A novel robust and fast Segmentation of the Color Images using Fuzzy Classification C-means

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Abstract— **This paper brings out a method for segmentation of color images based on fuzzy classification. It proceeds in a first step by a fine segmentation using the algorithm of fuzzy c-means (FCM). The method then applies a test fusion of fuzzy classes. The result is a coarse segmentation, where each region is the union of elementary regions grown from FCM. The fuzzy C-Means (FCM) clustering is an iterative partitioning method that produces optimal c-partitions, the standard FCM algorithm takes a long time to partition a large data set. The proposed FCM program must read the entire data set into a memory for processing. Our results show that the system performance is robust to different types of images.**

Keywords-Segmentation,Classification,FuzzyLogic,FCM, Merge regions, Optimal c-partitions.

I. INTRODUCTION

Image segmentation was, is and will be a major research topic for many image processing researchers. The reasons are obvious and applications countless. Most computer vision and image analysis problems require a segmentation stage in order to detect objects or divide the image into regions, which can be considered homogeneous according to a given criterion, such as color, motion, texture, etc [1, 2].

Sometime it's necessary to adjust computer vision to human vision. It is necessary when we are segmenting images, segmented by people to try to replace them with computers to help them in segmentation of images. Typical application is in medicine, e.g. segmentation of MRI images and dermatological images.

In this paper we used fuzzy c-means clustering method as pre-processing method for basic region growing in segmentation method. The basic difference from other approaches is extension of feature space, which results in better segmentation.

For test images we used five RGB color images. These images were firstly converted into L*u*v* color space [3, 4]. Fuzzy c-means method was applied to the converted images with extended feature space. Segmentation method based on region growing was applied at the end of segmentation process. The same method was used in [2, 3, 4]. It was used with simple defuzzification rule; the method was enhanced with thresholding parameter T and in [6] was used with

To get a good partition, it requires elements of U the following constraints:

another defuzzification rule. The results were obtained by experimental simulations in Matlab.

The image segmentation is to create a partition image in homogeneous subsets called regions, according to some criterion [4] .In the case of segmenting a color image, the features used are the components of color pixels. Generally the methods of segmentation are in two approaches [3]:

Contour approach and Region approach.

The two approaches are complementary [7,8,9,10,11], and none has proven its superiority over the other, each has advantages and application areas. The contour extraction usually has the advantage [12] of providing contour well located and works well when the zones on both sides of the contour have different average intensities.

The methods that extract regions are unclear on the contours. In approaches that extract regions, classification methods are widely used.

They define a partition of color space [13], and do not take into account the spatial arrangement of pixels. In the data space, regions can be regarded as areas of high density separated by regions of low density.

II. RELATED WORK

A. *The algorithm of fuzzy c-means (FCM)*

The algorithm of fuzzy c-means (fuzzy c-means) is a classification algorithm based on fuzzy optimization of a quadratic criterion of classification where each class is represented by its center of gravity

The algorithm requires knowing the number of classes in advance and generates classes through an iterative process minimizing an objective function. Thus, it provides a fuzzy partition of the image by giving each pixel a degree of belonging to a given region.

The algorithm uses all pixels $\Delta = \{x_1, x_2, ..., x_n \}$ is a vector of three components (eg. RGB), and the number of region c. The values of the degrees of membership are grouped in a matrix $U = [U_{ik}]$ for $1 \le i \le n, 1 \le k \le c$ where U_{ik} means the membership degree of pixel i to class k .

$$U_{ik} \in [0,1]$$

$$\sum_k U_{ik} = 1 \text{ , and } \forall i$$

In this work the robust and fast segmentation of the image color, the FCM algorithm is changing the partition (U matrix) by minimizing the following objective function:

$$J_m(U,C) = \sum_i \sum_k (u_{ik})^m . \|x_i - c_k\|^2 \qquad (1)$$

Where $m > 1$ is a parameter controlling the degree of fuzzy (generally $m = 2$);

c_k : the center of Class k.

B. The FCM algorithm

1. Choose the number of classes: c // a priori information, supervised algorithm.
2. Initializes the matrix U, and centers c_k (random initialization)
3. Changing the partition matrix and the two centers following equations.

$u_{ik} = 1/(\sum_{j=1,c} (d_{ik} / d_{ij})^{(2/(m-1))})$, // for the degrees of belonging (2)

Where: $d_{ij} = \|x_i - c_j\|$

$c_k = (\sum_i (u_{ik})^m .x_i) / \sum_i (u_{ik})^m)$,// for the centers (3)

4. Test of experimentation $\left|J^{(t+1)} - J^{(t)}\right| <$ threshold

III. PROBLEM SOLVNG

In this section we illustrate a different method used by fuzzy FCM and how to analysis to solve the problem.

Most classification methods used, including FCM, suffer from two defects [1]:

1. The number of clusters must be provided in advance (supervised algorithms).
2. Each region is characterized by a center, and the membership degrees are calculated involving the Euclidean distance from which a form necessarily hyper-spherical.

- Criterion fusion: fuzzy compactness criterion and overlapping classes.

Intuitively, two regions should be merged if they are close (in the color space) ,and if their union is a homogenous region. To do this, we identified two known quantities: overlapping and compactness.

- Cardinal, meeting (union), and intersection of fuzzy sets:

Let A , and B be two sets of fuzzy membership functions f_A and f_B respectively. We can extend the notions of cardinal meeting and the intersection of fuzzy sets "naturally" using the membership functions by:

Cardinal: $Card(A) = \sum_x f_A(x)$

Intersection: $f_{(A \cap B)}(x) = Min(f_A(x), f_B(x))$

Reunion: $f_{(A \cup B)}(x) = Max(f_A(x), f_B(x))$

- Overlap of two classes:

$$O_{ij}(c_1, c_2) = \frac{card(c_1 \cap c_2)}{card(c_1 \cup c_2)} \qquad (4)$$

Disjoint classes ← $0 \le O_{ij} \le 1$ → (classify completely confused)

Compactness of a class:

$$C = K_1 U K_2 U .... U K_p . \qquad (5)$$

The compactness of a class is defined as the average of overlap between its elementary components.

$$CP(C) = (1/p) . \sum_i Min_{j \neq i} (O_{ij}) \qquad (6)$$

Classify not compacts ← $0 \le CP \le 1$ →(classify compacts).

-The average compact between two clusters:

The average compactness of two classes C1 and C2 is the average compactness individual, weighted by the Cardinals.

$$CP_{12} = (Card(C_1).CP_1 + Card(C_2).CP_2) / (Card(C_1) + Card(C_2)) \qquad (7)$$

Fusion Rule:

Consider two classes C_i and C_j , $\alpha \in [0,1]$ threshold to choose

If : $O_{ij} > \alpha . CP_{ij}$.

Then to amalgamate C_i and C_j ,

It merges two classes if one considers that their overlap is quite high compared to the threshold dependent on natural classes in question.

Fewer classes are compact, if they are less demanding when the threshold of fusion, and therefore we tend to merge and vice versa.

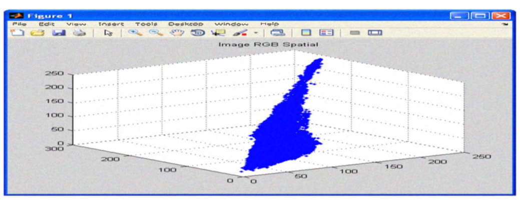
IV. RESULTS AND DISCUSSION

We have shown our experimentation with the Method used fast segmentation of the color Image using fuzzy classification C-means to perform the matrix calculations. The images were read into the Matlab command window and converted successfully to matrices representations. The parameters below allowed succeeding these following results:

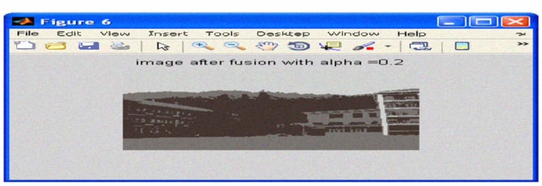
- - The number of unique pixel 16680; -The time of elimination redundancy: 0.25
- - The time of Fuzzy: 1.719; - The number of Fuzzy after cluster FCM: 3
- - The number of clusters after the melting stage: 3

Fig1 (a, b, c, d) show under mentioned illustration:
(a)-Original Image; (b)-Image RGB Spatial; (c)- Image after fusion with alpha=0.2; (d)-data after fcm 3class

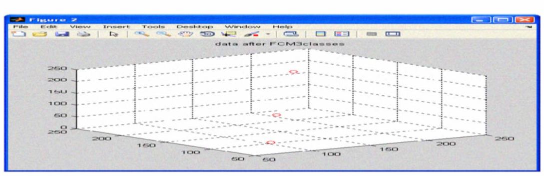
(a)



(b)



(c)



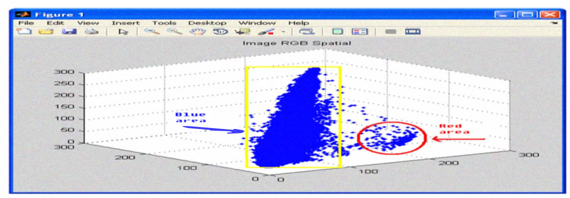
(d)

-The figure1(c) represent the initial segmentation in figure1 (a) and that obtained after the melting step for alpha=0.2.

The merger, by reducing the number of regions, yields a good segmentation for the homogenous regions. It is best visualized in the color space figure1(b), and figure 1(d)

-We have experimented with other images, the first observation we can remark is that the number of regions of the final segmentation increases with alpha. This is quite normal for a small tolerate fusion, and therefore the number of initial classes form the alpha threshold FCM decreases. The figure2(b) yellow color and red color represent the repartition of pixel in homogenous regions. The figure2(c) and figure2 (d) respectively image after fusion with alpha=0.2 and data after FCM 3classes.

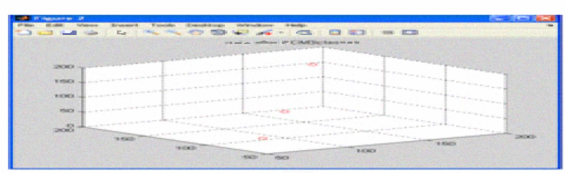
(a)



(b)

Fig2 (a, b, c, d) show under mentioned illustration:
Fig2(a)-Original Image; (b)-Image RGB Spatial; (c)- Image after fusion with alpha=0.2; (d)-data after fcm 3class.
The number of clustering show that the repartition of pixel follow the number of region dominate by color homogeneous.

(c)

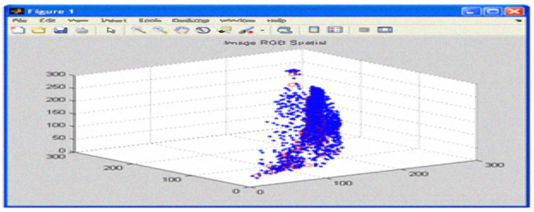


(d)

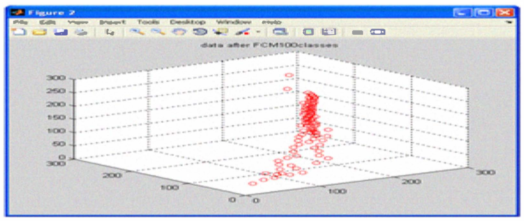
We can observe the effect of the merger on figure2(b) and figure2(c), where the merger has eliminated the uncertainty around the image, giving classes more precise and distinct.

We can remark when the number of classes increases alpha=100, respectively the figure 3(a) illustrate the number of cluster.

Fig3 (a, b, c, d) show under mentioned illustration:



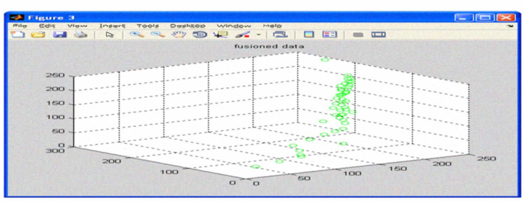
(a)



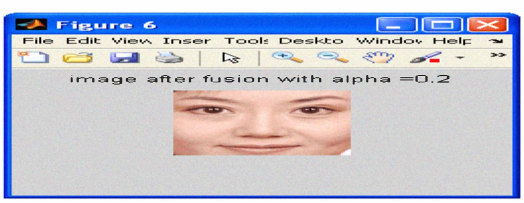
(b)

Fig3 :(a)-distrubtion Image RGB Spatial Clustering;
Fig3 :(b) data after FCM 100 classes.

The numbers of clustering show the repartition of pixel follow the number of region dominate by color homogeneous. When we increasing the parameter, the fusioned data, the distribution Gaussian realize follow the dominate of RGB color in the different region



(c)



(d)

Fig3:(c) Represent fusion data after FCM 100 classes.
Fig3:(d) Image after fusion with alpha=0.2

V. CONCLUSONS AND FUTURE WORK

We have presented a new method for segmenting color images based on fuzzy classification of color. It uses a fine initial segmentation obtained by applying the FCM algorithm, and a merger process, based on a criterion introduced for fuzzy regions.

The main advantage of this novel method is that, first it requires no prior information on the images to segment, and it's fast. Moreover, the threshold of fusion can easily control the fineness of the segmentation depending on desired uses. However, we can criticize this method the following points:

-to emphasize the color properties of pixels compared to the spatial properties (defects common to all methods based on classification);

-Involves a merger threshold often difficult to adjust;

-using the RGB color space which imperfectly reflects our perception of color;

-we can question the validity of segmentation called unsupervised in the sense that the method involves introducing a threshold in a certain manner of information on numbers of color classes to build.

-to emphasize the color properties of pixels compared to the spatial properties (defects common to all methods based on classification);

-fusion involves a threshold often difficult to adjust;

-using the RGB color space which imperfectly reflects our perception of color to analysis and improving the different algorithm in the future work.

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