FUZZY C-MEANS ALGORITHM FOR ADAPTIVE THRESHOLD ON ALPHA MATTING

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Abstract— **Image matting is a process of extracting the foreground object from an image that plays an important role in image editing. In this paper, FCM and Otsu algorithm, is used to generate the threshold value as an input of the alpha value. Mean Square Error (MSE) is used to measure the performance of both algorithms. The eexperimental results shows that the FCM algorithm produces a smaller threshold value so that the number of the error pixels was less than the Otsu algorithm.**

Keywords-component; Fuzzy C-Means; Alpha Matting; Adaptive Threshold;

I. Introduction

Extraction the foreground object from the whole images is important in editing images. Separation accuracy of the foreground object from background is determined by part or all of an image pixel that is called pulling matte or digital matting. In order to formulate a digital matting method, input image (*I*) is assumed as a combination of a foreground image (*F*) and a background image (*B*). The color of pixel *i*-th, is assumed as a linear combination that correspondent of a foreground and background colors [1], where α_i is the pixel's opacity component used to blend linearly between foreground and background.

$$I_i = \alpha_i F_i + (1 - \alpha_i) B_i \qquad (1)$$

Several methods are used in recent years, giving trimap as a starting point. Trimap is a rough drawing (usually hand-drawn) of the image input segmented into three regions; foreground (drawn in white), background (drawn in black) and unknown region (drawn in gray). Those three regions are typically used to solve the *F* and *B* simultaneously by iterative nonlinear optimization, which alternately is done by estimating *F* and *B* with α. In order to generate a good result of the unknown regions of the trimap should be made as small as possible. However, the weakness of this approach is difficulty in handling the images that have a pixel mixture or the foreground that has many holes [2].

Extracting the alpha matte from a natural image is used "closed-form" which is closely related to the colorization method [3]. The cost function is obtained from the assumption of local smoothness in the F and B, which are possible to be eliminated so that generates the quadratic cost function in α. The global optimum is used to this cost function to generate alpha matte that can be obtained by solving a sparse linear system. In order to differentiate F and B (see in fig. 6.b), scribble color (white for foreground and black for background) is used to calculate the alpha value of the closed-form method. This differentiation will be examined by eigenvectors of a sparse matrix that has close relationship with matrices used in spectral image segmentation algorithms. This approach also provides solid theory in instance analysis that provides valuable hints to recognize where the image scribbles should be placed. As an added value of the previous research, this paper proposed an alpha value generated by the adaptive threshold using Fuzzy C-Means (FCM) algorithm for pulling matte.

II. Related Work

The existance of image matting has a goal to solve compositing (eq. 1) for the unknown pixels. Most methods of image matting use trimap [4], [5], [6], [7], [8] as a companion to the image input for labeling foreground, background, or unknown pixels. This method usually carries out by utilizing some local regularity assumptions on F and B to estimate the value of each pixel in the unknown region. According to Bremen at al (2000) state that Knockout algorithm is segmented between F and B, following step is estimating the color probability of F and B into unknown region. The point is put in the unknown region, foreground F is counted from the pixel in perimeter of known foreground. The weight of the nearest pixel that known is set 1, and then this weight decreases directly proportional to the distance, for reaching the weight 0 is needed twice as distant as the nearest pixel. The same procedure is used to the beginning of calculating background based on the pixel from nearby known background. The assumption of some algorithms [7], [8] said that local foreground and background are come from the simple relatively color distribution. The Bayesian matting algorithm is the successful factor for Knockout Algorithm, where a mixture of oriented Gaussians is used to learn the local distribution and then α, F, and B are estimated as the most probably ones given in that distribution.

Meanwhile, in the Poisson matting method is performed by optimizing the pixel alpha, foreground as well as background colors statistically. To reduce errors that caused by misclassification of the complex color displaye in color sample [5], matte operations performed on the gradient directly. A smooth change intensity of the F and B are the basis for the formulation in Poisson Matting. Sun et al used global Poison matting as semi-automatic approach to estimate matte from an image gradient that given a user-supplied trimap. Robust calculation of the foreground and background has been performed by matting failure caused by a complex background that often cannot be solved by global Poisson matting. This robust calculation is also used to solve local Poisson matting, which manipulates a continuous gradient field in a local region. Several approaches were successfully used to extract the foreground from background object that have been proposed [9], [10], [11]. Several approaches have been performed to translate user-defined simple constraints (such as scribble or a bounding rectangle) to a min-cut problem. The completion of min-cut problem using binary segmentation which is then transformed into a trimap by erosion, however, the results are still fuzzy. Border matting [10] used a parametric alpha that put in a narrow strip around the hard boundary, cannot be performed for the similar cases to the hairs object, since the extent of the fuzzy region cannot be performed in this manner. The proposed method by [3] and [12] used boundary scribble for all images by reducing a quadratic cost function so that better suit for matting problem.

Wang and Cohen [13] propose a scribble-based interface for interactive matting. The scribble is used as parameter a foreground and background pixel. This approach has produced some impressive results, however the approach has expensive process. Guan et al [13] proposed another scribble-based matting approach by adding the random walk approach [5] with an iterative estimation of color models.

III. DESIGN OF ALGORTIHM

Fig 1. shows the framework of the proposed image matting.

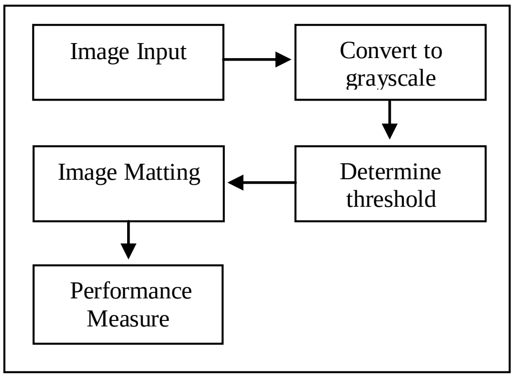

Fig. 1.Proposed Framework Overview

In general, the content of the image covers foreground, background, boundary areas and noise. Gray images can be used as an important feature to distinguish between the contents so that the value of the gray pixels is usually chosen as the clustering feature [14].

A. FCM (Fuzzy C-Means) Algorithm

FCM algorithm proposed by Bezdek in 1973 is the clustering methods of the "hard c-means" algorithm then improved by [15], and defined as follow. Let X={x1,x2, ... xn}, where X is data set, and xi includes the number of s attributes. Fuzzy clustering of X divided into classes ($2 \leq c \leq n$), and V = {v1, v2, ..., vc} is the c centers. Respectively the sample cannot be strictly divided into certain types, however a certain degree of membership can be a member of the other categories. the criteria of the FCM clustering is defined as the objective function as shown in (equation . 2).

$$J(U,V) = \sum_{k=1}^{n}\sum_{i=1}^{c}(u_{ik})^m\,(d_{ik})^2 \tag{2}$$

J (U, V) denotes the various types of the sample by the number of the cluster centers weighted is a weighted distance squared; (u_{ik}) shows the membership category of the i sample to x_k.

$$d_{ik} = \|x_k - v_j\| \tag{3}$$

where d_{ik} is Euclidean Distance of k sequences to the center I; m is a weighted index which is an important parameter in regulating the degree of fuzzy clustering, and $m \in (1, \infty)$.

$$u_{ik} = 1 \Bigg/ \sum_{j=1}^{c}\left(\frac{d_{ik}}{d_{jk}}\right)^{\frac{2}{m-1}} \quad \forall i, \forall k \tag{4}$$

cluster center V defined as

$$v_i = \sum_{k=1}^{N}(u_{ik})^m\, x_k \Bigg/ \sum_{k=1}^{N}(u_{ik})^m \tag{5}$$

Threshold value obtained from the average of the maximum in the class with the smallest center and minimum at the class with the middle center, where the cluster pixel values using a 3-class concept in the FCM [16]. Fig. 2. Shows the thresholds comparison by FCM and Otsu .

Fig. 2. Threshold Results

B. Mean Square Error (MSE)

MSE was used in order to measure the performance of image matting. Input images were comparing with the image after combined with the alpha parameter that obtained from threshold process.

IV. EXPERIMENTS AND RESULTS

The results show that the FCM algorithm was performed to generate a threshold value. The results of threshold values obtained from both algorithms were shown in the Table.1 and the fig. 3

Table 1. Threshold Result

Input Image	Threshold	
	FCM	OTSU
teddy.bmp	0,381355932	0,539215686
hair.bmp	0,335294118	0,423529412
bird.bmp	0,32745098	0,474509804
horse.bmp	0,331372549	0,470588235
lion.bmp	0,331372549	0,521568627

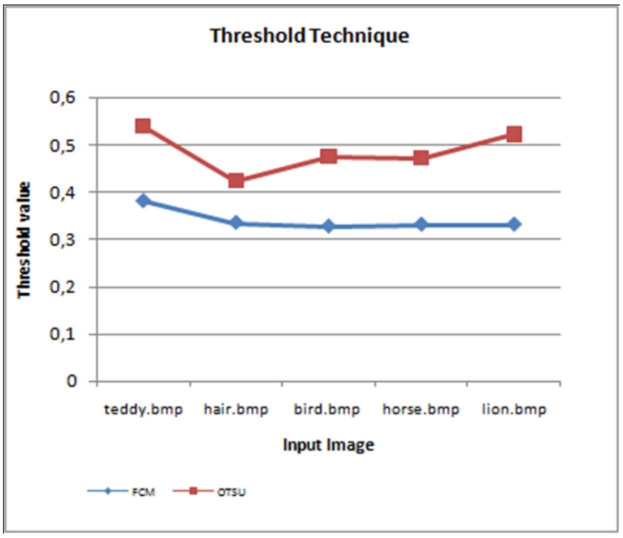

Fig. 3. Threshold Comparison

Next, threshold value was inserted into the alpha value and used for the purpose of matting [3], therefore the foreground object could be separated as illustrated in fig. 6.c. Furthermore, the foreground object that had been separated was blended with the input image as shown in fig. 6.e. This paper used MSE to measure the performance of image matting by comparing the input image as described in fig. 6.a, and the composite image as drawn in fig. 6.d. The measurement results were revealed in Table. 2 and fig. 4

Table 2.MSE of FCM and Otsu Algorithm

Input Image	Mean Square Error	
	FCM	OTSU
teddy.bmp	2841,424126	5669,397258
hair.bmp	1689,305723	2697,183302
bird.bmp	1785,980596	3751,389982
horse.bmp	2487,232621	5015,051846
lion.bmp	2043,379	5055,08185

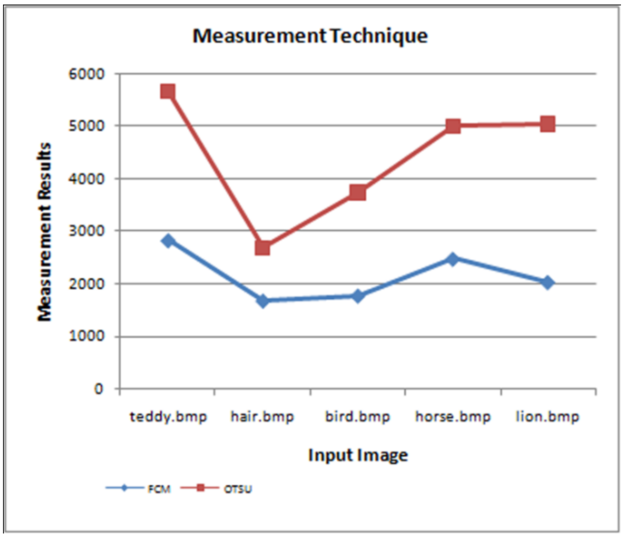

Fig. 4.Comparasion of Measurement Result

In addition, this paper also measured the processing time to evaluate the performance of image matting. Comparison of the time elapsed between the FCM algorithm and Otsu algorithm is shown ~~as~~ in table 3 and fig. 5 below.

Table 3. The Average Time Elapsed Results

Input Image	The Average Time Elapsed	
	FCM	OTSU
teddy.bmp	13,59544297	10,59543472
hair.bmp	15,85372108	11,24068757
bird.bmp	15,61203625	11,88594042
horse.bmp	14,17363956	12,53119328
lion.bmp	15,02731435	13,17644613

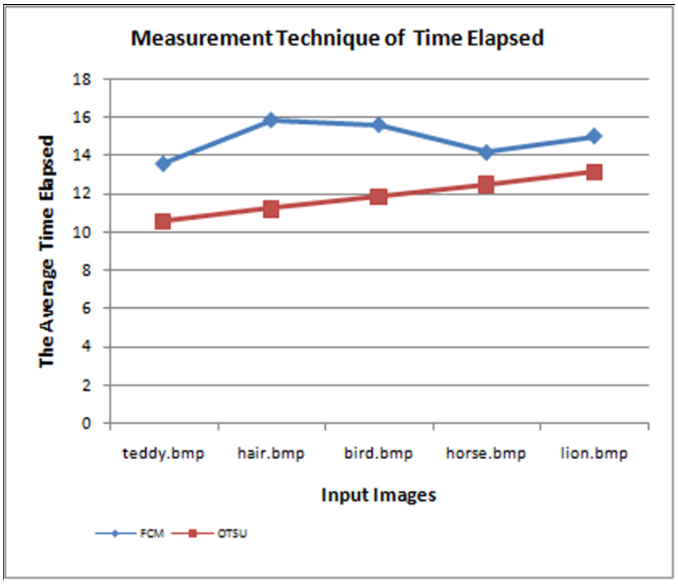

Fig. 5. Comparison of Processing Time

V. CONCLUSION

This paper was presented adaptive threshold value by using FCM for alpha matting and comparing with the Otsu algorithm . MSE was used to measure the performance of both algorithms. Experimental results showed that the FCM algorithm produced a smaller threshold value so that the number of the wrong pixels was less than the Otsu algorithm.

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(a) (b) (c) (d) (e)