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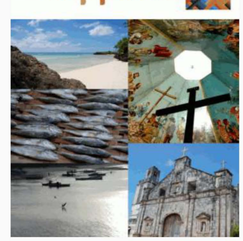

Adaptive Threshold for Background Subtraction in Moving Object Detection using Fuzzy C-Means Clustering

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Abstract—Background subtraction is the important part of moving object detection. The problem of background subtraction is threshold selection strategy. This paper proposed a Fuzzy C-Means (FCM) algorithm to produce an adaptive threshold for background subtraction in moving object detection. To evaluate the performance, FCM were compared against standard Otsu algorithm as threshold selection strategy. Mean Square Error (MSE) and Peak Signal Noise Ratio (PSNR) was used to measure the performance. Based on the experiment, the MSE of FCM is lower than MSE of Otsu and PSNR of FCM is higher than PSNR of Otsu. The result proved that FCM is promising to classify the pixels as foreground or background in moving object detection.

Keyword; fuzzy c-means, moving object segmentation, otsu algorithm

I. Introduction

Moving objects segmentation is one of the most fundamental tasks in the design of computer vision systems and remains an active field of video processing and computer vision research [1]. Video segmentation occupies a very important role in video processing, since video segmentation is so often the first step which must be successfully taken before subsequent tasks such as feature extraction, classification, and description.

Background subtraction is the first process for analyzing the video sequence in the visual surveillance application [2]. The aim of background subtraction is to extract the foreground from the background. Background modeling is the principal of background subtraction [3]. Background modeling uses new frame to update the background model. Background modeling is divided into recursive and non-recursive technique. Recursive technique uses input frame to update single background model recursively. Compare to recursive technique, non-recursive uses frame by frame to separate pixels as background or foreground. Frame difference is the simplest background modeling technique that use previous frame as a background for the current frame.

Frame differencing present low computational complexity [4]. Therefore, frame difference can be used in real-time moving object detection. Based on the advantages of frame difference, this paper decides to use temporal frame difference in moving object detection. The problem is frame difference needs determine the threshold to classify the pixel of foreground and background.

Otsu algorithm [5] is classic thresholding in image segmentation. Otsu maximizes the class variance into histogram-based thresholding. The shortcoming is Otsu could not converge to a global optimum while dealing with images discontinuous on grey level [6].

Clustering algorithm can be considered as technique to classify the pixel as foreground and background. Clustering algorithm can be divided into hard and soft clustering. Hard clustering means an object is only belong to one clustering, while soft clustering means an object can belongs to several cluster. Fuzzy C-Means (FCM) is soft clustering algorithm that produces a membership degree of each object to all clusters. FCM is unsupervised clustering algorithm that successfully to a number of clustering problems, such as color segmentation in [7] and image clustering in [8]. In this paper, adaptive threshold using FCM clustering is proposed to object moving detection.

The remainder of this paper is organized as follows. Section 2 presented the related work of object moving segmentation. Section 3 discussed our proposed method in object moving segmentation. Section 4 shows the experiment result. Finally, conclusion and future work are given in section 5.

II. Related Work

The study of Yumiba *et al.* [9] have proposed a spatio-temporal texture called ST-Patch features for object moving detection to cover dynamic change in backgrounds.

Ka Ki Ng and Edward J. Delp [4] proposed a method to determine the threshold automatically and dynamically depending on the intensities of the pixels in the current frame and a method to update the background model with learning rate depending on the differences of the pixels in the background model and the previous frame.

Kim *et al.* [10] proposed a robust foreground segmentation algorithm to classify between foreground and background using multiple threshold and morphological process. Mean and standard deviation are used for background subtraction.

Spagnolo *et al.* [11] proposed a reliable foreground segmentation that combines temporal image analysis with the reference background image to solve the problem of moving object segmentation using background subtraction. The aim of temporal image analysis is to detect the point in each image as moving or static.

III. Threshold Selection Strategy

In this section, threshold selection strategy between Otsu and Fuzzy C-Means algorithm are presented. Both techniques have been studied as an adaptive threshold in image segmentation [12][13].

A. Otsu Algorithm

The threshold of Otsu algorithm is initialized using t. The range value of t is between 1 and L, where $L = 255$. The probability of each pixel in the i^{th} level can be determined by using (1).

$$p_i = n_i / N \tag{1}$$

where n_i is the number of pixel in the i^{th} level and N is the total of number of pixels. The average gray level of an image use (2).

$$\mu_T = \sum_{i=1}^{L-1} i \times p_i \tag{2}$$

For single threshold, Otsu divide the pixels into two class $C_1 = \{0,1,...,t\}$ and $C_2 = \{t+1, t+2, ..., L-1\}$. The probability of class can be computed by using (3).

$$\omega_1(t) = \sum_{i=1}^{t} p_i \qquad \omega_2(t) = \sum_{i=1}^{L-1} p_i \tag{3}$$

$$\mu_1(t) = \sum_{i=1}^{t} \frac{i \times p_i}{\omega_1(t)} \qquad \mu_2(t) = \sum_{i=1}^{L-1} \frac{i \times p_i}{\omega_2(t)} \tag{4}$$

The value of t can be computed using (5).

$$t^* = \max_{1 \le k < L} \alpha_B^2(t) \tag{5}$$

where

$$\alpha_B^2(t) = \omega_1(t)\left(\mu_1(t) - \mu_T\right)^2 + \omega_2(t)\left(\mu_2(t) - \mu_T\right)^2 \tag{6}$$

B. Fuzzy C-Means Algorithm

Fuzzy C-Means is popular fuzzy clustering algorithm. FCM produces a membership matrix, which contains the degree of membership of a pixel to all the clusters. Therefore, FCM is soft clustering algorithm. FCM attempts to minimize the sum of square error (SSE).

$$SSE = \sum_{i=1}^{N} \sum_{j=1}^{C} u_{ij}^m \left\| x_i - c_j \right\|^2, 1 \le m \le \infty \tag{7}$$

where u_{ij} represents the membership of pixel x_i in the j^{th} cluster, c_j is the j^{th} cluster center.

$$\sum_{i=1}^{c} u_{ij} = 1, 1 \le j \le n \tag{7a}$$

$$u_{ij} \ge 0, 1 \le i \le c, 1 \le j \le n \tag{7b}$$

$$\sum_{i=1}^{n} u_{ij} = 1, 1 \le i \le c \tag{7c}$$

The FCM algorithm is composed of the following steps.

1. Get the input data from an image.
2. Choose the number of cluster and the value of ε ($\varepsilon > 0$).
3. Compute partition matrix using (8).

$$u_{ik} = \frac{1}{\sum_{j=1}^{c} \left(\frac{d_{ik}}{d_{jk}} \right)^{\frac{2}{m-1}}} \tag{8}$$

4. Update the cluster center using (9).

$$c_j = \frac{\sum_{k=1}^{n} u_{ik}^m x_k}{\sum_{k=1}^{n} u_{ik}^m} \tag{9}$$

5. Repeat step 3 to 4 where $\left\| c^k - c^{k+1} \right\| < \varepsilon$.

IV. Methodology of Object Moving Detection

The proposed video segmentation comprises several steps as illustrated in Figure 1. First, the video is split into single frame. Then, perform background subtraction using frame difference technique. In the frame different, previous frame is used as a background to detect the object in current frame.

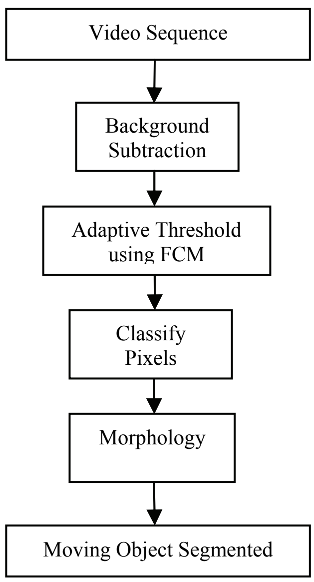

Figure 1. Block diagram of proposed moving objects detection

Next, FCM is used to classify the pixel as foreground or background in the process of background subtraction. Finally, morphology is performed to get the best object detection. Detail explanation of each step is described in the next subsection.

A. Background Subtraction

Background subtraction is used to recognition the intensity different of current image and the background image. This paper used frame difference, one of the non-recursive techniques in background subtraction. Let BF is binary foreground of an image.

$$BF(x,y,n)=\begin{cases}1, if \left|I(x,y,n)-I(x,y,n-1)\right|\geq\alpha \\ 0, otherwise\end{cases} \quad (10)$$

The threshold (α) for classify between foreground and background can be determined by human. Next, FCM is performed to produce the threshold.

B. Fuzzy C-Means Algorithm

FCM produces matrix u_{ik} that contains the membership degree of each object to each cluster. For threshold selection strategies using FCM, we refer to [12] which threshold is average value of the maximum in the class with the smallest center and the minimum in the class with the middle center.

C. Morphology

Morphology is performed to get the better segmentation result [14]. Morphology is used to manipulate the features in images based on shape [15]. Dilatation, erosion, opening, and closing are the basic operation of morphology. Opening and closing is sequential combination of dilatation and erosion. In [16] stated that the purpose of opening (erosion followed by dilatation) is filter detail and simplifies images by rounding corner from inside the objects, while closing (dilatation followed by erosion) can close small gaps inside the object. This paper uses closing to remove the imperfects of the foreground detection.

V. EXPERIMENTAL RESULT

This section presents the experimental results of the algorithms implemented for clustering moving objects. These experiments are conducted on a series of real video. All video processing is used for moving objects where the objective of the system is to cluster the objects on street. There are 200 frames of the video. We used MATLAB 2010b and ran on PC M 370 with processor i3, 2.40GHz, RAM 4.00 GB.

Mean Square Error (MSE) and Peak Signal to Noise Ratio (PSNR) are used to measure the performance of our moving object segmentation. MSE and PSNR were used to compute the different value of segmented image and ground truth image. The lower value of MSE the better is image detection. Otherwise, the higher value of PSNR the better is image detection [17]. MSE and PSNR can be measured by (11) and (12), respectively.

$$MSE(X,Y)=\frac{1}{MN}\sum_{i=1}^{M}\sum_{j=1}^{N}\left[X(i,j)-Y(i,j)\right] \quad (11)$$

$$PSNR(X,Y)=10.\log_{10}\left(\frac{\max^2}{MSE(X,Y)}\right) \quad (12)$$

where X is the ground truth image, Y is the segmentation image of size $M\times N$ and max is the maximum possible pixel value of the image.

In our experiment, we used two different video to evaluate our proposed object moving detection. The video are red car moving detection and human moving detection. Table I. shows the threshold of FCM and Otsu for each video. Figure 2 and Figure 3 show the MSE and PSNR of red car moving detection, respectively.

TABLE I. THRESHOLD FOR FCM AND OTSU

	Red Car Video	Human Video
FCM	0.303	0.233
Otsu	0.380	0.286

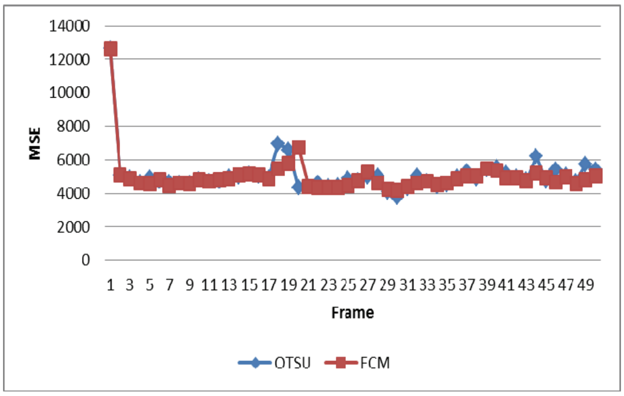

Figure 2. MSE of FCM and Otsu in red car moving detection

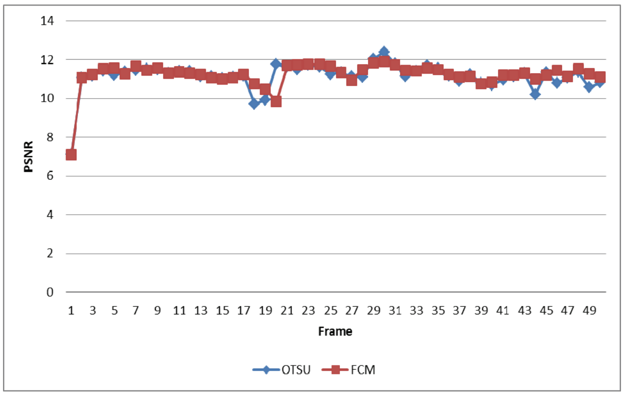

Figure 3. PSNR of FCM and Otsu in red car moving detection

The best performance of FCM (MSE= 4195.022 and PSNR= 11.90 dB) were obtained at frame 30. Averagely, MSE of FCM is 5004.44 and MSE of Otsu is 5098.39. Also, PSNR of FCM is 11.21 dB and PSNR of Otsu is 11.13 dB. The example frames of Figure 2 and Figure 3 can be shown in Figure 6.

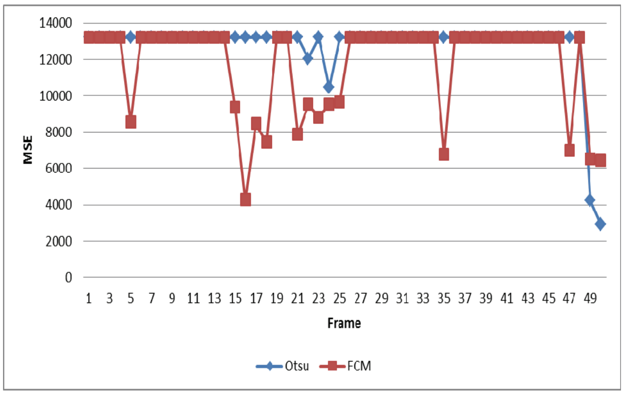

Figure 4. MSE of FCM and Otsu in human moving detection

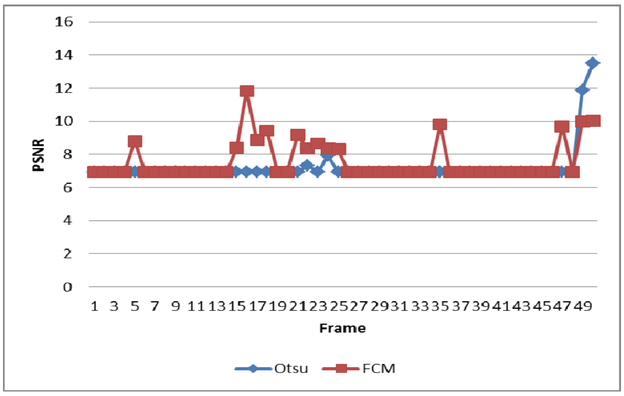

Figure 5. PSNR of FCM and Otsu in human moving detection

The second video is human moving detection. Figure 4 and Figure 5 show the MSE and PSNR of human moving detection, respectively. The graphs show the best performance of FCM (MSE= 4277.44 and PSNR= 11.82 dB) at frame 16. Averagely, MSE of FCM is 11720.88 and MSE of Otsu is 12750.09. Also, PSNR of FCM is 7.57 dB and PSNR of Otsu is 7.18 dB. The example frame of Figure 4 and Figure 5 can be shown in Figure 7.

VI. CONCLUSSION AND FUTURE WORK

This paper presents an adaptive technique to determine the threshold for background subtraction in moving object detection. The result shows that the performance of object moving detection using FCM thresholding is better than with standard Otsu algorithm. FCM produced lower MSE and higher PSNR compared to Otsu. As future work, we could perform another clustering technique in threshold selection strategy, such as hierarchical clustering algorithm.

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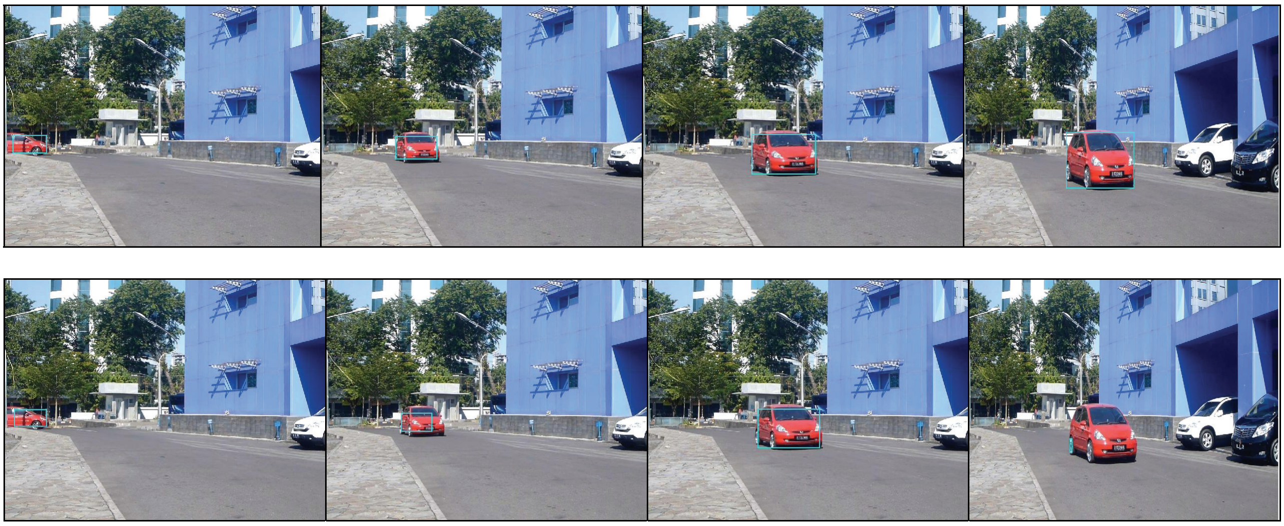

Figure 6 **First row**. Frames 17, 25, 39, and 40 (from left to right) of red car moving detection using FCM. **Second row**. Frames 17, 25, 39, and 40 (from left to right) of red car moving detection using Otsu.

Figure 7 **First row**. Frames 5, 10, 15, and 20 (from left to right) of human moving detection using FCM. **Second row**. Frames 5, 10, 15, and 20 (from left to right) of human moving detection using Otsu.