Fuzzy Statistical Modeling of Dynamic Backgrounds for Moving Object Detection in Infrared Videos

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Abstract

Mixture of Gaussians (MOG) is the most popular technique for background modeling and presents some limitations when dynamic changes occur in the scene like camera jitter and movement in the background. Furthermore, the MOG is initialized using a training sequence which may be noisy and/or insufficient to model correctly the background. All these critical situations generate false classification in the foreground detection mask due to the related uncertainty. In this context, we present a background modeling algorithm based on Type-2 Fuzzy Mixture of Gaussians which is particularly suitable for infrared videos. The use of the Type-2 Fuzzy Set Theory allows to take into account the uncertainty. The results using the OTCBVS benchmark/test dataset videos show the robustness of the proposed method in presence of dynamic backgrounds.

1. Introduction

Many video surveillance systems in visible spectrum [7, 38, 28] or infrared (IR) [10, 18, 3] need in the first step to detect moving objects in the scene. The basic operation used is the separation of the moving objects called foreground from the static information called the background. The process is called the background subtraction. In the literature, many background modeling methods have been developped and the most recent surveys can be found in [12]. These background modeling methods can be classified in the following categories: Basic Background Modeling [19, 23, 41], Statistical Background Modeling [36, 29, 11] and Background Estimation [32, 25, 6]. Reading the literature, two remarks can be made: The most used models are the statistical ones due to their robustness to the critical situations. The first way to represent statistically the background is to assume that the history over time of intensity values of a pixel can be modeled by a single Gaussian (SG) [36]. However, a unimodal model cannot handle dynamic backgrounds when there are waving trees, water rippling or moving algae. To solve this problem, the Mixture of Gaussians (MOG) has been used to model dynamic backgrounds [29]. This model has some disadvantages. Background having fast variations cannot be accurately modeled with just a few Gaussians (usually 3 to 5), causing problems for sensitive detection. So, a non-parametric technique [11] was developed for estimating background probabilities at each pixel from many recent samples over time using Kernel density estimation (KDE) but it is time consuming. In [27], Subspace Learning using Principal Component Analysis (SL-PCA) is applied on N images to construct a background model, which is represented by the mean image and the projection matrix comprising the first p significant eigenvectors of PCA. In this way, foreground segmentation is accomplished by computing the difference between the input image and its reconstruction. These four models define the first category using basic statistical model. The second category uses more sophisticated statistical models as Support Vector Machines (SVM) [22], Support Vector Regression (SVR) [35] and Support Vector Data Description (SVDD) [31]. The third category generalizes the models of the first category as the single general Gaussian (SGG) [17], the mixture of general Gaussians (MOGG) [2] and subspace learning using Incremental Component Analysis (SL-ICA) [34] or using Incremental Non-negative Matrix Factorization (SL-INMF) [5] or using Incremental Rank-(R1,R2,R3) Tensor (SL-IRT) [21]. The Table 1 shows an overview of the statistical background modeling. The first column indicates the categories and the second column the name of each method. Their corresponding acronym is indicated in the first parenthesis and the number of papers counted for each method in the second parenthesis. The third column gives the name of authors and the dates of the first related publication. We can see that the MOG ($\sim$100 papers) is the most used and improved due to a good compromise between robustness and time/memory requirements.

In the MOG initialization, an expectation-maximization (EM) algorithm is used and allows to estimate MOG param-

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Categories	Methods	Authors - Date
First category	Single Gaussian (SG)(5)	Wren et al. (1997) [36]
	Mixture Of Gaussians (MOG)($\sim$100)	Stauffer and Grimson (1999) [29]
	Kernel Density Estimation (KDE)(21)	Elgammal et al. (2000) [11]
	Subspace Learning using PCA (SL-PCA)(15)	Oliver et al. (1999) [27]
Second category	Support Vector Machines (SVM)(3)	Lin et al (2002) [22]
	Support Vector Regression (SVR)(2)	Wang et al. (2006) [35]
	Support Vector Data Description (SVDD)(5)	Tavakkoli et al. (2006) [31]
Third category	Single General Gaussian (SGG)(3)	Kim et al. (2007) [17]
	Mixture of General Gaussian (MoGG)(3)	Allili et al. (2008) [2]
	Subspace Learning using ICA (SL-ICA))(1)	Tsai and Lai (2009) [34]
	Subspace Learning using NMF (SL-INMF))(2)	Bucak and Gunsel (2009)[5]
	Subspace Learning using IRT (SL-IRT))(1)	Li et al. (2008) [21]

Table 1. Statistical Background Modeling: An Overview

eters from a training sequence according to the maximum-likelihood (ML) criterion. The MOG is completely certain once its parameters are specified. However, because of insufficient or noisy data in training sequence, the MOG may not accurately reflect the underlying distribution of the observations according to the ML estimation. It is problematical to use likelihoods that are themselves precise real numbers to evaluate MOG with uncertain parameters. To solve this problem, we propose to model the background by using a Type-2 Fuzzy Mixture of Gaussians Model (T2F-MOG) recently developed by Zeng et al. [39] to introduce descriptions of uncertain parameters in the MOG.
The rest of this paper is organized as follows: In the section 2, we present briefly related works on MOG's improvements. In the section 3, the T2-FMOG is used for background modeling. In the section 4, experiments on OTCBVS datasets show that T2-FMOG outperforms the crisp MOG when dynamic changes occurs.

2. Related works

The original MOG for background modeling was proposed by Stauffer and Grimson [29] and presents several advantages. Indeed, it can work without having to store an important set of input data in the running process. The multimodality of the model allows deal with multimodal backgrounds and gradual illumination changes. Despite it, this model presents some disadvantages: the number of Gaussians must be predetermined, the needfor good initializations, the dependence of the results on the true distribution law which can be non-Gaussian and slow recovery from failures. Others limitations are the needs for a series of training frames absent of moving objects and the amount of memory required in this step. To alleviate these limitations, numerous improvements have been proposed over the recent years as shown by the different acronyms found like AKGMM [14], TLGMM [37], STGMM [40], SKMGM [30], TAPPMOG [15] and S-TAPPMOG [8]. A recent complete survey of these improvements can be found in [4]. However, none of these improvements of the first category consider the uncertainty related to insufficient or noisy data in training sequence. Nevertheless, due to this uncertainty, the MOG may not accurately reflect the underlying distribution of the observations according to the ML estimation. Allili et al. [2] introduced this notion using Bayesian based estimators such as the minimum message length and the infinite Gaussian mixtures. Another way to take into account this uncertainty is to use fuzzy concepts with the MOG. A first approach developed by [33] consists in the fuzzy MOG (FMOG) that estimates its parameters based on the modified fuzzy C-means algorithm. So, the FMOG focuses on the precise parameter estimation of MOGs using fuzzy approaches rather than modeling MOGs uncertain parameters. On the other hand, Type-2 fuzzy sets (T2-FSs) [24] provide a theoretically well-founded framework to handle MOGs uncertain parameters. Their recent success achieved in pattern recognition has been largely attributed to their three-dimensional membership functions (MFs) for modeling uncertainties. Recently, Zeng et al. [39] introduce the Type-2 fuzzy sets in the MOG and called it Type-2 Fuzzy Gaussian Mixture Model (T2-FMOG). Experimental validations made in [39] show the superiority of T2-FMOG in pattern classification. In this context, we propose to apply the Type-2 FMOG for background modeling to take into account the uncertainty.

3. Background Modeling using Type-2 FMOG

Each pixel (x, y) is characterized by its IR intensity. So, the observation X_t at time t is a scalar. Then, the crisp MOG is composed of K mixture components of multivariate Gaussian as follows:

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

where the parameters are K is the number of distributions, $\omega_{i,t}$ is a weight associated to the ith Gaussian at time t with mean $\mu_{i,t}$ and standard deviation $\sigma i, t$. η is a Gaussian probability density function:

$$\eta\left(X_t, \mu, \sigma\right) = \frac{1}{\sigma\sqrt{2\pi}} \times exp\left(-\frac{1}{2}\left(\frac{X_t - \mu}{\sigma}\right)^2\right) \quad (2)$$

To take into account the uncertainty, we propose to use T2 membership functions which represent multivariate Gaussian with uncertain mean vector or covariance matrix, and replace the corresponding parts in (Equation 1) to produce the T2-FMOG with uncertain mean vector (T2-FMOG-UM) or uncertain variance (T2-FMOG-UV) as in [39].

For the T2-FMOG-UM, the multivariate Gaussian with uncertain mean vector is defined as:

$$\eta\left(X_t, \tilde{\mu}, \sigma\right) = \frac{1}{\sigma\sqrt{2\pi}} \times exp\left[-\frac{1}{2}\left(\frac{X_t - \tilde{\mu}}{\sigma}\right)^2\right] \quad (3)$$

with $\tilde{\mu} \in \left[\underline{\mu}, \overline{\mu}\right]$.

For the T2-FMOG-UV, the multivariate Gaussian with uncertain variance vector is given in the following formula:

$$\eta\left(X_t, \mu, \tilde{\sigma}\right) = \frac{1}{\tilde{\sigma}\sqrt{2\pi}} \times exp\left[-\frac{1}{2}\left(\frac{X_t - \mu}{\tilde{\sigma}}\right)^2\right] \quad (4)$$

where $\tilde{\sigma} \in [\underline{\sigma}, \overline{\sigma}]$.

$\tilde{\mu}$ and $\tilde{\sigma}$ denote the uncertain mean vector and the standard deviation respectively. Because, there is no prior knowledge about the parameter uncertainty, practically we assume that the mean and standard deviation vary within intervals with uniform possibilities, i.e., $\tilde{\mu} \in \left[\underline{\mu}, \overline{\mu}\right]$ or $\tilde{\sigma} \in [\underline{\sigma}, \overline{\sigma}]$. Each exponential component in Equation 3 and Equation 4 is the Gaussian primary membership function (MF) with uncertain mean or standard deviation as shown in Fig.1. The hatched region is the footprint of uncertainty (FOU). The thick solid and dashed lines denote the lower and upper MFs. In the Gaussian primary MF with uncertain mean, the upper MF is:

$$\overline{h}\left(X_t\right) = \begin{cases} \eta\left(X_t; \underline{\mu}, \sigma\right), & \text{if } X_t < \underline{\mu} \\ 1, & \text{if } \underline{\mu} \leq X_t < \overline{\mu} \\ \eta\left(X_t; \overline{\mu}, \sigma\right), & \text{if } X_t > \overline{\mu} \end{cases} \quad (5)$$

where $\eta\left(X_t; \underline{\mu}, \sigma\right) = exp\left[-\frac{1}{2}\left(\frac{X_t - \underline{\mu}}{\sigma}\right)^2\right]$ and $\eta\left(X_t; \overline{\mu}, \sigma\right) = exp\left[-\frac{1}{2}\left(\frac{X_t - \overline{\mu}}{\sigma}\right)^2\right]$.

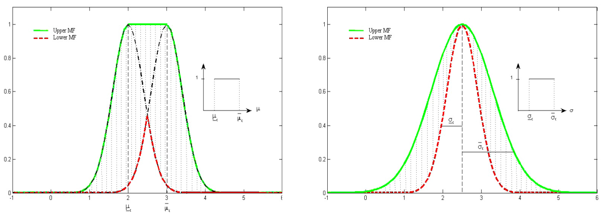

Figure 1. At the left, the Gaussian primary MF with uncertain mean. At the right, the Gaussian primary MF with uncertain std. Both of them have uniform possibilities. The hatched region is the FOU. The thick solid and dashed lines denote the upper and the lower MFs respectively.

The lower MF is:

$$\underline{h}\left(X_t\right) = \begin{cases} \eta\left(X_t; \overline{\mu}, \sigma\right), & \text{if } X_t \leq \frac{\underline{\mu} + \overline{\mu}}{2} \\ \eta\left(X_t; \underline{\mu}, \sigma\right), & \text{if } X_t > \frac{\underline{\mu} + \overline{\mu}}{2} \end{cases} \quad (6)$$

In the Gaussian primary MF with uncertain standard deviation, the upper MF is $\underline{h}\left(X_t\right) = \eta\left(X_t; \mu, \overline{\sigma}\right)$ and the lower MF is $\overline{h}\left(X_t\right) = \eta\left(X_t; \mu, \underline{\sigma}\right)$.

The factor k_m and k_ν control the intervals in which the parameter vary as follows:

$$\underline{\mu} = \mu - k_m\sigma, \quad \overline{\mu} = \mu + k_m\sigma, \quad k_m \in [0, 3], \quad (7)$$

$$\underline{\sigma} = k_\nu\sigma, \quad \overline{\sigma} = \frac{1}{k_\nu}\sigma, \quad k_\nu \in [0.3, 1]. \quad (8)$$

Because a one-dimensional gaussian has 99.7% of its probability mass in the range of $[\mu - 3\sigma, \mu + 3\sigma]$, the parameters k_m and k_ν have been choosen in the intervals: $k_m \in [0, 3]$ and $k_\nu \in [0.3, 1]$. These factors also control the area of the FOU. The bigger k_m or the smaller k_ν, the larger the FOU, which implies the greater uncertainty.

Both the T2-FMOG-UM and T2-FMOG-UV can be used to model the background and we can expect that the T2-FMOG-UM will be more robust than the T2-FMOG-UV. Indeed, only the means are estimated and tracked correctly over time in the MGM maintenance. The variance and the weights are unstable and unreliable as explained by Greiffenhagen et al. [13].

3.1. Training

To initialize the T2-FMOG, we have to estimate the parameters μ, σ and the factor k_m or k_ν. Zeng et al. [39] set the factors k_m and k_ν as constants according to prior knowledge. In our work, they are fixed depending to the video (see Section 4). Thus, parameters estimation of T2-FMOG includes three steps:

- Step 1: Choose K between 3 and 5.
- Step 2: Estimate MOG parameters by an EM algorithm.
- Step 3: Add the factor k_m or k_ν to MOG to produce T2-FMOG-UM or T2-FMOG-UV.

Once the training is made, a first foreground detection can be processed.

3.2. Foreground Detection

Foreground detection consists in classifying the current pixel as background or foreground. By using the ratio $= r_j = \omega_j / \sigma_j$, we firstly ordered the K Gaussians as in [29]. This ordering supposes that a background pixel corresponds to a high weight with a weak variance due to the fact that the background is more present than moving objects and that its value is practically constant. The first B Gaussian distributions which exceed certain threshold T are retained for a background distribution:

$$B = argmin_b \left(\sum_{i=1}^{b} \omega_{i,t} > T \right) \tag{9}$$

The other distributions are considered to represent a foreground distribution. When the new frame incomes at times $t+1$, a match test is made for each pixel. For this, we use the log-likelihood, and thus we are only concerned with the length between two bounds of the log-likelihood interval, i.e., $H(X_t) = \left| ln\left(\underline{h}(X_t)\right) - ln\left(\overline{h}(X_t)\right) \right|$. In Fig 1 (left side), the Gaussian primary MF with uncertain mean has:

$$H(X_t) = \begin{cases} \frac{2k_m|X_t-\mu|}{\sigma} \quad \text{if } X_t \leq \underline{\mu} \text{ or } X_t \geq \overline{\mu} \\ \frac{|X_t-\mu|}{2\sigma^2} + \frac{k_m|X_t-\mu|}{\sigma} + \frac{k_m^2}{2} \\ \quad \text{if } \underline{\mu} < X_t < \overline{\mu} \end{cases} \tag{10}$$

In Fig 1 (right side), the Gaussian primary MF with uncertain standard deviation has:

$$H(X_t) = \left(\frac{1}{1/k_\nu^2 - k_\nu^2} \right) \frac{|X_t - \mu|^2}{2\sigma^2} \tag{11}$$

μ and σ are the mean and the std of the original certain T1 MF without uncertainty. Both (10) and (11) are increasing functions in term of the deviation $|X_t - \mu|$. For example, given a fixed k_m, the farther the X_t deviates from μ_c, the larger $H(X_t)$ is in (12), which reflects a higher extent of the likelihood uncertainty. This relationship accords with the outlier analysis. If the outlier X_t deviates farther from the center of the class-conditional distribution, it has a larger $H(X_t)$ showing its greater uncertainty to the class model. So, a pixel is ascribed to a Gaussian if:

$$H(X_t) < k\sigma \tag{12}$$

Method	T2-FMOG-UM	T2-FMOG-UV	MOG
$S(A,B)$	48%	43%	36%

Table 2. Quantitative Evaluation

where k is a constant threshold determined experimentally and equal to 2.5. Then, two cases can occurs: (1) A match is found with one of the K Gaussians. In this case, if the Gaussian distribution is identified as a background one, the pixel is classified as background else the pixel is classified as foreground. (2) No match is found with any of the K Gaussians. In this case, the pixel is classified as foreground. At this step, a binary mask is obtained. Then, to make the next foreground detection, the parameters are updated using the same scheme as in [29].

4. Experimental Results

We have applied our algorithms on videos of the OTCBVS datasets [1] and compared them with the Mixture of Gaussians (MOG) modeling proposed by KaewTraKulPong and Bowden [16]. These three algorithms were implemented under Microsoft Visual C++ using the OpenCV library.

4.1. Dataset 01: OSU Thermal Pedestrian Database

The figure 2 shows the results obtained on the Sequence 1 [9] using the MOG [16], the T2-FMOG-UM and the T2-FMOG-UV on the frame 27. Silhouettes are well detected by the three algorithms but the T2-FMOG-UM gives less false detection followed by the T2-FMOG-UV and the crisp MOG.

Then, to evaluate quantitatively our method, we have used the similarity measure derived by Li et al. [20]. Let A be a detected region and B be the corresponding ground truth, the similarity between A and B can be defined as:

$$S(A,B) = \frac{A \cap B}{A \cup B} \tag{13}$$

If A and B are the same, $S(A,B)$ approaches 1, otherwise 0 i.e. A and B have the least similarity. The ground truth is marked manually. Table 2 shows similarity value obtained for this experiment. It confirms the qualitative evaluation.

4.2. Dataset 05: Terravic Motion IR Database

We have tested the proposed algorithm on the Terravic datasets [26] too. We have choosen the two sequences called Uneventful Background Motion because they present dynamic backgrounds as waving vegetations. In this sequence, nothing must be detected. The figure 3 shows the

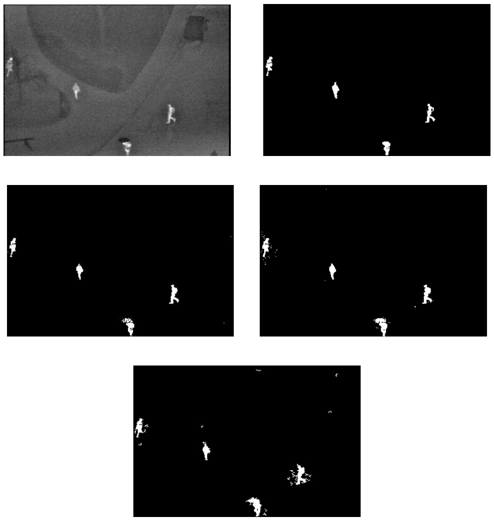

Figure 2. Sequence OSU - First row: The current image, the ground truth. Second row: Results with T2-FMOG-UM and the T2-FMOG-UV respectively. Third row: Result with the MOG

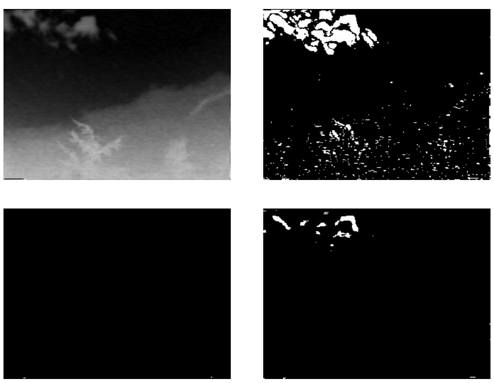

Figure 3. Sequence IRTR01 - First row: The current image, Result with the MOG [9]. Second Row: Result with T2-FMOG-UM, Result with T2-FMOG-UV

result obtained using the MOG, the T2-FMOG-UM and the T2-FMOG-UV on the frame 150 of the sequence IRTR01. The figure 4 shows the same experiments on the frame 150 of the sequence IRTR02. For these two experiments, the learning rates is the same for each method. k_m =2 for the T2-FMOG-UM and $k_\nu = 0.9$ for theT2-FMOG-UV. The motion causes substantial false positive detection in the MOG. The more robust is the T2-FMOG-UM followed by the T2-FMOG-UV. These results confirm the robustness of the proposed method in the presence of dynamic backgrounds.

5. Conclusion

In this paper, we have presented background modeling algorithms using the Type-2 Fuzzy Mixture of Gaussians.

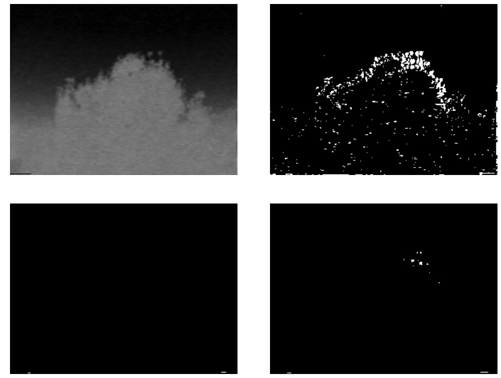

Figure 4. Sequence IRTR02 - First row: The current image, Result with the MOG [9]. Second Row: Result with T2-FMOG-UM, Result with T2-FMOG-UV

Experiments in infrared video datasets show that the T2-FMOG-UM is more robust than the crisp MOG in the case of dynamic backgrounds (waving vegetations). One future direction of this work is an adaptive version of the T2-FMOG-UM which allows to determine dynamically the optimal number of Gaussians. Future developments of this work concern two directions: the first one concerns a complete study on the parameter estimations of the T2-FMOG and the second one focuses on an adaptive version of the T2-FMOG which allows to determine dynamically the optimal number of Gaussians.

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