

A Novel Background Subtraction for Dynamic Texture Scenes by Exploitation of Fuzzy Colour bar Graph and Morphological Operations

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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.

1. INTRODUCTION

Detection, tracking and counting of humans in video sequences is important for a number of applications, such as video surveillance [3] 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 [6], 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 [2], optical flow, point statistics and classification, and feature matching and tracking. Background subtraction method is an important first step for many vision problems[7] 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.

2. 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.

3. 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.

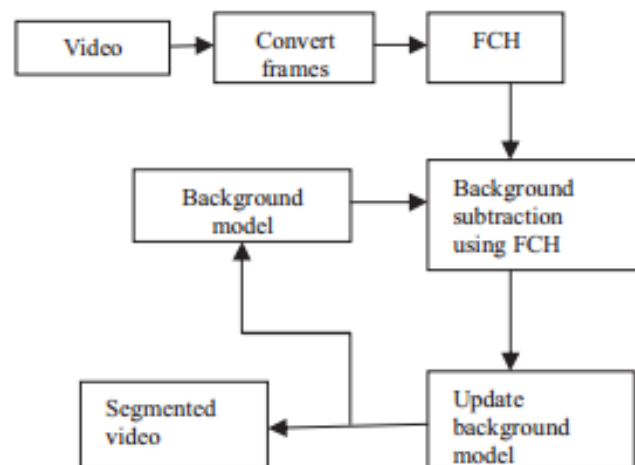


Fig1. Proposed model for object detection

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:

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

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

Algorithm1. *Background subtraction using local FCH features*

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

4. 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.

Algorithm2. *Background Subtraction for a frame f*

- Step 1: for $i \leftarrow 1$ to height of frame do
- Step 2: for $j \leftarrow 1$ 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 $TL(i, j) \leq f(i, j) \leq TU(i, j)$ then
- Step 7: $S_f(i, j) = 0$ //Background pixels
- Step 8: else
- Step 9: $S_f(i, j) = 1$ //Foreground pixel
- Step 10: end if
- Step 11: end for
- Step 12: end for

5. MORPHOLOGICAL OPERATIONS

Morphology is a mathematical framework for the analysis of spatial structures and is based on set theory. It is a strong tool for performing many image processing tasks. Mathematical morphology is completely based on set theory. Morphological sets represent important value. By using set operations many useful operators can be defined. The important morphological operations are basically dilation, erosion, open and close operations. Morphological operations make use of a structuring element M ; which can be either a set or a function that corresponds to a neighbourhood-function related to the image function $g(x)$ [10]. In general, a dilation (denoted by \oplus) is every operator that commutes with the supremum operation. On the other hand, erosion (denoted by \ominus) is every operator that commutes with the infimum operation. There is a homomorphism between the image function g and the set B of all pixels with image function value 1. The structuring element $M(x)$ is a function that assigns a subset of $N \times N$ to every pixel of the image function. Then dilation, an increasing transformation, is defined as,

$$B \oplus M = \bigcup_{x \in B} M(x),$$

Whereas, erosion, a decreasing transformation, is defined as

$$B \ominus M = \{x | M(x) \subseteq B\}.$$

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In the same manner, opening and closing of set B by structuring element M are respectively defined as

$$B \circ M = ((B \ominus M) \oplus M),$$

$$\text{and } B \bullet M = ((B \oplus M) \ominus M).$$

6. RESULTS

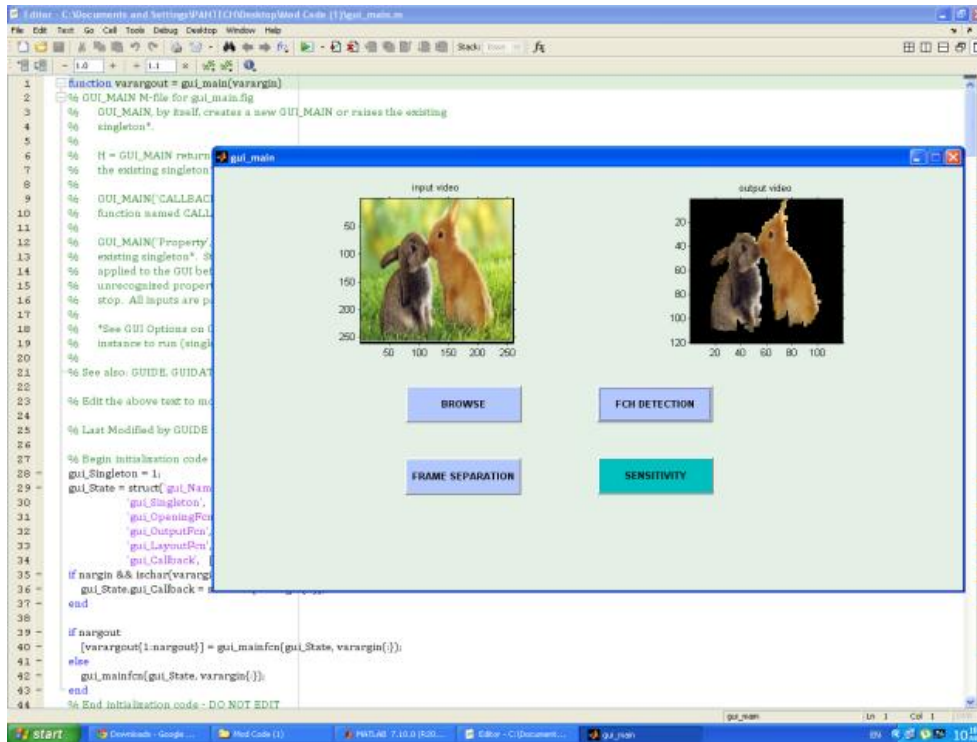


Fig2. Input video

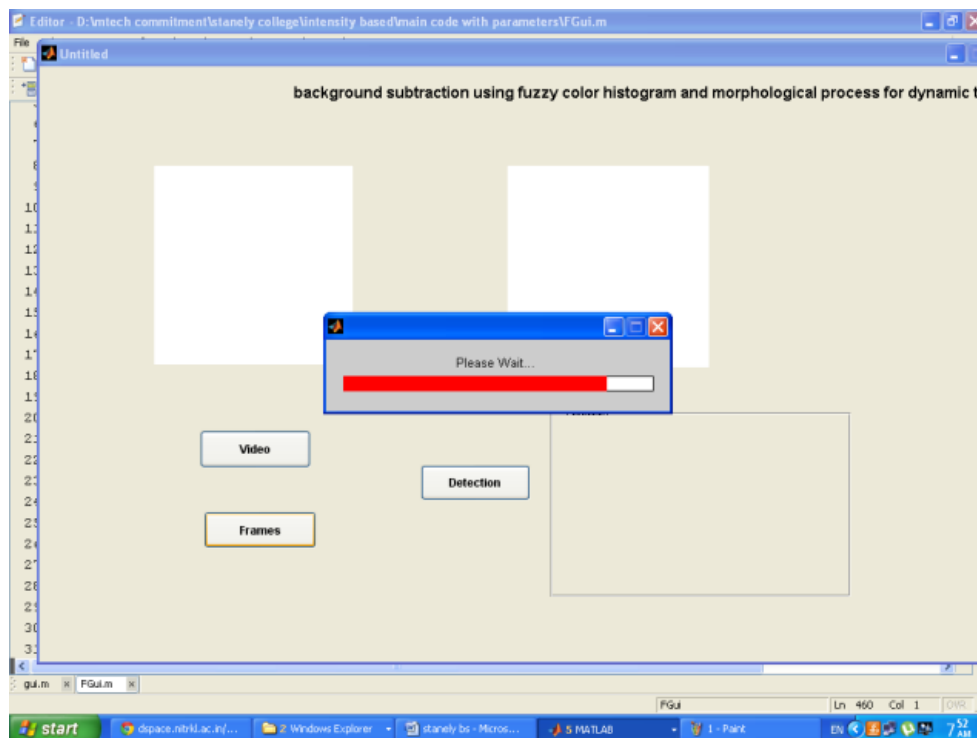


Fig2. Frame separation of video

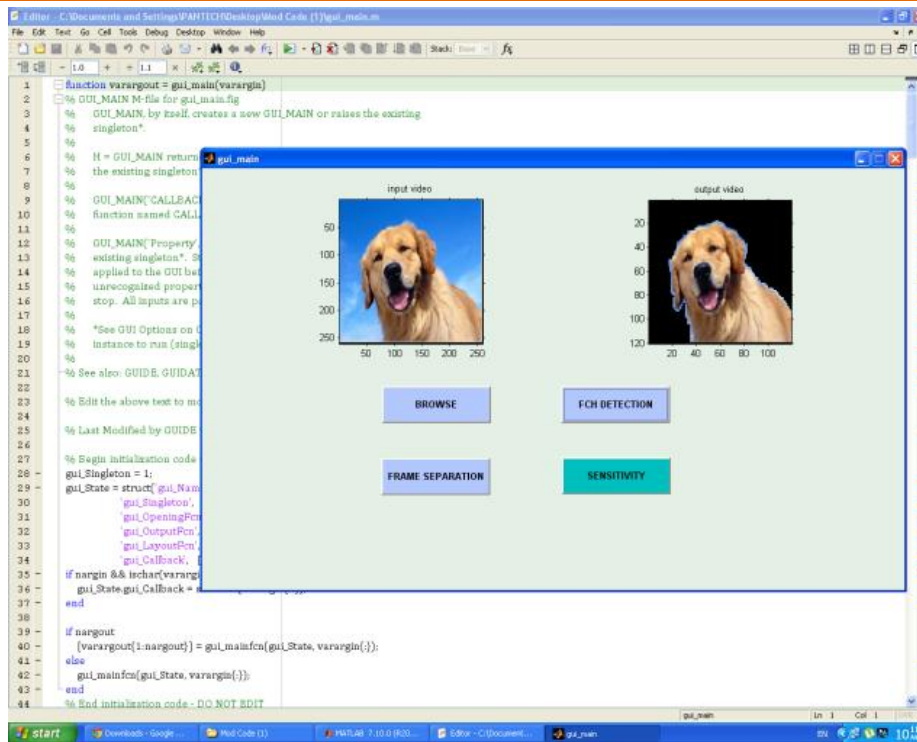


Fig3. Object detection using FCH

Values we obtained are as follows:

Sensitivity – 99.2391

RMSE -0.26195

PSNR -53.9485

Table1.

	Input Video 1	Input Video 2
Sensitivity	99.2391	98.7836
RMSE	0.26195	0.2955
PSNR	53.9485	52.9428

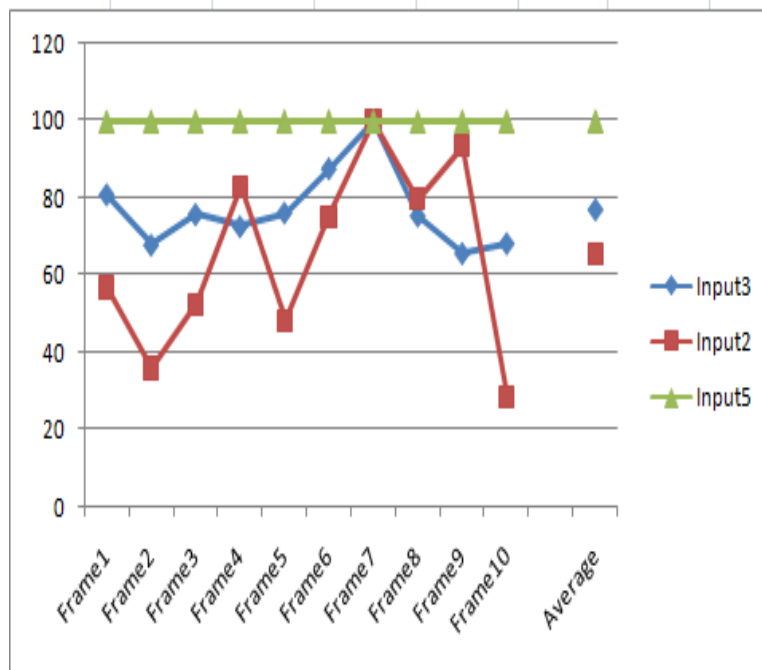


Fig4. Sensitivities of individual frames in a video

7. CONCLUSION AND FUTURE WORK

In this paper, we introduce a novel descriptor 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.

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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