ISSN (Online) : 2278-1021
ISSN (Print) : 2319-5940

International Journal of Advanced Research in Computer and Communication Engineering
Vol. 3, Issue 8, August 2014

Object Identification Based on Background Subtraction and Morphological Process

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Abstract: Background subtraction in dynamic scenes is an important and challenging task. This paper proposes an efficient motion detection system based on background subtraction using fuzzy colour histogram and morphological processing. Here two methods are used effectively for object detection followed by people counting and compare these performance based on accurate estimation. In dynamic texture scenes, morphological process and filtering are used effectively for unwanted pixel removal from the background. We introduce a background subtraction algorithm for temporally dynamic texture scenes using a clustering-based feature, called fuzzy colour histogram (FCH), which has an ability of greatly attenuating colour variations generated by background motions while still highlighting moving objects detection. Experimental results demonstrate that proposed method is effective for motion detection system based on background subtraction using fuzzy colour histogram and morphological processing, compared to several other competitive methods.

Keywords: Background Subtraction, Dynamic texture scenes, Fuzzy colour Histogram, Morphological Processing, Object Detection

I. INTRODUCTION

Detection, tracking and counting of humans in video sequences is important for a number of applications, such as video surveillance and human-computer interaction. Study of moving objects is an interesting subject of research in computer vision. It has applications in numerous fields, such as video compression, video surveillance, human-computer interaction, video indexing and retrieval etc. Object detection and object tracking are two closely related processes. The former involves locating object in the frames of a video sequence, while the latter represents the process of monitoring the object's spatial and temporal changes in each frame. There are few common moving object detection methods such as, Inter-frame differencing, background subtraction, optical flow, point statistics and classification, and feature matching and tracking. Background subtraction method is an important first step for many vision problems in which the object is separated from background clutter, by comparing the motion patterns, and assists subsequent higher-level operations, such as tracking, object recognition, etc. Background subtraction algorithms are expected to be robust both in the short term and throughout the lifetime of the vision system, because the environment can change substantially.

II. RELATED WORKS

Colour histograms are easy to compute, and they are invariant to the rotation and translation of image content. However, colour histograms have several inherent problems for the task of detecting moving objects. The first concern is their sensitivity to noisy interference such as lighting intensity changes and quantization errors. The second problem is their high dimensionality on representation. Even with coarse quantization over a chosen colour space, colour histogram feature spaces often occupy more than one hundred dimensions (i.e., histogram bins) which significantly increases the computation of distance measurement on the retrieval stage. Finally, colour histograms do not include any spatial information and are therefore incompetent to support image indexing and retrieval based on local image contents. In the following, we briefly describe several existing approaches that have been attempting to address these concerns.

A large number of background subtraction methods [1][2] 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 [3] is to model each pixel in a video frame with a single Gaussian distribution. Many authors have proposed improvements and extensions [4] for using more than one Gaussian distribution per pixel to model very complex non-static backgrounds. Although the above background subtraction methods have different modelling schemes, most of them use standard colour or intensity information, which limit their application in the dynamic environment. In [5], the authors detected people by fusing colour and edge information, which is an illumination invariant feature. Edge information uniquely is not sufficient, because part of the background might be uniform.

In [7], 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 colour, edge, stereo, motion and texture [8]. The combination of several measuring features can strengthen the pixels classification as foreground or background. In [9], the authors have used Sugeno integral to aggregate colour and texture features. In [9], Choquet integral seems to be more suitable than Sugeno integral, since the scale is continuum in the foreground detection.

III. PROPOSED METHOD

We propose a simple and robust method for background subtraction in dynamic texture scenes. The underlying principle behind our model is that colour variations generated by background motions are greatly attenuated in a fuzzy manner. Therefore, compared to preceding methods using local kernels, the future method does not require estimation of any parameters (i.e., nonparametric). This is quite advantageous for achieving the robust background subtraction in a wide range of scenes with spatiotemporal dynamics. Specifically, we propose to get the local features from the fuzzy colour histogram (FCH). Then, the background model is dependably constructed by computing the similarity between local FCH features with an online update procedure. To verify the advantage of the proposed method, we finally compare ours with competitive background subtraction models proposed in the literature using various dynamic texture scenes.

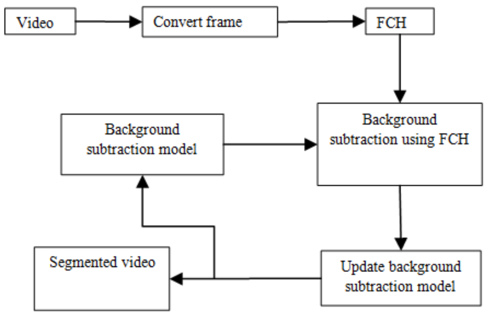

Fig 1: Proposed model for object detection

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 Bj (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 Bj (k) = 0.

(a) Algorithm 1: Background subtraction using local FCH features

Step 1: Construct a membership matrix using fuzzy – means Clustering.
Step 2: Quantize RGB colours 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 uir 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 Bj (k)
Step 6: Update the background model using $F_j^{\wedge}$ (k).
Step 7: Go back to Step 2 until the input is terminated (k=k+1)

(b) 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.

(c)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 pixels
Step 8: else
Step 9: Sf (i, j) = 1 //Foreground pixel
Step 10: end if
Step 11: end for
Step 12: end for

IV. SIMULATION RESULTS

We have taken a dynamic texture scene video as input where background is non static. In background we have water and tree, water is in motion and tree consists of moving leaves.

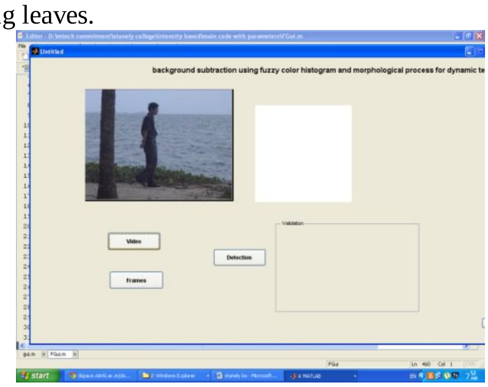

Fig 2: Input video

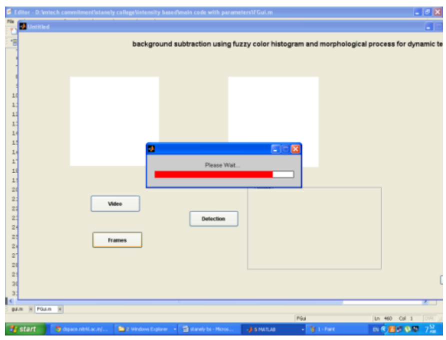

Fig 3: Frame separation of video

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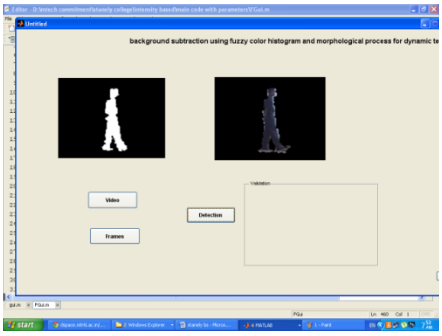

Fig 4: Object detection using FCH

To know efficiency of this method we have calculated sensitivity, PSNR and RMSE values for the input video. Sensitivity is also called as true positive rate and measures the proportion of actual positives which are correctly identified.

$$\text{Sensitivity} = \frac{\text{number of true positives}}{\text{number of true positives} + \text{number of false negetives}}$$

1. True positive = correctly identified
2. False positive = incorrectly identified
3. True negative = correctly rejected
4. False negative = incorrectly rejected

The MSE is often called reconstruction error variance σ_q^2. The MSE between the original image f and the ground truth image g is defined as:

$$\textbf{MSE} = \sigma_q^2 = \frac{1}{N}\sum_{j,k}(f[j,k]-g[j,k])$$

Where the sum over j, k denotes the sum over all pixels in the image and N is the number of pixels in each image.

$$\text{RMSE} = \sqrt{\text{MSE}}$$

From that the peak signal-to-noise ratio is defined as the ratio between signal variance and reconstruction error variance.

$$\text{PSNR} = 10\log_{10}\left(\frac{\text{MAX}^2}{\text{MSE}}\right) = 20\log_{10}\left(\frac{\text{MAX}}{\text{RMSE}}\right)$$

Values we obtained are as follows:

Sensitivity – 99.2391
RMSE -0.26195
PSNR -53.9485

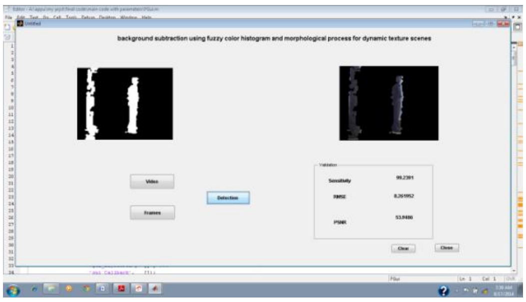

Fig 5: Parameter analysis

V. CONCLUSION

In this paper, we introduce a novel description on representing Background subtraction for dynamic texture using fuzzy c -means clustering algorithm, called fuzzy colour histogram (FCH).Based on extensive experimental results, our FCH is less sensitive and more robust than CCH (Conventional colour histogram) on dealing with illumination changes such as lighting intensity changes, region-of-interest background subtraction, and possibly other uncovered aspects in new applications.

VI. FUTURE WORK

Finally, exploiting FCH into other image processing frame- works and even extending similar soft clustering approach to other low-level visual features (e.g., shape, texture, etc.) are also recommended

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BIOGRAPHIES

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