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Video Background Subtraction using Multi Background Model & Robust Threshold

VinkyDhingra[1], Vaishali Wadhwa[2]

M.Tech. Student, Computer Science and Engineering, N.C.College of Engineering, Panipat, India [1]

Associate Professor, Computer Science and Engineering, N.C.College of Engineering, Panipat, India [2]

Abstract: Video object segmentation and tracking are two essential building blocks of smart surveillance systems. An efficient moving object segmentation algorithm suitable for real-time content-based multimedia communication systems is proposed in this paper. First, the basic idea is to construct a reliable background image using background registration technique. The moving object region is then separated from the background region by comparing the current frame with the constructed background image. An efficient thresholding approach is developed and whole algorithm is divided into four steps and frame difference mask, background difference mask are generated using proposed threshold scheme.

Keywords: Background registration, Thresholding, Background difference mask, Frame difference mask.

I. INTRODUCTION

Identifying moving objects from a video sequence is a critical and fundamental task in traffic monitoring and analysis, video surveillance, gesture recognition in human-machine interface and human detection and tracking. A basic approach to identifying the moving objects is background subtraction, where each video frame is compared against a background model. Pixels in the current frame that deviate significantly from the background are considered to be moving objects. These foreground pixels are further processed for object localization and tracking. Since background subtraction is often the first step in many computer vision applications, it is important that the extracted foreground pixels accurately correspond to the moving objects of interest. There are several problems that a efficient background subtraction algorithm must solve. The algorithm should adapt to illumination changes at different times of the day and handle weather condition such as snow or fog that modifies the background. Changing shadow cast by dynamic objects, should be removed so that features can be extracted from the objects in subsequent processing. In addition, to accommodate the real-time needs of various applications, a background subtraction algorithm must be inexpensive and have low memory requirements, while still being able to accurately identify moving objects in the video.

II. RELATED WORK

For object detection in surveillance system, background modeling plays a vital role. Stauffer and Grimson developed a complex procedure to accommodate permanent changes in the background scene[1].Wren et al. have proposed to model the background independently at each pixel location which is based on computation of Gaussian probability density function (pdf) on the previous pixel values [2]. Here each pixel is modeled separately by a mixture of three to five Gaussians.

TheW4model presented by Haritaoglu et al. is a simple and effective method [3]. It uses three values to represent each pixel in the background image namely, the minimum intensity, the maximum intensity, and the maximum intensity difference between consecutive frames of the training sequence. Jacques et al. brought a small improvement to the W4 model together with the incorporation of a technique for shadow detection and removal [4]. Choi et al. in their work of [5] have distinguished shadows from moving objects by cascading three estimators, which use the properties of brightness, chromaticity and local intensity ratio. A novel method for shadow removal using Markov random fields (MRF) is proposed by Liu et al. in [6], where shadow model is constructed in a hierarchical manner. At the pixel level, Gaussian mixture model (GMM) is used, whereas at the global level a statistical feature of the shadow is utilized. Yannick Benezeth [7] presented a comparative study of several state of the art background subtraction methods. Approaches ranging from simple background subtraction with global thresholding to more sophisticated statistical methods have been implemented and tested on different videos with ground truth. Vinayak G Ukinkar [8] presented the basic idea to detect the moving object at foreground and background conditional environment. A mixture of Gaussians classification model for each pixel using an unsupervised technique is an efficient, incremental version of Expectation Maximization (EM) is used for the purpose. Kalyan Kumar Hati [9] proposed an intensity range based object detection scheme for videos with fixed background and static cameras. Therefore, from the existing literature, it is observed that most of the simple schemes are ineffective on videos with dynamic background. and these videos are well handled by complex techniques with higher computational cost. So, we proposed a simple scheme that uses gray level occurrence matrix (GLCM) for thresholding and simulation has been carried out on standard videos and real-time videos as well.

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III PROPOSED WORK

In this section proposed thresholding technique for image background subtraction is explained. We use local thresholding; it removes the need of using again local edge detection algorithm like canny edge detection. Gray level co –occurrence matrix (GLCM) also called text on co-occurrence matrix (TCM) fulfills our purpose. It is a local contrast mapping method. Here basically TCM serves two purposes: make image's local contrast map, unaffected by the illumination variation of image and local edge detection. Further, the GLCM functions characterize the texture of an image by calculating how often pairs of pixel with specific values and in a specified spatial relationship occur in an image, creating a GLCM, and then extracting statistical measures from this matrix. A gray-level co-occurrence matrix (GLCM) is generated by calculating how often a pixel with the intensity (gray-level) value i occurs in a specific spatial relationship to a pixel with the value j. By default, the spatial relationship is defined as the pixel of interest and the pixel to its immediate right (horizontally adjacent), but you can specify other spatial relationships between the two pixels. Each element (i,j) in the resultant glcm is simply the sum of the number of times that the pixel with value occurred in the specified spatial relationship to a pixel with value j in the input image. The number of gray levels in the image determines the size of the GLCM. GLCM of an image is computed using a displacement vector d, defined by its radius δ and orientation θ. To illustrate, the following figure shows how glcm calculates the first three values in a GLCM. In the output GLCM, element (1,1) contains the value 1 because there is only one instance in the input image where two horizontally adjacent pixels have the values 1 and 1, respectively. glcm(1,2) contains the value 2 because there are two instances where two horizontally adjacent pixels have the values 1 and 2. Element (1,3) in the GLCM has the value 0 because there are no instances of two horizontally adjacent pixels with the values 1 and 3. Graycomatrix continues processing the input image, scanning the image for other pixel pairs (i,j) and recording the sums in the corresponding elements of the GLCM. Figure1 shows this concept.

I

1	1	5	6	8
2	3	5	7	1
4	5	7	1	2
8	5	1	2	5

GLCM

	1	2	3	4	5	6	7	8
1	1	2	0	0	1	0	0	0
2	0	0	1	0	1	0	0	0
3	0	0	0	0	1	0	0	0
4	0	0	0	0	1	0	0	0
5	1	0	0	0	0	1	2	0
6	0	0	0	0	0	0	0	1
7	2	0	0	0	0	0	0	0
8	0	0	0	0	1	0	0	0

Figure1

A single GLCM matrix might not able to define all texture features of image, so multiple GLCM at different orientations are calculated. Above given example was with 0^o orientation i.e. horizontally matching pairs are checked. Further it can be done at angle 45^o, 90^o, 135^o

In actual every pixel has eight neighboring pixels allowing eight choices for θ, which are 0°, 45°, 90°, 135°, 180°, 225°, 270° or 315°. However, taking into consideration the definition of GLCM, the co-occurring pairs obtained by choosing θ equal to 0° would be similar to those obtained by choosing θ equal to 180°. This concept extends to 45°, 90° and 135° as well. Hence, one has four choices to select the value of θ. In the last example matching pairs have been taken up to one distance, this constitutes the radius of GLCM. Various research studies show δ values ranging from 1, 2 to 10.

Applying large displacement value to a fine texture would yield a GLCM that does not capture detailed textural information. From the previous studies, it has been concluded that overall classification accuracies with $\delta = 1, 2, 4, 8$ are acceptable with the best results for $\delta = 1$ and 2. This conclusion is justified, as a pixel is more correlated to other closely located pixel than the one located far away. Also, displacement value equal to the size of the texture element improves classification.

IV METHODOLOGY

Video can be considered as multiple frames. Each frame is different from other in pixel values. But those which are equal are treated as background pixels as background don't moves but there is problem when background consists of slow moving objects like swaying of trees which must be considered as background, but due to difference of each frame to next frame these also appear into foreground as pixels value changes for these too. To avoid this problem we have used multi background registration concept. In this frame difference mask along with background difference mask is generated and both are used to decide which pixel constitutes the foreground. Here is the work given in detail:

Step1 Frame Difference**:** In Frame Difference, the frame difference between current frame and previous frame, which is stored in Frame Buffer, is calculated and threshold. Frame Difference mask (FDM) is calculated.

Step2Background Registration**:** Background Registration can extract background information from video sequences. According to FDM, pixels not moving for a long time are considered as reliable background pixels. Stationary Index, Background Indicator, and background information is calculated here.

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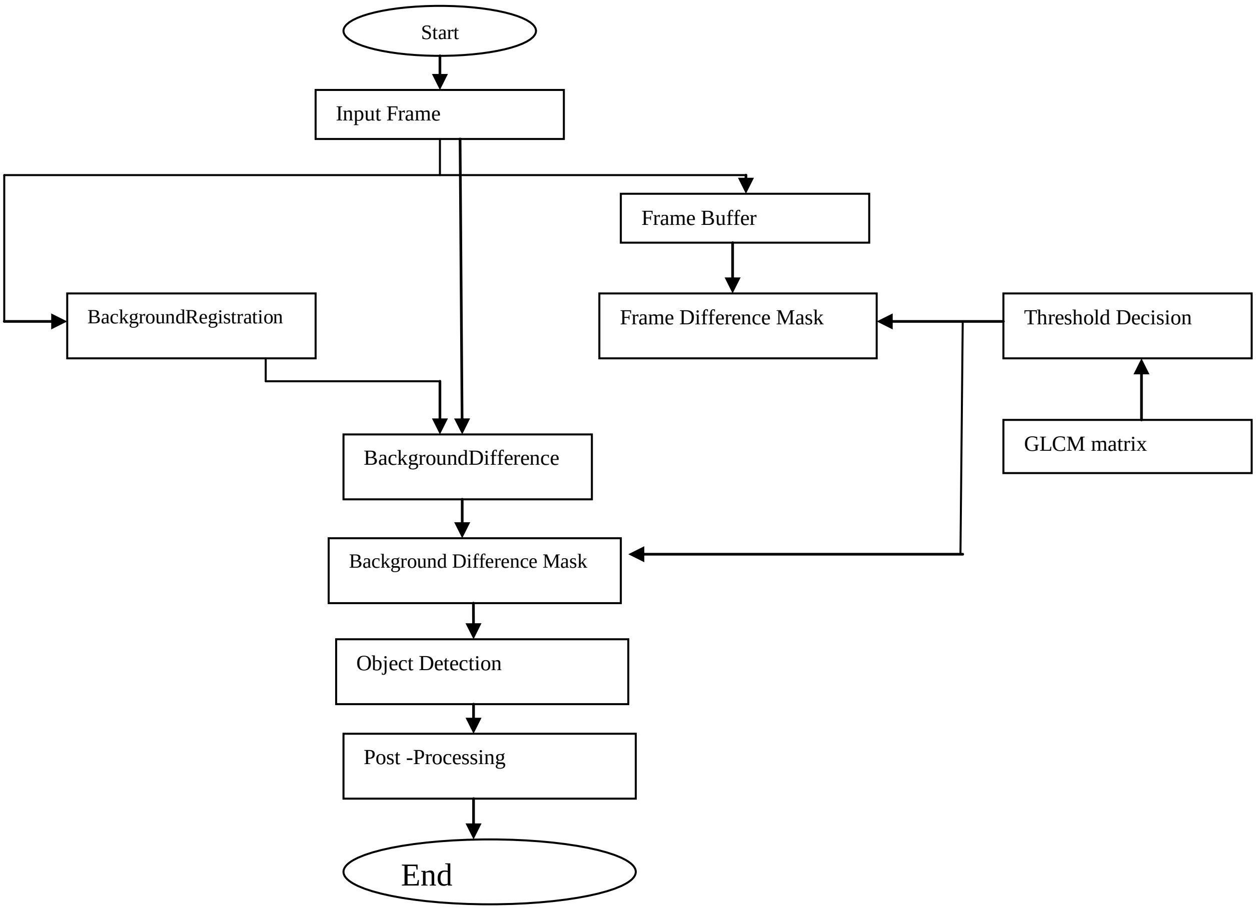
Figure 2



The initial values all are set to "0." Stationary Index records the possibility if a pixel is in background region. If SI is high, the possibility is high; otherwise, it is low. If a pixel is "not moving" for many consecutive frames, the possibility should be high, which is the main concept of SI equation. When the possibility is high enough, the current pixel information of the position is registered into the background buffer.

Step3Background Difference**:** The procedure of Background Difference is similar to that of Frame difference. What is different is that the previous frame is substituted by background frame. After Background Difference, another change detection mask named Background Difference Mask is generated.

Step4Object Detection: Both of FDM and BDM are input into Object Detection to produce Initial Object Mask (IOM). In IOM every frame is passed through morphological imclose operation which will fill the pixels in 3*3 neighborhoods. In post processing work done till now is used conditionally to extract background and foreground separately.

V. CONCLUSION

We proposed an efficient moving segmentation algorithm. A background registration technique is used to construct reliable background information from the video sequence. Then, each incoming frame is compared with the background image. If the luminance value of a pixel differs significantly from the background image, the pixel is marked as moving object; otherwise, the pixel is regarded as background. The adaptive background thresholding algorithm is used which uses gray level co-occurrence matrix and local mean to calculate the threshold value corresponding to each pixel. In the proposed algorithm, a morphological gradient operation is used to filter out the shadow area while preserving the object shape. In order to achieve the real-time requirement for many multimedia communication systems, our algorithm avoids the use of computation intensive operations. In addition, we optimize the implementation of the algorithm to achieve an even faster processing time.

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