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RESEARCH ARTICLE

OBJECT DETECTION SCHEME FOR DYNAMIC VIDEOS BASED ON LOCAL ILLUMINATION BASED TECHNIQUES

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Abstract: The paper presents the object detection for dynamic texture scenes using illumination based techniques. They are two types of illumination technique. First one is illumination based background subtraction (ILBS) and second one is illumination based frame difference (ILFS). Illumination frame difference is identifying the objects accurately in dynamic texture scene compare to illumination background subtraction. It has less computation complexity, less computation cost and less space of memory. The experimental results show that ILFS is efficient and robust for the dynamic environment and compare to ILBS.

Index Terms— Background modeling, background subtraction, video segmentation, video surveillance

I. INTRODUCTION

Detection and tracking of has been an important research topic in computer vision domain. The paper [1] presents an active contour-based method to track multiple cars using a background model to implement motion-based image segmentation. The However, the system is too slow for real-time applications. 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]. Stauffer and Grimson developed a complex procedure to accommodate permanent changes in the background scene [3]. 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 [4]. 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 [5]. McHugh et al. proposed an adaptive thresholding technique by means of two statistical models [6]. In most of the suggested schemes, the object detected is accompanied with misclassified foreground objects due to illumination variation or motion in the background. Moreover, shadows are falsely detected as foreground objects during object extraction.

The suggested background model initially determines the nature of each pixel as stationary or non-stationary and considers only the stationary pixels for background model formation. In the background model, for each pixel location a range of values are defined. Subsequently, in object extraction phase our scheme employs a local threshold, unlike the use of global threshold in conventional schemes.

The organization of this paper is as follow. Section II presents ILBS scheme. ILFS technique is introduced in section III. In section IV, implementation. Simulation results are reported in section V and conclusions are presented in VI.

II. LIBS SCHEME

The LIBS scheme is also called local threshold based background subtraction method. In this technique to finding the stationary pixels in the frames required for background modeling and then detect the objects by compare the dynamic background and current frame.

The algorithm of LIBS scheme as given by

Read dynamic texture video and then convert in to frames fr

background^i=rgb2gray(background frame)

Fr^{i-1}=rgb2gray(fr^{i-1});
object_frame=abs(double(background^i)-double(Fr^{i-1})
δ-> represent the standard deviation of object_frame
***for** j=1:width*
***for** k=1:height*
***If** object_frame(k,j)>width/2×δ*
Fg(k,j)=label (fr(k,j)) as stationary i.e pixel is zero
else
Fd(k,j)= label (fr(k,j)) as non-stationary i.e pixel is non zero
End
End
End
End

In this algorithm to find the objects from video. If any noise occurs in frame, to remove those noise using morphological operation. The dilation and erosion methods are used in morphological operation. This technique has less accuracy and cannot detect the objects accurately as shown figures in result section. It has less computation complexity compare to existing methods like mixture of Gaussian.

A. dynamic background model

In dynamic background model, the first frame is considered as the background model. However, this model is susceptible to illumination variation and also to change of first frame is small in the background like waving of leaves etc. to update the next back ground model at higher computational cost and thereby making them unsuitable for real time deployment. On the other hand, the background model should react quickly to changes in background. So to avoid that problem, we propose an intensity range based background model in LIBS technique. Here the RGB frame sequences of a video are converted to gray level frames using rgb2gray command in MATLAB. Initially, few frames are considered for background modeling and pixels in these frames are classified as stationary or non-stationary depends up on standard deviations of current frame. The background is then modeled taking all the stationary pixels into zero. Background model thus developed defines a range of values for each background pixel location. After finding the dynamic background model to finding the foreground objects using LIBS technique. It is used to subtraction the back ground model and current frame and then apply the local threshold to get the accurate objects. The algorithm of foreground objects in given by

for i to height of frame do

for j to width of frame do

Threshold $T(i, j)= 1/C*[M(i, j)+N(i, j)]$

$T_L(I,J)= M(i, j)- T(i, j)$

$T_U(I,J)= N(i, j)+ T(i, j)$

If $T_L(I,J) <= f <= T_U(I,J)$ *then*

$Sf(i, j)=0$ *//Background pixel*

else

$Sf(i, j)=1$ *//Foreground pixel*

end if

end for

end for

Where Tu is the upper threshold and Tl is the lower threshold. These local thresholds help in successful detection of objects suppressing shadows if any.

III. ILFS TECHNIQUE

ILFS technique is also called as Consecutive frame difference. It is a popular approach used in detection moving objects in dynamic texture videos. Traditionally, through the subtracting the previous frame from the current frame, we get the moving objects.

In dynamic texture scenes background model is changes to frame to frame but Background modeling is not require ILFS algorithms. Many researchers have been devoted to developing a background model that is robust against environmental changes.

The ILFS technique is worked well in dynamic and non-dynamic texture scenes. The algorithm of ILFS technique as shown below

Read dynamic texture video and then convert in to frames fr

Fr^i=rgb2gray(fr^i)

Fr^{i-1}=rgb2gray(fr^{i-1});
object_frame=abs(double(Fr^i)-double(Fr^{i-1})
δ-> represent the standard deviation of object_frame
***for** j=1:width*
***for** k=1:height*
***If** object_frame(k,j)>width/2×δ*
Fg(k,j)=label (fr(k,j)) as stationary i.e pixel is zero
else
Fd(k,j)= label (fr(k,j)) as non-stationary i.e pixel is non zero
End
End
End
End

In this algorithm to find the objects from video. If any noise occurs in frame, to remove those noise using morphological operation. The dilation and erosion methods are used in morphological operation. This technique has less accuracy and cannot detect the objects accurately as shown figures in result section. It has less computation complexity compare to ILBS technique.

The i and i-1 gray scaled images are differentiated and their absolute difference is used to identify the movement between frames. The threshold value is determined such that the pixel values on either side of this value are established to be either a background or a foreground pixel. The noise collected due to differencing is removed by applying the threshold value to the images. Pixels below the threshold are removed from the differenced frame leaving behind our object of interest. As described in equation, the absolute difference between two frames needs to be greater than the threshold for the object to be detected.

$$|F2-F1|>T$$

Here F1 is the initial frame and F2 is the following frame and T is the Threshold value. In this technique is applied to the videos having dynamic textured background, the detection accuracy is poor and noisy output. These methods are sensitive over the changes occurred in the background. They cannot adapt the background changes and consider the movements in the background as the object of interest (foreground).

Percentage of correct classification (PCC) is used as the metric for comparison, and is defined as,

$$PCC = \frac{TP + TN}{TPF} \times 100$$

Where TP is true positive that represents the number of correctly detected foreground pixels and TN is true negative representing the number of correctly detected background pixels.TPF represents the total number of pixels in the frame. TP and TN are measured from a pre-defined ground truth.

IV. EXPERIMENTAL RESULTS

The LIBS and LIFS techniques are simulated using MATLAB.

Fig. 1. 100th frame from video

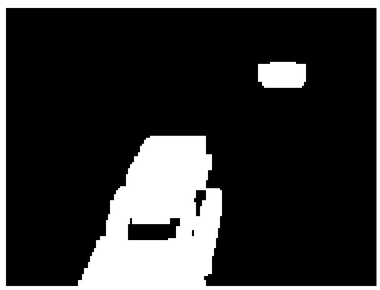

Fig.2. ILBS technique of 100th frame from video

Orginal frames

Fig.3. 10th frame from video

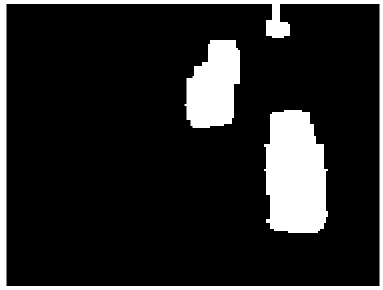

Fig.4. ILFS technique of 100th frame from video

V. CONCLUSION

In this work we have proposed ILBS and ILFS techniques. It is a simple robust scheme of background modeling and local threshold based object detection. In this project, we are using dynamic texture Videos with variant illumination background, textured background, and low motion background are considered for simulation to test the generalized behavior of the scheme. ILBS compared with the ILFS, both qualitatively and quantitatively. In general, it is observed that the suggested scheme outperforms others and detects objects in all possible scenarios considered.

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