

A COLOR DIFFERENTIATED FUZZY C-MEANS (CDFCM) BASED IMAGE SEGMENTATION ALGORITHM*

Min-Jen Tsai and Hsuan-Shao Chang

Institute of Information Management, National Chiao Tung University, R.O.C.

ABSTRACT

Image segmentation is a very important process in digital image/video processing and computer vision applications. It is often used to partition an image into separated parts for further processes. For some applications (i.e., concept-based image retrieval), a successful segmentation algorithm is necessary to identify the objects effectively. In addition, how to tag the objects after the segmentation associated with keywords is also a challenge for researchers. In this study, we proposed a color differentiated fuzzy c-means (CDFCM) framework for effective image segmentation to achieve segmented objects within image which is useful for further annotation. In our experiments, we compared our approach with other FCM techniques on synthetic image with excellent performance. Furthermore, CDFCM outperforms other approaches by using the Berkeley image segmentation data set with layered annotation, which can be applied for additional operations.

Index Terms— image segmentation, color differentiated fuzzy c-means (CDFCM).

1. INTRODUCTION

Image segmentation is an important process for image and video research. The complexity of segmentation is based on complexity of image, such issues as occlusion, cluttering, and low contrast edges, object overlapping etc. Usually, these problems will affect the success of image segmentation.

Many researchers innovated novel approaches for image segmentation such as clustering methods, histogram-based methods, region growing methods [14], level set methods...etc. However, it seldom considered with a hybrid framework to mix different approaches to complement original weakness of single approach.

A segmentation method could be used for object recognition, occlusion boundary estimation within motion or stereo system, image compression, image editing, or image database look-up. Recently, researchers have incorporated local spatial information into the original Fuzzy C-means (FCM) algorithm to improve the performance of image segmentation [1-4]. Yugander. et al [15] purposed two types to improve FCM, one is supervised algorithm which is provided a collection of labeled pattern of the description of class, and the second one is an unsupervised algorithm which is designed to group unlabeled objects into meaningful clusters

based on similarity between objects. Tolias and Panas [4] developed a Sugeno-type rule-based system to enhance the results of fuzzy clustering by imposing spatial constraints. Pham [5] modified the FCM objective function by including a spatial penalty on the membership functions. The penalty term leads to an iterative algorithm, which is very similar to the original FCM and allows the estimation of spatially smooth membership functions. Ahmed et al. [6] modified the objective function of FCM to compensate for the gray inhomogeneity and allow the labeling of a pixel to be influenced by the labels in its immediate neighborhood, and they call the algorithm as FCM_S.

However, the main disadvantage of FCM_S is that it computes the neighborhood term in each iteration step, which is very time-consuming. In order to reduce this problem, Chen and Zhang [7] have provided a solution which has two variants, FCM_S1 and FCM_S2, which simplified the neighborhood term of the objective function of FCM_S.

For practical applications, there are several researches have been discussed in [8]. In traditional method, tagging and labeling the photo are the straight forward approach if we want to make our photo collection data systemized. However, that would lead to labor intensive works with human interaction [9]. On the other hand, the effective image retrieval application is also widely needed while segmentation plays the key technique to achieve high accuracy rate.

Furthermore, semantic-based image retrieval is getting notable attention for image research recently. Therefore, keyword based information search or data mining is widely required for practical applications. To achieve such a goal, a trustful and useful annotation of object segmentation is the key factor for retrieval success. Annotation of objects in images is yet an important but complex work of semantic-based image retrieval. In this study, we proposed a color differentiated fuzzy c-means (CDFCM) image segmentation framework for image/video application which provide effective solution to detect objects within an image. The main contributions of this paper are listed as following:

1. Reduce color gradation influence to image segmentation process.
2. CDFCM can tag the main object with major annotation and link with other objects with their own tags.

The rest of this paper is organized as followed. In section 2, the CDFCM methodology is explained in details and the experimental comparisons between CDFCM, FCM_S, FCM_S1, and FCM_S2 are illustrated in Section 3. Finally, the conclusion and future works are drawn in section 4.

2. CDFCM FRAMEWORK

Recently, many researchers have incorporated local spatial information into the original FCM algorithm to improve the

*This work was supported by the National Science Council in Taiwan, Republic of China, under Grant NSC99-2410-H-009-053-MY2 and NSC101-2410-H-009-006-MY2.

performance of image segmentation [10]. Ahmed et al. [6] proposed a modification to the standard FCM by introducing a term that allow the labeling of a pixel to be influenced by labels in its immediate neighborhood [11]. Szilagyi et al. [12] proposed the EnFCM algorithm to speed up the segmentation process for gray-level image. EnFCM provides comparable segmenting quality in considerably fact manner for the brain image used there as FCM_S, but the segmenting quality depends on the chosen window size. Due to previous researches, FCM has been working well on image segmentation researches. However, it is still hard to apply the approach on complex image data. Common issues are class center and color noise interference issues.

An edge detection approach reduces the information content in a complex image and is used in applications ranging from retinal preprocessing. It is a highly-studied computational problem used to determine the boundaries of objects within an image [10].

Although FCM_S1 and FCM_S2, as two extensions to FCM_S have yielded effective segmentation for image, both of them still have some disadvantages. The main disadvantage of color differentiated images is the color noise influence and local spatial information.

Therefore, we applied the edge detection for set boundaries of objects to enhance segmenting procedures and improve the traditional FCM scheme to Color differentiated FCM (CDFCM) approach. Our objective of this research is to automatically segment image into layered components.

CDFCM can be considered as a general framework which can be decomposed into following two steps as *edge detection* and *object evaluation*.

Following steps explain the proposed CDFCM approach. To achieve our goal, we modify a g parameter to be the biased field evaluating-parameter which helps to evaluate gradients among neighbor pixels. We compare color differentiated clustering with **RGB** value.

The procedures of CDFCM are shown with following steps.

- Step 1. Initialize the root node and set layer of object O $\{O \in 0, 1, 2, \dots, n; n$ is the amount of objects $\}$ as $L[O]=1$ of objects in image
- Step 2. At this step, edge detection is executed for marking boundaries of objects. According to these boundaries, system scans the image to get the first node of each object and each object is analyzed systematically.
- Step 3. We set the root of each discontinued edges as the root node.
- Step 4. Compute the correlations of neighbors by Color differentiated Fuzzy C-means approach for root node (target node).
- Step 5. Check whether every edge of the object and every object inside the image has been marked. If it is yes, go to step 6, otherwise, go to step 4.
- Step 6. Check whether more edge can be recognized. If it is no, go to step 7, otherwise, go back to step 2 and $L[O] = L[O] + 1$.
- Step 7. Output segmentation results

The modified objective function of CDFCM is defined as follows:

Parameters:

c : cluster number; n : pixel number; g : the biased field; α : This is used to control the effect of the neighbors term; v : cluster center; m : weighting exponent; \bar{y}_k : the averaged intensity of the k -th pixel's neighborhood; y_k is the color value of the k -th pixel; v_i represents the prototype value of the i -th cluster; u_{ik}

represents the fuzzy membership function of the k -th pixel with respect to cluster i . g_k means the biased field at the k -th; Pixels relationship value w_{ij} means that the j pixel correlation rate of i pixel. The maximum number of j are 8.

Objective function:

Minimize

$$J = \sum_{i=1}^c \sum_{k=1}^n u_{ik}^m \|y_k - g_k - v_{i1}\| + \alpha \sum_{i=1}^c \sum_{k=1}^n u_{ik}^m \|\bar{y}_k - g_k - v_{i2}\| + \lambda \left(1 - \sum_{i=1}^c u_{ik}\right) \quad (1)$$

Constraint

- Relationship w

$$\sum_{j=1}^n w_{ij} = 1; j = 1, \dots, n \quad (2)$$

- Compute cluster centers

$$C_i = \frac{\sum_{j=1}^n w_{ji}^m X_j}{\sum_{j=1}^n w_{ji}^m} \quad (3)$$

- Update weight matrices w

$$w_{ij} = 1 / \sum_{s=1}^c \left(\|X_j - C_i\| / \|X_j - C_s\| \right)^{1/(m-1)} \quad (4)$$

- Membership function

$$u_{ik}^* = 1 / \sum_{j=1}^c \left((d_{ik} + \alpha r_{ik}) / (d_{jk} + \alpha r_{jk}) \right)^{1/(m-1)} \quad (5)$$

$$d_{ik} = \|y_k - g_k - v_{i1}\|$$

$$r_{jk} = \|\bar{y}_k - g_k - v_{j2}\|$$

- Clustering centers

$$v_{i1}^* = \frac{\sum_{k=1}^n u_{ik}^m (y_k - g_k)}{\sum_{k=1}^n u_{ik}^m} \quad (6)$$

$$v_{i2}^* = \frac{\sum_{k=1}^n u_{ik}^m (\bar{y}_k - g_k)}{\sum_{k=1}^n u_{ik}^m}, i = 1, \dots, c. \quad (7)$$

- the biased field at the k -th pixel:

$$g_k^* = \frac{1}{(1 + \alpha)} \left\{ y_k + \alpha \bar{y}_k - \frac{\left[\sum_{i=1}^c u_{ik}^m (v_{i1} + v_{i2}) \right]}{\sum_{i=1}^c u_{ik}^m} \right\} \quad (8)$$

3. EXPERIMENTAL RESULTS

In this section, we compare CDFCM approach with FCM_S, FCM_S1, FCM_S2 with a synthetic image and a real picture.

The first experiment is a synthetic test where noise is applied to a 64×64 pixel image including two intensity classes with values of 0 and 90 as shown in Fig. 1. According to Fig. 1, the synthetic experiment result demonstrates that CDFCM has better clustering result than FCM_S, FCM_S1, FCM_S2. The image is almost classified into two classes with noise by CDFCM. The noise pattern used in this experiment is Gaussian white noise of $N(0,100)$. The parameters used for CDFCM in noisy image are $c=2$ and initial α is 3.8 which is obtained by searching the interval [0.2, 8] with respect to the optimal segmentation accuracy (SA), where SA is defined as the sum of the total pixel numbers divided by sum of the correctly classified pixel numbers.

Another experiment, a photo of President Obama is applied with CDFCM framework and compared with traditional FCM segmentation approach.

CDFCM segmentation result is shown as Fig 2(D). Based on this experiment, according to the definition of CDFCM framework, objects of image could be segmented with layers (detected by continuous edges) as shown as Fig 2(E). At first cycle, first object has been segmented. And the second cycle, other objects are segmented in Fig 2(F). At the final cycle, different objects are also obtained as shown in Fig 2(G).

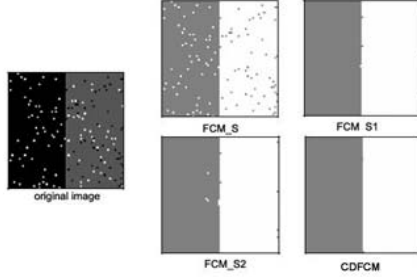


Fig. 1 Synthetic experiment results

According to the experimental results, we can separate objects in details for further processes (e.g. annotate keywords for objects). By comparing the segmentation results from traditional approach and CDFCM, we can systemically annotate objects by image recognition approaches from different L values. Such arrangement can leverage the traditional segmentation approaches for layered annotation with semantic keyword retrieval, further get better retrieval accuracy performance.

In addition, we compare CDFCM with the technique of Martin et. al. [13] by using the Berkeley segmentation data set to verify effectiveness of CDFCM. From Fig. 3, CDFCM clearly outperforms the method of [13] since the objects in Fig. 3(a)-(d), are clearly identified in Fig. 3(e)-3(h). Especially, the rock's contour in Fig. 3(g) is depicted by CDFCM but failed in Fig. 3(k) from [13]. The results demonstrate that CDFCM is superior to [13] and it also provides further layered information for the images.

4. CONCLUSION AND FUTURE WORK

From the simulation results, the proposed Color differentiated Fuzzy C-means (CDFCM) framework successfully segments the color photo image into layered annotation. In Sec. 3, the

experimental results illustrate its superiority in Fig. 1-3. Accordingly, the conclusion and further research direction will be discussed in this section.

4.1. Conclusion

We have proposed a CDFCM framework for object detection in a synthetic image and a complex photo image. Experiments test the sensitivity of framework with the other approaches. For evaluating the correlation of each pixel from the same layer L/O , we modified FCM to be Color differentiated FCM. We use a g parameter to be the biased field at k -th pixel. And we modified the FCM clustering approach to be Color differentiated FCM (CDFCM).

CDFCM contains two parameters for colorful image data, g parameter and RGB transformation parameter. The g parameter is designed for allowing color inaccuracy of an image. CDFCM framework has a layer parameter that used for testing if the object overlapping or contained by other objects.

The synthetic image experimental result shows that our proposed framework is workable and has better classification result than FCM_S, FCM_S1 and FCM_S2. The results of color image experiment in Fig. 4 and Fig. 5 also shows that the CDFCM framework is workable at real photo segmentation with complexity object data.

4.2. Future works

Since experimental results demonstrate that CDFCM has the capability for image segmentation in details, we can easily apply the technique for further processes based on layered approach. However, there are several issues which are simplified in this research. For example, edge is assumed continuous. In addition, computational time of this research still need to be improved by parallel processing for better efficiency. Furthermore, we didn't consider the relationship among objects that is in the same layer. This issue needs to be addressed in the application of segmentation on color image data. Because each object has been cut in parts, in some situation, there are strong relationships among close objects. Under such condition, a better edge detection is needed for CDFCM framework in order to achieve better results. The other key issue in this research is object extraction process of an image which contain with complex image structure. It will cause more computational time and segmentation results may influence object annotation processes.

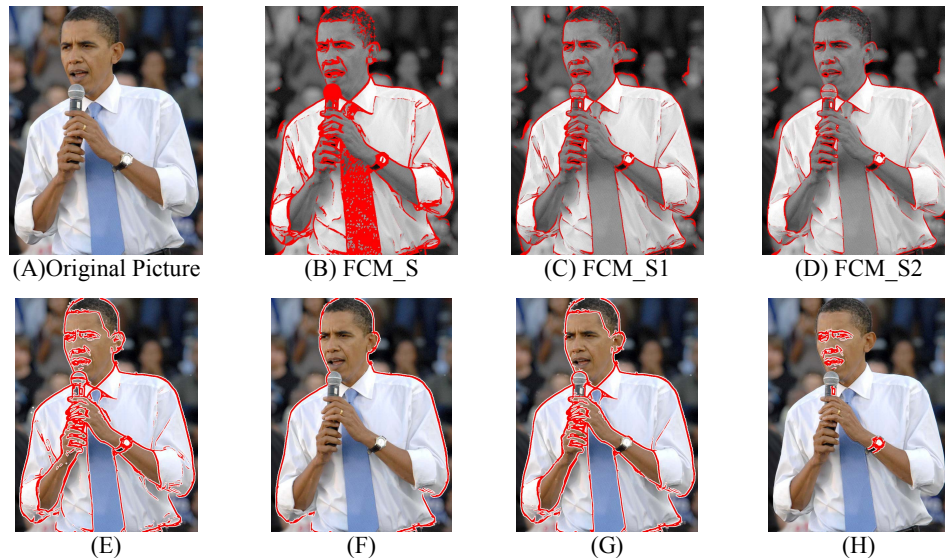


Fig 2. CDFCM segmentation and object extraction. (A) is the original picture. (B), (C), (D) are segmented results by FCM_S, FCM_S1, FCM_S2 algorithms respectively. (E), (F), (G), (H) are segmented results by CDFCM.








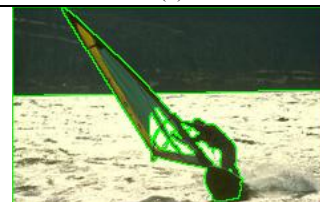
Original images	CDFCM method	D. Martin et. al. [13] method
 (a)	 (e)	 (i)
 (b)	 (f)	 (j)
 (c)	 (g)	 (k)
 (d)	 (h)	 (l)

Fig 3. More segmentation experiments by using Berkeley image segmentation data set

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