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Fuzzy Foreground Detection for Infrared Videos

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Abstract

We present a foreground detection algorithm based on a fuzzy integral that is particularly suitable for infrared videos. The proposed detection of moving objects is based on fusing intensity and textures using fuzzy integral. The detection results are then used to update the background in a fuzzy way. This method allows to robustly detect moving object in presence of cloudy and rainy conditions. Our theoretical and experimental results show that the proposed method gives similar results than the KaewTraKulPong and Bowden approach based on Mixture Of Gaussians (MOG) with less memory requirement and time consuming. The results using the OTCBVS benchmark/test dataset videos show the robustness of the proposed method.

1. Introduction

Many video surveillance systems in visible spectrum [9] or infrared (IR) [3, 12] 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 subtraction methods can be found to be robust to the challenges met in video sequence. These different methods are classified following the model used:

- **Basic Background Modeling (BBM):** In this case, Background Representation is modeled using the average [13] or the median [16] or the histogram analysis over time [31]. Once the model is computed, the foreground detection is made as follows:

$$d(I_t(x, y) - B_{t-1}(x, y)) > T \quad (1)$$

Otherwise, pixels are classified as background. Where T is a constant threshold, $I_t(x, y)$ and $B_t(x, y)$ are respectively the current and the background images at time t .

- **Statistical Background Modeling (SBM):** Background Representation is modeled using a single Gaussian [7, 28, 30] or a Mixture of Gaussians [22, 25] or a Kernel Density Estimation [6, 9]. Statistical variables are used in the foreground detection to classify the pixels as foreground or background. Recent SBM use Generalized Gaussian Mixture Modeling [1], Bayesian approaches [20, 21], Support Vector Regression learning approaches [27] or Codebook [5, 11, 14].
- **Background Estimation (BE):** Background representation is estimated using a filter. For the foreground detection, any pixel of the current image that deviates significantly from its predicted value is declared foreground. This filter may be a Wiener filter [26], a Kalman filter [17] or a Tchebychev filter [2].

All these methods present the same following steps and issues: background modeling, background initialization, background maintenance, foreground detection, choice of the picture's element (pixel, a block or a cluster), choice of the features which characterize the picture's element (color features, edge features, stereo features, motion features and texture features). Often, these features are used separately and the most used is the color one. The combination of several measuring features can strengthen the pixel's classification as background or foreground. In a general way, the Choquet and Sugeno integrals have been successfully applied widely in classification problems [24], in decision making [19] and also in data modelling [23] to aggregate different criteria. In the context of foreground detection, these integrals seem to be good model candidates for fusing different measures from different features. Each integral has its particularity. The Choquet integral requires to interpret the scale as a continuum and the Sugeno integral allows to work with an ordinal scale. Recently, Zhang and Xu [29] have used texture feature and color features to compute similarity measures between current and background pixels. Then, the measures are aggregated by applying the Sugeno integral. The assumption made by the authors reflects that the scale is ordinal. The foreground objects are detected by

thresholding the results of the Sugeno integral. In this work, the scheme used is based on Zhang’s algorithm. In the foreground detection, the values to be merged are the ratios of background pixel’s features between a current image and the background image. The difference between these continuous values is real. In this context, the Choquet integral seems to be more suitable than Sugeno integral. So we propose to use the Choquet integral to aggregate infrared (IR) intensity and texture features instead of the Sugeno integral. The rest of this paper is organized as follows: In Section 2, we present a brief overview of the complete system. The Section 3 details the proposed fuzzy foreground detection based on the Choquet integral. Section 4 describes the fuzzy background maintenance adopted for this system. Finally in the section 5, we compare our method with the MOG [10] using the OTCBVS videos datasets ¹.

2. System Overview

The first step of many video analysis systems is the segmentation of foreground objects from the background. This task is a crucial prerequisite for the effectiveness of the global system. A background removal algorithm should be able to cope with a number of weather changes causing noise. These changes can be handled in the different steps of the background removal process: background representation, background initialization, background maintenance and foreground detection. The choice of the picture element size and the features is essential too. The figure 1 shows the proposed complete system to detect moving objects (cars, persons, ...) in IR video sequence. The different steps are the following:

- *The background initialization* is made by using the average of the N first video frames where objects were present.
- *The background maintenance* uses an update rule which is necessary to adapt well the system over time to some environmental changes. For this, the selective maintenance scheme usually adopted in the literature is determined as follows:

$$B_{t+1}(x, y) = (1 - \alpha) B_t(x, y) + \alpha I_{t+1}(x, y) \quad (2)$$

if (x, y) is background

$$B_{t+1}(x, y) = (1 - \beta) B_t(x, y) + \beta I_{t+1}(x, y) \quad (3)$$

if (x, y) is foreground

Here, the idea is to adapt very quickly a pixel classified as background and very slowly a pixel classified as foreground. Note that this background maintenance scheme allows the adaptation of the system to illumination changes but also the incorporation of motionless

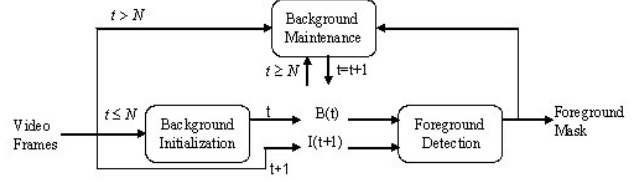


Figure 1. System overview.

foreground objects. The learning rate α determines the speed of the adaptation to illumination variations and the learning rate β controls the incorporation of motionless foreground objects. The drawback of the selective maintenance is mainly due to the crisp decision which attributes a different rule following the classification in background or foreground. To solve this problem, we propose a fuzzy background maintenance developed in detail in section 4.

- *The foreground detection* is made in a fuzzy way using the Choquet integral and is developed in the following section.

3. Fuzzy foreground detection using the Choquet integral

3.1. Overview of the Foreground Detection

Foreground detection is based on a comparison between current and background images. In general, a simple subtraction is made between these two images to detect regions corresponding to foreground. Another way to establish this comparison consists in defining a similarity measure between pixels in current and background images. In this case, pixels corresponding to background should be similar in the two images while pixels corresponding to foreground should not be similar. In Figure 2, the foreground detection process is presented in details. First, the IR intensity and the texture features are extracted from the background image B_t and the current image I_{t+1} . The similarity measures are computed for each feature which are then aggregated by the Choquet integral. The Background/Foreground classification is finally made by thresholding the Choquet integral’s result. In the following subsections, we describe the rationale for selecting and fusing the set of the adopted features.

3.2. Choice of Features

As seen before, the choice of the feature is essential. In IR video, the most used feature is IR intensity but texture feature can be a further tool to gain more robustness against weather changes (clouds, rain). To solve these problems, Nadimi and Bhanu [18] proposed to use color features in addition of IR intensity. On the other hand, Latecki et al

¹<http://www.cse.ohio-state.edu/otcbvs-bench>

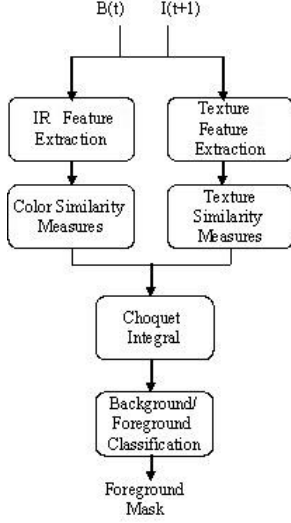


Figure 2. Foreground detection process.

[12] propose to use spatiotemporal texture features. In a similar way, we choose to add, to the intensity feature, the Local Binary Pattern for texture [8]. In the following we present the similarity measures for these two features.

3.2.1 IR Intensity Similarity Measure

The intensity similarity measure $S_k^C(x, y)$ at the pixel (x, y) is computed as in [29]:

$$S^C(x, y) = \begin{cases} \frac{I^C(x, y)}{I^B(x, y)} & \text{if } I^C(x, y) < I^B(x, y) \\ 1 & \text{if } I^C(x, y) = I^B(x, y) \\ \frac{I^B(x, y)}{I^C(x, y)} & \text{if } I^C(x, y) > I^B(x, y) \end{cases} \quad (4)$$

where B and C represent respectively the background and the current images at time t . B can be obtained using any of the background modelling method. Note that $S^C(x, y)$ is between 0 and 1. Furthermore, $S^C(x, y)$ is closed to one if the IR intensities $I^C(x, y)$ and $I^B(x, y)$ are very similar.

3.2.2 Texture Similarity Measure

The Local Binary Pattern (LBP) is developed by Heikkila and Pietikinen [8] for the texture extraction. The LBP is invariant to monotonic changes in grey scale, which makes it robust against illumination changes. This operator labels the pixels of an image block by thresholding the the eight-neighbors of a pixel using the value of the center pixel. The LBP code for a neighbourhood was produced by multiplying the thresholded values with weights given to the corresponding pixels, and summing up the result as in figure 3:

$$LBP(x, y) = \sum_{i=0}^{N-1} s(g_i - g) 2^i \quad (5)$$

where g corresponds to the grey value of the center pixel (x, y) and g_i to the grey values of the N neighbourhood pixels. The function s is defined as follows:

$$s(x) = \begin{cases} 1 & \text{if } x \geq 0 \\ 0 & \text{if } x < 0 \end{cases} \quad (6)$$

The original LBP operator worked with the 3×3 neigh-

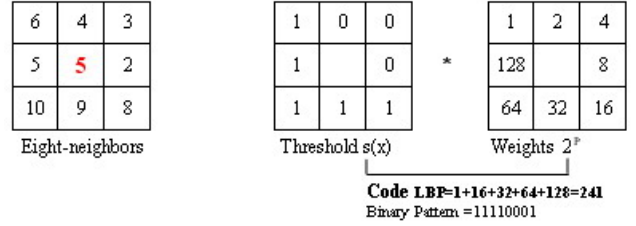


Figure 3. Computing the code LBP.

bourhood of a pixel. Note that the value of the code LBP varies between 0 and 255 like the IR intensity.

Then, for each block texture in the current image and the background image, the texture similarity $S^T(x, y)$ at the center pixel of the corresponding block (x, y) is computed as follows:

$$S^T(x, y) = \begin{cases} \frac{L^C(x, y)}{L^B(x, y)} & \text{if } L^C(x, y) < L^B(x, y) \\ 1 & \text{if } L^C(x, y) = L^B(x, y) \\ \frac{L^B(x, y)}{L^C(x, y)} & \text{if } L^C(x, y) > L^B(x, y) \end{cases} \quad (7)$$

where $L^B(x, y)$ and $L^C(x, y)$ are respectively the texture LBP of pixel (x, y) in the background and current images at time t . Note that $S^T(x, y)$ is between 0 and 1. Furthermore, $S^T(x, y)$ is close to one if $L^B(x, y)$ and $L^C(x, y)$ are very similar. Many fusion techniques can be used to fuse the color and the texture features. For this operation, we have chosen a fuzzy approach.

3.3. Aggregation of Features by Fuzzy Integrals

The mathematical operators used for aggregation are multiples. In literature [4], we find the basic ones like the average, the median, the minimum and the maximum, as well as some generalizations like the Ordered Weighted Average (OWA) having the minimum and the maximum as particular cases and the k-order statistics. Then, the family of fuzzy integrals has presented through its discret version a generalization of OWA or the weighted average using the Choquet integral, as well as the minimum and the maximum using the Sugeno integral. The advantage of fuzzy integrals is that they take into account the importance of the coalition of any subset of criteria.

Now, we summarized briefly necessary concepts around fuzzy integrals (Sugeno and Choquet).

Let μ be a fuzzy measure on a finite set X of criteria and $h : X \rightarrow [0, 1]$ be a fuzzy subset of X .

Definition 1 The Sugeno integral of h with respect to μ is defined by:

$$S_\mu = \text{Max} \left(\text{Min} \left(h(x_{\sigma(i)}), \mu(A_{\sigma(i)}) \right) \right) \quad (8)$$

where σ is a permutation of the indices such that $h_{\sigma(1)} \leq \dots \leq h_{\sigma(n)}$ and $A_{\sigma(i)} = \{\sigma(1), \dots, \sigma(i)\}$

Definition 2 The Choquet integral of h with respect to μ is defined by:

$$C_\mu = \sum_{i=0}^n h(x_{\sigma(i)}) (\mu(A_{\sigma(i)}) - \mu(A_{\sigma(i+1)})) \quad (9)$$

with the same notations as above.

An interesting interpretation of the fuzzy integrals arises in the context of the source fusion. The measure μ can be viewed as the factor which describes the relevance of the sources of information where h denotes the values the criteria have reported. The fuzzy integrals then aggregates non-linearly the outcomes of all criteria. The Choquet integral is adapted for cardinal aggregation while Sugeno integral is more suitable for ordinal aggregation. More details can be found in [19, 23, 24].

In fusion of different criteria or sources, the fuzzy measures take on an interesting interpretation. A pixel can be evaluated based on criteria or sources providing information about the state of the pixel whether pixel corresponds to background or foreground. The more criteria provide information about the pixel, the more relevant the decision of pixel's state. Let $X = \{x_1, x_2, x_3\}$, with each criterion, we associate a fuzzy measure, $\mu(x_1) = \mu(\{x_1\})$, $\mu(x_2) = \mu(\{x_2\})$ and $\mu(x_3) = \mu(\{x_3\})$ such that the higher the $\mu(x_i)$, the more important the corresponding criterion in the decision. To compute the fuzzy measure of the union of any two disjoint sets whose fuzzy measures are given, we use an operational version proposed by Sugeno which called λ -fuzzy measure. To avoid excessive notation, let denote this measure by μ_λ -fuzzy measure, where λ is a paramater of the fuzzy measure used to describe an interaction between the criteria that are combined. Its value can be determined through the boundary condition, i.e. $\mu(X) = \mu(\{x_1, x_2, x_3\}) = 1$. The fuzzy density values over a given set $K \subset X$ is computed as:

$$\mu_\lambda(K) = \frac{1}{\lambda} \left[\prod_{x_i \in K} (1 + \lambda \mu_\lambda(x_i)) - 1 \right] \quad (10)$$

In the following section, we describe the use of the Choquet integral in the context of foreground detection.

3.4. Application to Foreground Detection

3.4.1 Choice of the Choquet integral

TAs defined above, the similarity measures are obtained by dividing the feature values (IR and texture) in background and current images with endpoints denoted by 0 and 1. Where 0 means that the pixels at the same location in background and current images respectively are not similar and 1 means that these pixels are similar i.e. pixel corresponding to background. In such a case, the scale is continuum and is constructed as a cardinal one where the distances or the differences between values can be defined. For example the distance between 0.1 and 0.2 is the same than the distance between 0.8 and 0.9, because numbers have a real meaning. While in the case of an ordinal scale, the numbers correspond to modalities when an order relation on the scale should be defined. A typical example of this former when we define a scale [a, b, c, d, e] to evaluate the level of some students, where "a" corresponds to "excellent" and "e" to "very bad". So that, the difference between "b" (very good) and "c" (good) is not necessary the same as the difference between "c" (good) and "d" (bad). Hence, operations other than comparison on a cardinal scale can be allowed like standard arithmetic operations, typically addition and multiplication. In this sense, the Choquet integral is considered as more suitable than the Sugeno integral because of its ability to aggregate well features on a cardinal scale and to use such arithmetic operations.

3.4.2 Classification Background/Foreground

For each pixel, IR intensity and texture similarity measures are computed as explained before from the background and the current frame. Then, the set of criteria $X = \{x_1, x_2\}$ is defined with, (x_1) is the IR intensity features of the pixel and x_2 = texture feature obtained by the LBP.

For each x_i , let $\mu(x_i)$ be the degree of importance of the feature x_i in the decision whether pixel corresponds to background or foreground. The fuzzy functions $h(x_i)$ are defined in $[0, 1]$ so that, $h(x_1) = S^C(x, y)$ and $h(x_2) = S^T(x, y)$. To compute the value of Choquet integral for each pixel, we need firstly to rearrange the features x_i in the set X with respect to the order: $h(x_1) \geq h(x_2)$.

The pixel at position (x, y) is considered as foreground if its Choquet integral value is less than a certain constant threshold Th :

$$\text{if } C_\mu(x, y) < Th \text{ then } (x, y) \text{ is foreground.} \quad (11)$$

which means that pixels at the same position in the background and the current images are not similar. Th is a constant value depending on each video data set.

4. Fuzzy Background Maintenance

As seen in section 2, the disadvantage of the selective maintenance is mainly due to the crisp decision which attributes a different rule following the classification in background or foreground. To solve this problem, we propose to take into account the uncertainty of the classification. This can be made by graduate the update rule using the result of the Choquet integral as follows:

$$B_{t+1}(x, y) = \mu_F B_t((1 - \beta) B_t(x, y) + \beta I_t(x, y)) + (1 - \mu_F) \cdot ((1 - \alpha) B_t(x, y) + \alpha I_t(x, y)) \quad (12)$$

where $\mu_F = 1 - \mu_B$.

μ_F and μ_B are respectively the fuzzy membership values of the pixel (x, y) to the class foreground and background. μ_B is a function of $C_\mu(x, y)$ such as $\mu_B = 1$ for $Max(C_\mu(x, y))$ and $\mu_B = 0$ for $Min(C_\mu(x, y))$.

We can remark that the adaptive maintenance is a generalized version of the selective maintenance. Indeed, if the pixel is classified as background with the Choquet integral value equal to one, we retrieve the Equation (2), and if the pixel is classified as foreground with the Choquet integral value equal to zero, the Equation (12) is equal to the Equation (3).

5. Experimental Results

We have applied our algorithm to the OCTBVS datasets. Firstly, we have compared our method with the improved Mixture Of Gaussian (MOG) modeling proposed by Kaew-TrakulPong and Bowden [10]. These two algorithms were implemented under Microsoft Visual C++ using the OpenCV library. The figure 4 shows the results obtained on the Collection 1 using the MOG and the Choquet integral algorithms respectively. The results are almost similar but the MOG is more sensitive to noise which leads to false alarm. Furthermore, the proposed background subtraction system based on the Choquet integral outperforms the MOG in term of memory and time. Indeed, our algorithm has the same time and memory requirements as the simple Running Average and gives better accuracy. Table 1 presents a comparative performance analysis based on speed, memory requirements and accuracy. Then, to evaluate quantitatively our method, we have used the similarity measure derived by Li [15]. Let A be a detected region and B be the corresponding ground truth, the similarity between A and B can be defined as:

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

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 are marked manually. Table 2 shows the similarity value obtained for the previous experiments. Although the detection

Method	Speed	Memory	Accuracy
Running Average	Fast	Low	Low/Medium
MOG	Interm.	Interm.	Medium/High
Proposed Method	Fast	Low	Medium/High

Table 1. Performance analysis

Method	MOG	Choquet
$S(A, B)$	58%	60%

Table 2. Quantitative Evaluation

performance of these two algorithms are similar, the superiority of the proposed fuzzy algorithm is shown in time consuming which is important for real time application. The figure 5 shows the results obtained using the Choquet integral for the Collections 2 and 7, which contain cloudy and rainy conditions respectively. Silhouettes are all detected without noise and so can be directly used for tracking.

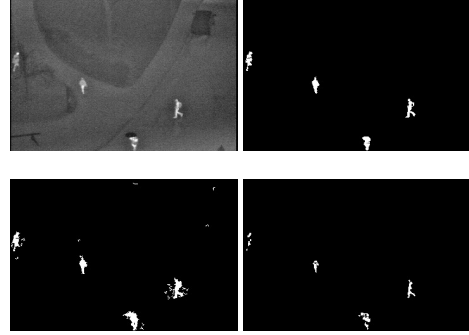


Figure 4. First row: The current image, the Groundtruth. Second row: Result with MOG, Result with Choquet integral.



Figure 5. First row: Collection 2 - Current image, Result with Choquet integral. Second row: Collection 7 - Current image, Result with Choquet integral.

6. Conclusion

In this paper, we have presented a foreground detection method using the Choquet integral for fuse IR intensity and texture features. Experiments in infrared videos datasets show that the MOG and the proposed algorithm based on the Choquet integral give similar results. On the other hand, the former outperforms the MOG in term of memory and complexity. Further research consists in fusing others features like edge or motion features.

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