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A Novel Background Subtraction Algorithm for Dynamic Texture Scenes

Rehana Begum[1], G. Minni[2]

[1]M. Tech, Nimra College of Engineering & Technology, Vijayawada, A.P., India.

[2]Asst. Professor, Dept. of CSE, Nimra College of Engineering & Technology, Vijayawada, A.P., India

ABSTRACT: *Background subtraction process is often one of the first tasks in machine vision applications, making it a critical part of the system. The output of background subtraction process is an input to a higher-level process that can be, for example, the tracking of an identified object. The performance of background subtraction process depends mainly on the background modeling technique used to model the scene background. Especially natural images put many challenging demands on background modeling since they are usually dynamic in nature including illumination changes, swaying vegetation, rippling water, flickering monitors etc. A robust background subtraction algorithm should also handle situations where new stationary objects are introduced to or old ones removed from the scene. This paper presents a novel background subtraction algorithm for dynamic texture scenes using fuzzy color histogram. The rationale behind the model is that color variations generated by background motions are greatly attenuated in a fuzzy manner.*

Keywords**:** *Fuzzy color histogram, Subtraction, Texture.*

I. INTRODUCTION

Natural scenes are often composed of several entities, from which usually only a small portion are relevant to tasks such as area surveillance, object recognition, event detection, or path planning. In fact the ability to separate various informative regions from the background clutter is an essential requirement to perform these assignments successfully. Biological systems have developed to be remarkably effective in focusing their visual attention to relevant targets, as opposed to the computer vision where background subtraction(Figure 1) is still an unsolved problem.

Commonly background subtraction has been approached by the detecting moving objects against a static background [1][2]. While effective in certain scenes, this approach has severe problems when the scenes are dynamic nature or the camera is not static. These situations have been addressed by trying to compensate for the camera movements [3] [4], and by continuously updating the background subtraction model. However accurate camera movement estimation is not an easy problem and rapid background subtraction updating is often technically difficult, if not impossible. Furthermore these methods are not applicable at all if we have a single image instead of video frames, or if the objects of interest are not moving against the background. In this paper, we propose a simple and robust method for background subtraction in dynamic texture scenes. The rationale behind the model is that color variations generated by background motions are greatly attenuated in a fuzzy manner.

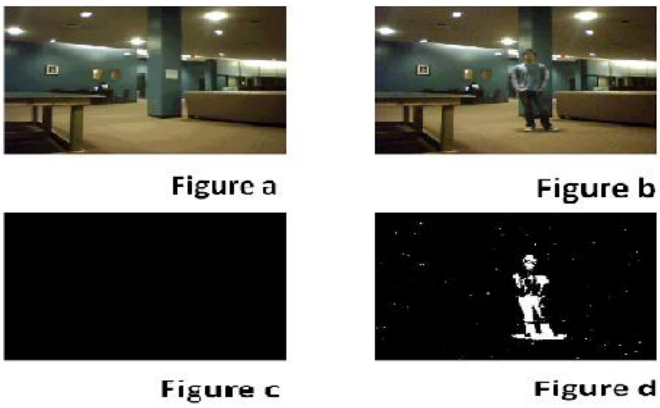

Figure 1: Background subtraction

II. EXISTING WORK

A large number of background subtraction methods [5][6] that have been proposed, but the task remains challenging due to many factors, such as illumination variation, moving object's shadow, addition or removal of stationary objects and scene motion. Pixel-wise methods such as temporal difference and the median filtering, assume that the observation sequence of each pixel is independent to each other and background scene is static. A very popular technique in [7] is to model each pixel in a video frame with a single Gaussian distribution. Many authors have proposed improvements and extensions [8] for using more than one Gaussian distribution per pixel to model very complex non-static backgrounds. Although the above background subtraction methods have different modeling schemes, most of them use standard color or intensity information, which limit their application in the dynamic environment. In [9], the authors detected people by fusing color and edge information, which is an illumination invariant feature. Edge information uniquely is not sufficient, because some part of the background might be uniform.

In [10], the authors concluded that the performance depends largely on the ideal combination of the used information, background model, and classification and combination strategies. In the different existing methods, the features commonly used to handle critical situations are color, edge, stereo, motion and texture [11]. The combination of several measuring features can strengthen the pixels classification as foreground or background. In [12], the authors have used Sugeno integral to aggregate color and texture features. In [12], Choquet integral seems to be more suitable than Sugeno integral, since the scale is continuum in the foreground detection.

III. PROPOSED WORK

A. Fuzzy Membership Based Local Histogram Features

Detection of specific dynamic textures (DTs), such as smoke or fire, is one of the most frequent surveillance applications of temporal dynamic texture analysis. In these applications, the detection is usually based on specific features (frequency, color, etc.) of the phenomena to be detected. A different task is detection of any dynamic texture in a video frame. The idea of using Fuzzy color histogram (FCH) in a local manner to obtain the reliable background model in dynamic texture scenes is motivated by the observation that the background motions do not make severe alterations of the scene structure even though they are widely distributed or occur abruptly in the spatiotemporal domain, and color variations yielded by such irrelevant motions can thus be efficiently attenuated by considering the local statistics defined in a fuzzy manner, i.e., regarding the effect of each pixel value to all the color attributes rather than only one matched color in the local region. In a probability view point, the conventional color histogram (CCH) can be regarded as the probability density function. Thus, the probability for pixels in the image to belong to the ith color bin w_i can be defined as follows:

$$h_i = \sum_{j=1}^{N} P(\omega_i \mid \mathbf{x}_j) P(\mathbf{x}_j) = \frac{1}{N} \sum_{j=1}^{N} P(\omega_i \mid \mathbf{x}_j)$$

where N denotes the total number of pixels.

The fuzzy c- means (FCM) algorithm finds a minimum of a heuristic global cost function defined as follows:

$$J = \sum_{i=1}^{c} \sum_{j=1}^{m} [P(\omega_i \mid \mathbf{x}_j)]^b ||\mathbf{x}_j - \mathbf{v}_i||^2$$

where x and v values denote the feature vector (e.g., values of each color channel) and the cluster center, respectively. Value b is a constant to control the degree of blending of the different clusters.

For the robust background subtraction process in dynamic texture scenes, we finally define the local FCH feature vector at the jth pixel position of the kth video frame as follows:

$$\mathbf{F}_j(k) = (f_{j,1}^k, f_{j,2}^k, \ldots, f_{j,c}^k), \quad f_{j,i}^k = \sum_{q \in W_j^k} u_{iq}$$

where w_j^k denotes the set of neighboring pixels centered at the position j. u_{iq} denotes the membership value, indicating the belongingness of the color feature computed at the pixel position q to the color bin i.

B. Background Subtraction With Local FCH Features

In this section, we describe the algorithm of background subtraction based on our local FCH features. To classify a given pixel into either background or moving objects in the current frame, we first compare the observed FCH vector with the model FCH vector renewed by the online update as expressed in:

$$B_j(k) = \begin{cases} 1, & \text{if } S(\mathbf{F}_j(k), \widehat{\mathbf{F}}_j(k)) > \tau \\ 0, & \text{otherwise,} \end{cases}$$

where $B_j(k) = 1$ denotes that the th pixel in the th video frame is determined as the background whereas the corresponding pixel belongs to moving objects if $B_j(k) = 0$.

The similarity measure S(.,.), which adopts normalized histogram intersection for simple computation, is defined as follows:

$$S(\mathbf{F}_j(k), \widehat{\mathbf{F}}_j(k)) = \frac{\sum_{i=1}^{c} \min\left[f_{j,i}^k, \widehat{f}_{j,i}^k\right]}{\max\left[\sum_{i=1}^{c} f_{j,i}^k, \sum_{i=1}^{c} \widehat{f}_{j,i}^k\right]}$$

Where $\hat{F_j}(k)$ denotes the background model of the jth pixel position in the kth video frame.

In order to maintain the reliable background model in dynamic texture scenes, we need to update it at each pixel position in an online manner as follows:

$$\widehat{\mathbf{F}}_j(k) = (1-\alpha)\cdot\widehat{\mathbf{F}}_j(k-1) + \alpha\cdot\mathbf{F}_j(k), \quad k \geq 1$$

Where $\hat{F_j}(0) = F_j(0)$.

The main steps of the proposed method is summarized in Algorithm 1.

Algorithm 1: Background subtraction using local FCH features
Step 1: Construct a membership matrix using fuzzy –means Clustering.
Step 2: Quantize RGB colors of each pixel at the th video frame into one of m histogram bins (e.g., rth bin where r=1,2,…..m).
Step 3: Find the membership value u_{ir} at each pixel position i-1,2,….,c.
Step 4: Compute local FCH features at each pixel position of the kth video frame.
Step 5: Classify each pixel into background or not based on $B_j(k)$.
Step 6: Update the background model using $\hat{F_j}(k)$.
Step 7: Go back to Step 2 until the input is terminated (k=k+1)
.
C. Extraction of Foreground Object

After successfully developing the background subtraction model, a local thresholding based background subtraction is used to find the foreground objects. A constant value C is considered that helps in computing the local lower threshold (TL) and the local upper threshold (TU). These local thresholds help in successful detection of the objects suppressing shadows if any. The steps of the algorithm are outlined in Algorithm 2.

Algorithm 2: Background Subtraction for a frame f
Step 1: for i ← 1 to height of frame do
Step 2: for j ← 1 to width of frame do
Step 3: Threshold T(i, j) = [M(i, j) + N(i, j)] / C
Step 4: TL(i, j) = M(i, j) − T(i, j)
Step 5: TU(i, j) = N(i, j) + T(i, j)
Step 6: if TL(i, j) ≤ f(i, j) ≤ TU(i, j) then
Step 7: Sf (i, j) = 0 //Background pixel
Step 8: else
Step 9: Sf (i, j) = 1 //Foreground pixel
Step 10: end if
Step 11: end for
Step 12: end for

IV. CONCLUSIONS

One of the most important aspects of an intelligent vision surveillance system is background subtraction method, which is used as a preprocessing step for object detection and tracking in vision systems. In this paper, we present a simple and robust method for background subtraction for dynamic texture scenes. The proposed work does not require estimation of any parameters (i.e., nonparametric). This is fairly desirable for achieving the robust background subtraction in a wide range of scenes with the spatiotemporal dynamics. Specifically, the work propose to derive the local features from the fuzzy color histogram (FCH). Then, the background subtraction model is reliably constructed by computing the similarity between local FCH features with an online update procedure.

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