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Fuzzy C-Means Clustering with Spatial Information for Color Image Segmentation

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Abstract-- **Spatial information enhances the quality of clustering which is not utilized in the conventional FCM. Normally fuzzy c-means (FCM) algorithm is not used for color image segmentation and also it is not robust against noise. In this paper, we presented a modified version of fuzzy c-means (FCM) algorithm that incorporates spatial information into the membership function for clustering of color images [7, 8]. We used HSV model for decomposition of color image and then FCM is applied separately on each component of HSV model. For optimal clustering, grayscale image is used. Additionally, spatial information is incorporated in each model separately. The spatial function is the summation of the membership function in the neighborhood of each pixel under consideration. The advantages of this new method are: (a) it yields regions more homogeneous than those of other methods for color images; (b) it reduces the spurious blobs; and (c) it removes noisy spots. It is less sensitive to noise as compared with other techniques. This technique is a powerful method for noisy color image segmentation and works for both single and multiple-feature data with spatial information.**

***Keywords*—**color image segmentation, fuzzy c-means, spatial fuzzy c-means, cluster validity.

I. INTRODUCTION

Image segmentation refers to the process of partitioning a digital image into multiple regions (sets of pixels). The goal of segmentation is to simplify and/or change the representation of an image into something that is more meaningful and easier to analyze. The result of image segmentation is a set of regions that collectively cover the entire image, or a set of contours extracted from the image. Each of the pixels in a region is similar with respect to some characteristic or computed property, such as color, intensity, or texture. Adjacent regions are significantly different with respect to the same characteristic (s).The major application of image segmentation is Medical imaging, where it is used to locate tumors and other pathologies, measure tissue volumes, computer-guided surgery and treatment planning. Image segmentation can be treated as a clustering problem where the features describing each pixel correspond to a pattern, and each image region (i.e. a segment) corresponds to a cluster. Therefore many clustering algorithms have widely been used to solve the segmentation problem (e.g., K-means, FCM, ISODATA and Snob).

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A. FCM

Fuzzy c-means (FCM) clustering [1,2,3] is an unsupervised method that has been successfully applied to feature analysis, clustering, and classifier designs in fields such as astronomy, geology, medical imaging, target recognition, and image segmentation. An image can be represented in various feature spaces, and the FCM algorithm classifies the image by grouping similar data points in the feature space into clusters. This clustering is achieved by iteratively minimizing a cost function that is dependent on the distance of the pixels to the cluster centers in the feature domain.

Fuzzy c-means clustering is an easy and well improved tool, which has been applied in many medical fields. However, in c-means algorithms, like in all other optimization procedures, which look for the global minimum of a function, there is the danger to come into local minima. Therefore the result of such a classification has to be regarded as an optimum solution with a determined degree of the accuracy.

B. Spatial FCM (sFCM)

One of the important characteristics of an image is that neighboring pixels are highly correlated. In other words, these neighboring pixels possess similar feature values, and the probability of belonging to the same cluster is higher. This spatial relationship is important in clustering, but it is not utilized in a standard FCM algorithm.

To exploit the spatial information, a spatial function is used, where neighborhood represents a square window centered on pixel x_j in the spatial domain. A 3x3 window was used throughout this work. Just like the membership function, the spatial function hij represents the probability that pixel x_j belongs to ith cluster. The spatial function of a pixel for a

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cluster is huge if the majority of its neighbor belongs to the similar clusters. Hence, it is robust against noise.

C. HSV Model

HSV stands for hue, saturation, value. It is a representation of points in an RGB color space which attempts to describe perceptual color relationships more accurately than RGB, while remaining computationally simple. The HSV model is commonly used in computer graphics applications. This model was first formally described in 1978 by Alvy Ray Smith [9] though the concept of describing colors by these three dimensions, or equivalents such as hue, chroma, and tint, was introduced much earlier.[10].d

FCM has three limitations and we proposed solutions to these limitations.

1. Need Optimal Number of clusters.
2. Not robust against noise.
3. Work only on grayscale images.

With the use of validity functions, spatial information and HSV modeling, standard FCM be used for the segmentation of color images.

The paper is organized as follows. Section 2 has related work information. Section 3 describes the detailed mechanism of FCM, sFCM and cluster validity respectively. Section 4 contains implementation of our novel technique. Section 5 describes the results, future work and conclusion drawn from the design of and the work with the proposed system. Section 6 composed of the references used in this paper

II. Related Work

Juraj.Horvath has described the process of color image segmentation [7]. Color image was converted into LUV format and then FCM algorithm is applied for segmentation. A similar approach was used in [14].

Robert Mearns Yerkes proposed a technique for fuzzy c-means clustering with spatial information. In which neighboring pixel information is incorporated into the under consideration pixel information [11]. HORVÁTH is also using the quite similar approach. But this technique is not appropriate for the color images [13].

In addition to the specific algorithms we investigate, our work differs from the above in that we extracted H, S, and V information from image and the FCM is applied on each layer. We have also emphasized on noise reduction techniques with clustering.

III. Methodology

A. FCM Clustering

Fuzzy c-means (FCM) is a method of clustering which allows one piece of data to be in the right position to two or more clusters. This method (developed by Dunn in 1973 and improved by Bezdek in 1981) is frequently used in pattern recognition. FCM starts with an initial guess for the cluster centers, which are proposed to mark the mean location of each cluster. The initial guess for these cluster centers is most likely incorrect. Additionally, FCM assigns every data point a membership rank for every cluster. By iteratively updating the cluster centers and the membership grades for each data point, FCM iteratively moves the cluster centers to the correct place within a dataset. This iteration is based on minimizing an objective function that symbolizes the distance from any given data point to a cluster center weighted by that data point's membership rank.

The FCM algorithm assigns pixels to each group by using fuzzy memberships. Let XZ (x1, x2,., xN) indicates an image with N pixels to be partitioned into c clusters, where x_i represents multispectral (features) data. The algorithm is an iterative optimization that minimizes the cost function defined as follows:

$$J = \sum_{j=1}^{N} \sum_{i=1}^{C} U_{ij}^{m} \left\| x_j - V_i \right\|^2 \tag{1}$$

Where u_{ij} represents the membership of pixel x_j in the ith cluster, v_i is the ith cluster center, ||..|| is a norm metric, and m is a constant. The parameter m controls the fuzziness of the resulting partition, and m=2 is used in this study as it was the special case presented by Joe Dunn in 1974. It controls the weight of fuzziness for the partition. The cost function is minimized when pixels close to the centroid of their clusters and are assigned high membership values, and low membership values are assigned to pixels with data far from the centroid. The membership function represents the probability that a pixel belongs to a specific cluster. In the FCM algorithm, the probability is dependent solely on the distance between the pixel and each individual cluster center in the feature domain. The membership functions and cluster centers are updated by the following:

$$U_{ij} = \frac{1}{\sum_{k=1}^{c} \left(\frac{x_j - v_i}{x_j - v_k} \right)^{2/(m-1)}} \tag{2}$$

and

$$v_i = \frac{\sum_{j=1}^{N} U_{ij}^{m} x_j}{\sum_{j=1}^{N} U_{ij}^{m}} \tag{3}$$

Starting with an initial guess for each cluster center, the FCM converges to a solution for v_i representing the local minimum or a saddle point of the cost function. Convergence can be detected by comparing the changes in the membership function or the cluster center at two successive iteration steps.

B. sFCM Method

One of the significant uniqueness of an image is that neighboring pixels are extremely correlated. In other terms these neighboring pixels hold similar feature values, and the probability that they belong to the same cluster is great. This spatial relationship is important in clustering, but it is not utilized in a standard FCM algorithm. To develop the spatial information, a spatial function is defined as

$$h_{ij} = \sum_{k \in NB(x_j)} U_{ik} \tag{4}$$

Where NB (x_j) stands for a square window centered on pixel xj in the spatial domain. A 3x3 window was used throughout this effort. Just like the membership function, the spatial function h_{ij} stands for the probability that pixel x_j belongs to ith cluster. The spatial function of a pixel for a cluster is large if the bulk of its neighborhood belongs to the same clusters. The spatial function is included into membership function as follows:

$$U'_{ij} = \frac{U_{ij}^p h_{ij}^q}{\sum_{k=1}^{C} U_{kj}^p h_{kj}^q} \tag{5}$$

where p and q are parameters to control the relative importance of both functions. In a homogenous region, the spatial function simply fortifies the original membership, and the clustering result remains unchanged. However, for a noisy pixel, this formula reduces the weighting of a noisy cluster by the labels of its neighboring pixels. As a result, misclassified pixels from noisy regions or spurious blobs can easily be corrected. We separately applied this sFCM on each component of HSV model. The spatial FCM with parameter p and q is denoted sFCMp,q. Note that $sFCM_{1,0}$ is identical to the conventional FCM. The clustering is a two-pass process, at each iteration for each component of the HSV model. The first pass is the same as that in standard FCM to calculate the membership function in the spectral domain. In the second pass, the membership information of each pixel is mapped to the spatial domain, and the spatial function is computed from that. The FCM iteration proceeds with the new membership that is incorporated with the spatial function. The iteration is stopped when the maximum difference between two cluster centers at two successive iterations is less than a threshold (0.02). After the convergence, defuzzification is applied to assign each pixel to a specific cluster for which the membership is maximal. [4]

C. *Cluster validity function*

Two types of cluster validity functions, fuzzy partition and feature structure, are often used to evaluate the performance of clustering in different clustering methods. The representative functions for the fuzzy partition are partition coefficient Vpc and partition entropy Vpe . They are defined as follows

$$V_{pe} = \frac{-\sum_{j}^{N}\sum_{i}^{C} U_{ij} log U_{ij}}{N} \tag{6}$$

and

$$V_{pc} = \frac{-\sum_{j}^{N}\sum_{i}^{C} U_{ij}^{\ 2}}{N} \tag{7}$$

The idea of these validity functions is that the partition with less fuzziness means better performance. As a result, the best clustering is achieved when the value V_{pc} is maximal or V_{pe} is minimal. Disadvantages of Vpc and Vpe are that they measure only the fuzzy partition and lack a direct connection to the featuring property. Other validity functions based on the feature structure are available [6]. For example, Xie and Beni [5] defined the validity function as

$$V_{xb} = \frac{\sum_{j}^{N}\sum_{i}^{C} U_{ij}^2 \left\|X_j - V_i\right\|^2}{N * (\min i \neq k)\left\{\left\|V_k - V_i\right\|^2\right\}} \tag{8}$$

A good clustering result generates samples that are compacted within one cluster and samples that are separated between different clusters. Minimizing Vxb is expected to lead to a good clustering. Xie and Beni validity function is considered to as a better validity function amongst others as shown in table [1].

D. *Conversion from RGB to HSV*

Let r, g, and b be the red, green, and blue coordinates, respectively, of a color in RGB space. Let max be the greatest of r, g, and b, and min the least. To find the hue angle h [0, 360] for HSV space, compute:

$$h = \begin{cases} 0 & \text{if } \max = \min \\ (60^\circ \times \frac{g-b}{\max - \min} + 0^\circ) \bmod 360^\circ, & \text{if } \max = r \\ 60^\circ \times \frac{b-r}{\max - \min} + 120^\circ, & \text{if } \max = g \\ 60^\circ \times \frac{r-g}{\max - \min} + 240^\circ, & \text{if } \max = b \end{cases}$$

To find saturation s HSV space, compute:

$$s = \begin{cases} 0, & \text{if } \max = 0 \\ \frac{\max - \min}{\max} = 1 - \frac{\min}{\max}, & \text{otherwise} \end{cases}$$

And to find V, we compute:

$$v = \max$$

TABLE I
CLUSTER INDEX VALUES IN THREE DIFFERENT SCHEMES FOR FIGURE 4B

Index	C=2	C=3	C=4	C=5	C=6	C=7	C=8
PC	0.57	0.61	**0.72**	0.56	0.53	0.51	0.50
PE	0.08	0.12	**0.03**	0.18	0.32	0.36	0.48
XB	0.21	0.19	**0.12**	0.32	0.32	0.34	0.38

E. Conversion from HSV to RGB

Similarly, given a color defined by (h, s, v) values in HSV space, with h as above, and with s and v varying between 0 and 1, representing the saturation and value, respectively, a corresponding (r, g, b) triplet in RGB space can be computed:

$$h_i = \left\lfloor \frac{h}{60} \right\rfloor \bmod 6$$

$$f = \frac{h}{60} - \left\lfloor \frac{h}{60} \right\rfloor$$

$$p = v \times (1 - s)$$

$$q = v \times (1 - f \times s)$$

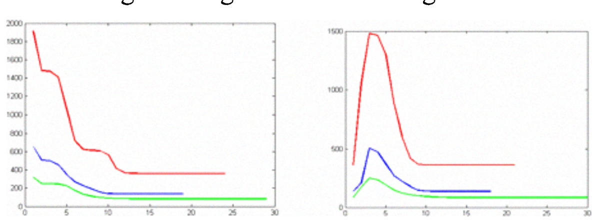
$$t = v \times (1 - (1 - f) \times s)$$

$$(r, g, b) = \begin{cases} (v, t, p), & \text{if } h_i = 0 \\ (q, v, p), & \text{if } h_i = 1 \\ (p, v, t), & \text{if } h_i = 2 \\ (p, q, v), & \text{if } h_i = 3 \\ (t, p, v), & \text{if } h_i = 4 \\ (v, p, q), & \text{if } h_i = 5 \end{cases}$$

IV. IMPLEMENTATION

This algorithm is implemented in Matlab®. The whole process model is explained in a figure. 2.

Color image is taken as input to the system and converted to gray scale image for extracting optimal number of clusters by applying FCM algorithm. We have used Xie and Beni's [5] validity function which is considered as the best [11]. In parallel 3 layers of HSV model are extracted from color image. Each layer of the image is passed through a two-pass process for clustering. In first pass simple FCM algorithm is applied on each layer for calculating the fuzzy membership. And in the second pass spatial information is incorporated in the calculated fuzzy membership of each layer. A 3x3 window is used throughout this work for incorporating spatial information. After sFCM layers are defuzzified to get the crisp set of values. HSV layers are then combined and converted to RGB model for generating the clustered image.



a) FCM Objective Function b) sFCM objective Function

Fig.1. Objective function behaviour of FCM and sFCM

Figure 1 shows the behaviour/change in objective function of FCM (Figure 1, a) and sFCM (Figure 1, b) on Hue (represented by red color) Saturation (represented by green color) and Value (represented by blue color). In FCM objective function is iteratively decreasing but in sFCM this objective function is first increased and after a peak it is going to be decreased. When the system is converged then objective function is stable and it has no reduction or change in it.

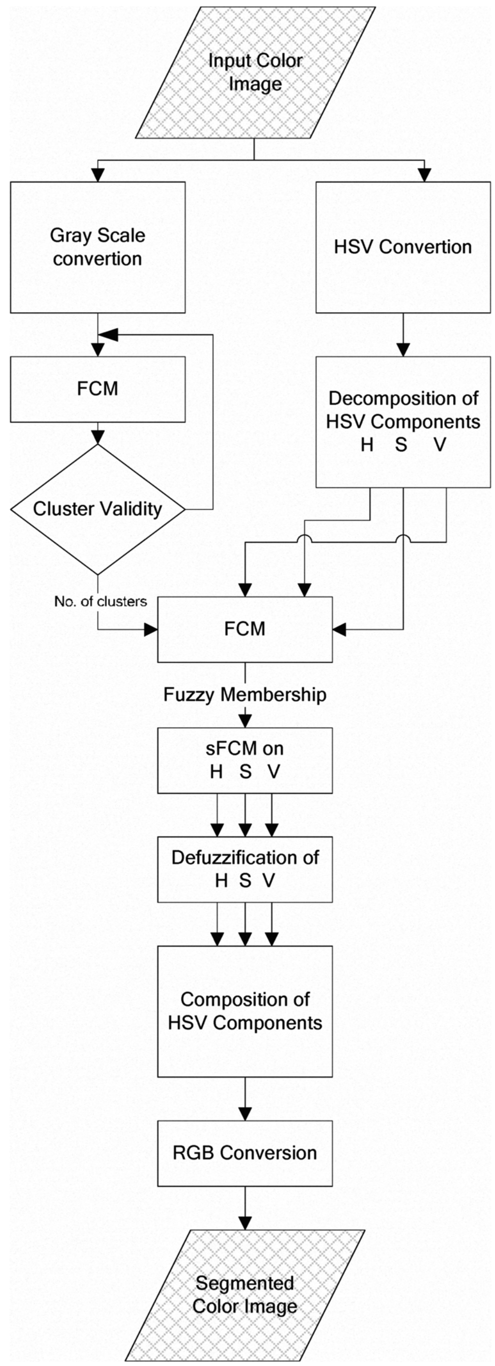
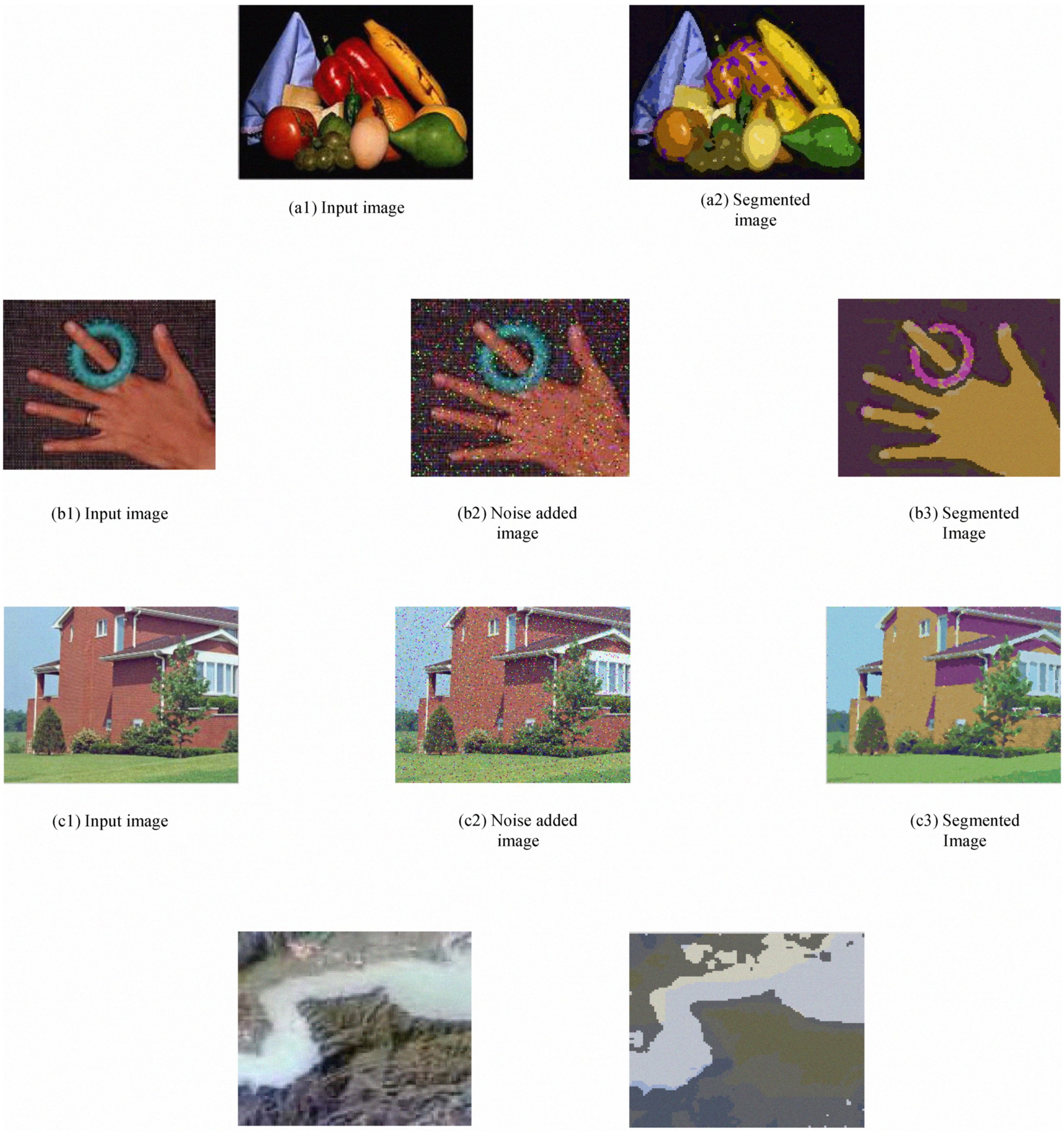


Fig. 2. General flowchart

V. RESULTS

Although we tested our algorithm over a large number of images with varying range of complexity, here we show the experimental results for four standard images only. Visual results are given below. We have also tested on the noisy environment. We have added salt & pepper noise in the images as shown in figure b2 and figure c2 below. Our algorithm has shown good results in the case of noisy environment also.



(a1) Input image

(a2) Segmented image

(b1) Input image

(b2) Noise added image

(b3) Segmented Image

(c1) Input image

(c2) Noise added image

(c3) Segmented Image

(d1) Input image

(d2) Segmented Image

Fig. 3. Visual results of algorithm.

VI. CONCLUSION & FUTURE WORK

This paper has presented a novel approach for fuzzy clustering of color images. An important quality of the proposed algorithm is that it is able to find the optimal number of clusters by using cluster validity functions (means that the number of clusters does not have to be known in advance). Furthermore, the proposed algorithm uses spatial information of each pixel. The new method was tested on different color images and evaluated by using various cluster validity functions. Preliminary results proved that the effect of noise in segmentation was significantly less with the novel algorithm than with the simple FCM.

Although the segmentation results are very much satisfactory and the technique is robust against noise as well, but even then many improvements can be done to make this work as a part of some automated system. In presented technique, objective function behavior fluctuates and no decision can be made on the basis of statistical values of objective function (in sFCM). Objective function first increase and then decreases continuously. Some methodology can be developed to evaluate the segmentation techniques on the statistical basis, so that quantifiable results can be obtained.

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