-Temporal Neighborhood Analysis(ASTNA) 2. Object segmentation based on color and depth 3. Multidimensional clustering based on range and color	1. Cristani et al [23] 2. Harville et al [22] 3. Darell et al [24]
7	Foreground Aperture	1. Separate foreground model with single Gaussian distribution	1. Utasi et al [25]

4. CONCLUSION

This paper presents the extensive survey of various GMM approaches to deal with different background challenges. It also provides brief description of GMM approaches. Background challenges that can be tackled by various GMM versions include shadow, slow and sudden illumination change, multimodality, camera jitter, bootstrap, camouflage, foreground aperture. Among these issues, shadow, illumination change are extensively explored by researcher while foreground aperture remains less attentive. Various GMM versions can handle multiple issues concurrently. This study helps researcher to select appropriate version of GMM based on their application. This survey on GMM approaches with rich bibliography content can give valuable insight into this important background challenges and encourage new research.

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