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# A New Process for Selecting the Best Background Representatives based on GMM

Nebili Wafa, Seridi Hamid, and Kouahla Mohamed Nadjib

LabSTIC, Computer Science Department, 8 Mai 1945 Guelma University, POB 401
Guelma, Algeria
(nebili.wafa, seridi.hamid, kouahla.nadjib)@univ-guelma.dz

**Abstract.** Background subtraction is an essential step in the process of monitoring videos. Several works have been proposed to differentiate the background pixels from the foreground ones. Mixtures of Gaussian (GMM) are among the most popular models for this problem. However, they suffer from some inconveniences related to light variations and complex scene. This paper proposes an improvement of the GMM by proposing a new technique of ordering the Gaussians distributions in the selection phase of the scene's best representatives. This approach replaces the usual ranking of Gaussian according to the value of $w_{k,t}/\sigma_t$ with sorting according to their covariance measure which is calculated between each pixel and each of these Gaussians. The obtained results on the Wallflower dataset has proven the effectiveness of the proposed approach compared to standard GMM.

**Keywords:** GMM, Video Surveillanc, Background Subtraction

## 1 Introduction

Various applications of video surveillance such as the detection and tracking of moving objects begin with background subtraction phase. Background subtraction is a binary classification operation that gives a label [9] to each pixel of a video sequence, for example: the pixels of the moving objects (foreground) take the value 255 and the pixels of the static objects are labeled with 0.

In recent years, video change detection or Background Subtraction (BS) has proved to be a difficult task that has attracted the attention of researchers in computer vision. This task requires a robust and efficient method that must ensure a good separation between the background and the foreground, with gain in execution time and memory space.

Work presented in [43] have demonstrated that GMM offers a good compromise between quality and execution time compared to other methods. GMM is a statistical model that describes pixel variations by several Gaussian distributions [35]. However, local variations in brightness reduce the performance of this method [17].

Several studies have showed that the order of Gaussians in GMM influence the results quality.

This paper proposes a novel mechanism that uses the covariance measure instead of the value of $w_{k,t}/\sigma_t$ to arrange the Gaussian in the GMM background model proposed by Stauffer et al. [35].

The remainder of the paper is organized as follows: Section 2 discusses the related works. Section 3 explains GMM method, while Section 4 presents the proposed approach. Results are discussed in Section 5. Section 6 concludes the paper and highlights some future perspectives.

## 2 Related Work

In recent years, various approaches, methods and systems have been proposed and developed to inspect dynamic regions and static regions. One of the most intuitive approaches is to compute the absolute difference ($\Delta_t$) either between two successive frames [9], or between a reference image $I_R$, without any moving object and the current image. In order to determine the objects in motion, a binary mask is applied according to a predefined threshold on the pixels of the resulting image [16].

Another approach to subtract the background is to describe the history of the last $n$ pixel values by a Gaussian probability distribution [42]. However, modeling by a single Gaussian is sensitive to fast pixel variations. Indeed, a single Gaussian can not memorize the old states of the pixel. This requires migration to a robust and multimodal approach.

Authors in [18] have proposed the first model which describes the variance of the recent values of each pixel by a mixture of the Gaussians. In this model, the Expectation Maximization (EM) algorithm is used to initialize and estimate the parameters of each Gaussian. In [14] authors have estimated the probability density function of the recent $N$ values of each pixel by a kernel estimator

(KDE). Furthermore, authors in [19] have provided a nonparametric estimation of the background pattern. They used the concept of a visual dictionary words to model the pixels of the background.

Indeed, each pixel of the image is represented by a set of three values (visual word) which describes its current state. These values are initially estimated during the learning phase and are updated regularly over time to build a robust modeling.

In addition, several works have taken spatial information into consideration. Oliver et al. have proposed a sub-spatial learning based on PCA (SL-PCA) [26]. The aim is to make a learning of the $N$ background images using PCA. Moving objects are identified according to the input image and the reconstructed image from its projection in the reduced dimension space. While, Tsai and Lai have provided in [37] a quick schema (SL-ICA) for background subtraction with Independent Component Analysis (ICA). Also, Bucak and Gunsel [6] have presented a decomposition of video content by an incremental non-negative matrix factorization (NMF).

Other methods in [1], [21], [20], [23] and [44] have focused on the selection and combination of good characteristics (color, texture, outlines) to improve the result quality.

Recently, some research works have introduced the fuzzy concept to develop more efficient and robust methods for modeling the background, such as [11], [34], [4], [12], [13] and [45].

Moreover, work presented in [43], has shown that GMM offers a good compromise between quality and execution time compared to other methods. The first GMM model was proposed by [18]. However, Stauffer and Grimson [35] have presented a standard GMM with efficient update equations.

Several works and contributions have been proposed to improve the quality of GMM. Among these methods, some of them focus on improving the model adaptation speed, such as [28] and [22]. While other studies have been interested in hybrid models, such as GMM and K-means [8], GMM and fuzzy logic [13], GMM and adaptive background [10], Markov Random Fields [29], GMM and Block matching [16], GMM with PSO [41] to overcome GMM problems. There are also several works that have invested in the characteristics type [7], [32] or in the acquisition material [31].

In addition to spatio-temporal methods [33], some researchers have used local contextual information around a pixel, such as the region [15], [27], the block [39] and the cluster [3], [38].

In the last years, there have been several methods that used deep learning for subtracting the background, among them : FgSegNet_S (FPM) [25], Cascade CNN [40], DeepBS [2], Deep background subtraction with scene-specific convolutional neural networks [5]. However, deep leaning methods require a large number of simples and needs more time for training.

## 3 Gaussian Mixture Model (GMM)

In the dynamic background, the variations of the pixel are so fast, that a single Gaussian cannot memorize their old states. This problem leads to the appearance of a multimodal background representation with a mixture of $K$ Gaussian.
The initial version of GMM was proposed by [18], however, Stauffer and Grimson have proposed an adaptive GMM method with efficient update equations to model a dynamic background in image sequences.
GMM represents the history of each pixel with $K$ Gaussian distributions. For example, the alteration of night and day is modelled using two Gaussians: one Gaussian models the variation of temporal intensity of pixel during the night; the other Gaussian represents the different local intensities produced by the day [30].
The principle of the method is simple: using a pixel $P$, their current state can be determined by comparing their value with the corresponding GMM model. A high probability of belonging to these Gaussian mixtures indicates a background pixel. The probability of observing the current pixel value ($P_t$) is determined as follows:

$$P(P_t) = \sum_{i=1}^{k} w_{i,t}\eta(u_{i,t}, \Sigma_{i,t}, P_t) \tag{1}$$

With :

$$\eta(P_t, u, \Sigma) = \frac{1}{2\pi^{\frac{n}{2}}|\Sigma|^{\frac{1}{2}}} e^{-\frac{1}{2}(P_t-u_t)^T \Sigma^{-1}(P_t-u_t)} \tag{2}$$

After initialization of the Gaussian parameters $(w_k, u_K, \sigma_k)$, each pixel search in its $K$ existing distributions the Gaussians that corresponding to it.

$$\frac{P_t - u_i}{\sigma_i} < 2.5 \tag{3}$$

If the equation (3) is realized, the parameters of the corresponding Gaussian are updated by the equations (4), (5), (6), (7).

$$w_{i,t} = (1-\alpha)w_{i,t-1} + \alpha \tag{4}$$

$$u_{i,t} = (1-\phi_i)u_{i,t-1} + \phi_i \times P_t \tag{5}$$

$$\sigma^2_{i,t} = (1-\phi_i)\sigma^2_{i,t-1} + \phi_i \times (P_t - u_{i,t})^T(P_t - u_{i,t}) \tag{6}$$

$$\phi_i = \alpha \times \eta(P_t|u_i, \sigma_i) \tag{7}$$

For the other distributions that do not satisfy the equation (3), their weight is updated according to the equation (8).

$$w_{i,t} = (1-\alpha)w_{i,t-1} \tag{8}$$

After updating the parameters, a normalization step is performed to ensure that the sum of the weights always equals 1. If the match with all the $K$ distributions is not found, the parameters of the least probable Gaussian will be replaced by the mean, variance and weight of the current pixel according to the following equations:

$$\sigma_i^2 = \sigma_t^2 \tag{9}$$

$$w_i = \phi_t \tag{10}$$

$$u_t = P_t \tag{11}$$

For classify the pixels to foreground and background pixels, the distributions will be ordered according to $w_{i,t}/\sigma_{i,t}$ value. The first distributions $\beta$ that verify equation (12) are selected to represent the background.

$$\beta = argmin(\sum_{i=1}^{k} w_{i,t} > B) \tag{12}$$

Table 1: Symbols considered in this proposition

| Symbol | Meaning |
|---|---|
| $P_t$ | The value of the pixel $P$ in time $t$ |
| $K$ | The number of Gaussians associated at pixel $P$ in time $t$ |
| $w_{i,t}$ | The calculated weight for the $i^{th}$ Gaussian at time $t$ |
| $u_{i,t}$ | The average of the $i^{th}$ Gaussian at time $t$ |
| $\Sigma_{i,t}$ | The covariance matrix of the $i^{th}$ Gaussian at time $t$ |
| $\alpha$ | Learning rate |
| $\sigma^2_{i,t}$ | The covariance of the $i^{th}$ Gaussian at time $t$ where the covariance matrix is of the form $\Sigma_{i,t} = \sigma_i^2 I$ |
| $B$ | The minimum part of the data corresponding to the background |

## 4 Proposition

The in-depth study made on Gaussian mixtures shows the important role played by Gaussian ordonnancement in the selection phase of background representatives on the quality of the background subtraction result.
Based on this principle, a novel ordering of Gaussians distribution was proposed. The covariance measure between the pixel $P_t$ and each of this Gaussians $g_i$ (equation (13)) was used instead of the value $w_{k,t}/\sigma_t$. This mechanism represents a legal sort. It allows to arrange the Gaussians according to their similarity to the current pixel.

$$cov(P_t, g_i) = (P_t - u_{P_t})(u_i - u_{g_i}) \tag{13}$$

Where,
$u_{P_t} = \frac{1}{n}\sum_{l=1}^{n} P_{t_l}$ and $u_{g_i} = \sum_{l=1}^{n} u_{g_l}$

A group of Gaussian representatives $G_i$ was created similarly to pixel $P_t$. Therefore, the covariance between $P_t$ and $u_{g_i}$ is smaller than the model $g_i$ which is closer and more representative of $P_t$.

$$G_i = g_1, g_2, .., g_k \tag{14}$$

Where,
$cov(P_t, u_{g_1}) < cov(P_t, u_{g_2}).. < cov(P_t, u_{g_k})$
Gaussians which represent the state of $P_t$ are the first $\beta$ distributions that verify equation (12).
In terms of learning phase, the same classical GMM principle was applied, presented in section 3. In addition, each pixel was characterized by its intensity $H$ in HSV color space.

# 5 Tests and Results

The system presented in this paper was implemented in Python on a computer with an Intel Core i7 and a 8GB memory capacity. This section presents the

Table 2: Description of Wallflower dataset

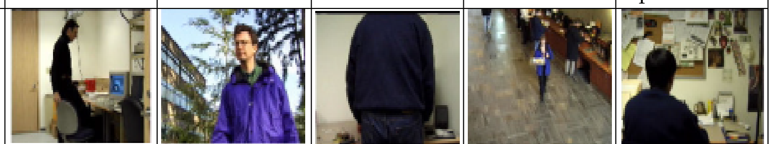
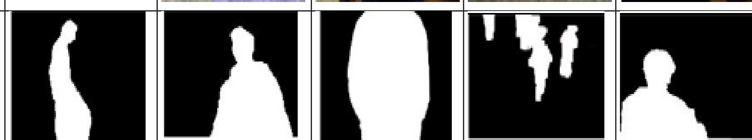
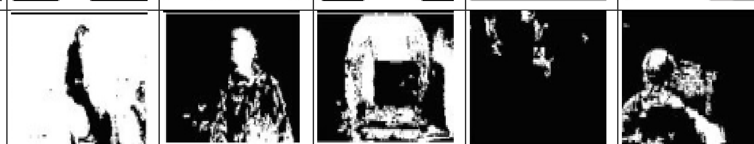
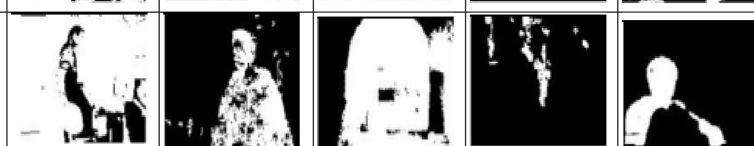
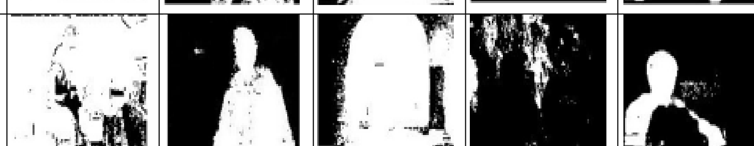
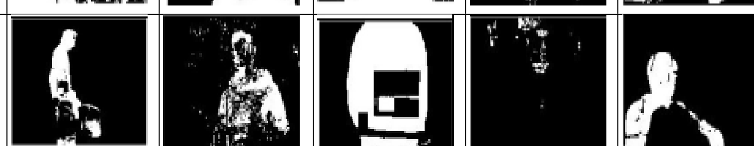
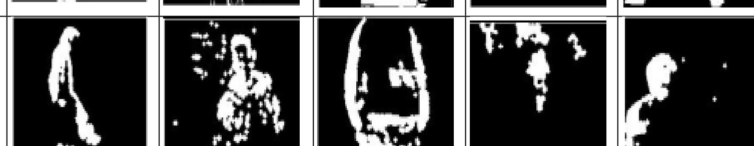
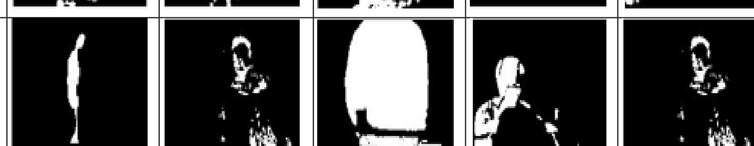
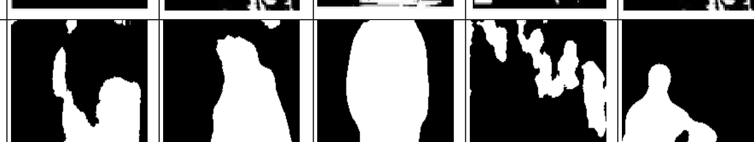
| Video name | Number of frames | Resolution | Image evaluated |
|---|---|---|---|
| Moved Object | 1745 | 160 × 120 | 00985 |
| Time of Day | 5890 | 160 × 120 | 01850 |
| Light Switch | 2715 | 160 × 120 | 01865 |
| Waving Trees | 243 | 160 × 120 | 00247 |
| Camouflage | 281 | 160 × 120 | 00251 |
| Bootstrap | 3055 | 160 × 120 | 00299 |
| Foreground Aperture | 2113 | 160 × 120 | 00489 |

results of the proposed method on some videos from the Wallflower dataset [36]. This dataset contains a total of 7 videos (Moved Object ($MO$), Time of Day ($TD$), Light Switch ($LS$), Waving Trees ($WT$), Camouflage ($Ca$), Bootstrap ($Bo$), Foreground Aperture ($FA$)) with a spatial resolution of $160 \times 120$, as shown in Table 2. To ensure the stability of the system during test phase the parameters values were fixed: Gaussians number $K$, learning rate $\alpha$ and minimum portion measure $B$ respectively to 5, 0.001 and 0.3. This choice was fixed after several empirical tests. The same parameters were used for all videos in the dataset. Some videos were chosen from the Wallflower dataset (LS, WT, Ca, Bo, FA), which cover only the most difficult situations to model.

## 5.1 Qualitative Evaluation

As preliminary results, a qualitative evaluation was made on the Wallflower dataset. Table 3 presents the obtained results of the proposed system on Wallflower

Table 3: Comparison of qualitative results with well-known background subtraction methods on Wallflower dataset

| | Light switch | Waving Trees | Camouflage | Bootstrap | Foreground Aperture |
|---|---|---|---|---|---|
| Tests images |  | | | | |
| Ground Truth |  | | | | |
| SG [42] |  | | | | |
| MOG [35] |  | | | | |
| KDE [14] |  | | | | |
| SL-ICA [37] |  | | | | |
| SL-INMF [6] |  | | | | |
| SL-IRT [24] |  | | | | |
| Proposed |  | | | | |

dataset compared with the most pertinent literature works in the modeling of the background. These results clearly showed that the proposed system overcomes other related literature methods in videos with small variations in the background. The qualitative results is not sufficient, since the observable result does not ensure a delicate representation of the system performance. For this reason the quantitative analysis is necessary to describe system robustness with an objective way.

### 5.2 Quantitative evaluation

This evaluation aims to describe the efficacy of the proposed method on moving object detection. To evaluate the proposed method, False Positive (FP), False Negative (FN) and Total Error of the image evaluated of each video were calculated (Table 4).
Where,

- **False negative (FN):** the result is negative(0), but the ground truth is positive (255).
- **False positive (FP):** the result is positive(255), but the ground truth is negative(0).

Table 4: Comparison of quantitative results with well-known background subtraction methods on Wallflower dataset

| | Error | Light switch | Waving Trees | Camouflage | Bootstrap | Foreground Aperture | Total errors |
|---|---|---|---|---|---|---|---|
| SG[42] | FN | 1857 | 3110 | 4101 | 2215 | 3464 | 20038 |
| | FP | 1512 | 357 | 2040 | 92 | 1290 | |
| MOG [35] | FN | 1633 | 1323 | 398 | 1874 | 2442 | 26025 |
| | FP | 14169 | 341 | 3098 | 217 | 530 | |
| KDE [14] | FN | 760 | 170 | 238 | 1755 | 2413 | 25027 |
| | FP | 14153 | 589 | 3392 | 933 | 624 | |
| SL-ICA [37] | FN | 1557 | 3372 | 3054 | 2560 | 2721 | 14109 |
| | FP | 210 | 148 | 43 | 16 | 428 | |
| SL-INMF [6] | FN | 1593 | 3317 | 6626 | 1401 | 3412 | 17893 |
| | FP | 303 | 652 | 234 | 190 | 165 | |
| SL-IRT [24] | FN | 2822 | 4525 | 1491 | 1734 | 2438 | 16735 |
| | FP | 1512 | 7 | 114 | 2080 | 12 | |
| Proposed | FN | 1099 | 8 | 199 | 684 | 768 | 10463 |
| | FP | 3551 | 1291 | 3 | 2528 | 332 | |

The proposed method overcomes all other methods with total errors of 10463. In Camouflage video this approach achieved good results. It was ranked at first position with 199 FN and 3 FP. In Waving Trees video the proposed method

achieved acceptable results with 8 FN and 1291 FP.
Moreover, the results showed that there 684 FN in Bootstrap video, so the proposed method was in the first position, but the result was poor in FP.

In the Foreground Apeture, the proposed system was among top 3 with first position in FN and third position in FP. In Light Switch the method was ranked at the second position in FN and it achieved acceptable results in FP.
Furthermore, the proposed system gives worse FP in Waving Trees, Light Switch and Bootstrap. This is due to the nature of the method that uses a pixel-based approach to detect moving objects and a non-static background inevitably engenders such behavior of the proposed system.

## 6 Conclusion and Future Work Perspective

This paper proposed a new approach which allows to reduce the drawbacks of GMM for background subtraction. The approach consists of replacing the conventual ordering method of the Gaussians. It represents the background of a new method based on the covariance measurement between the pixel and each of these Gaussians. Obtained results on several videos from a public benchmark Wollflower showed the effectiveness of this new process compared to standard GMM.
Considering the promising results presented in this article, the choice to change the Gaussian modeling to other characteristics (texture, contour) in order to increase the precession of this method represents a future work perspective.

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