Modified Fuzzy C-Mean in Medical Image Segmentation

Nevin. A. Mohamed, M. N. Ahmed and A. Farag
Computer Vision and Image Processing Laboratory
University of Louisville, E.E. Dept., Louisville, KY 40292
E-mail:(nevin,mohamed,farag)@cairo.spd.louisville.edu, Phone:(502)-852-6130, Fax:(502)852-1580

Abstract— **This paper describes the application of fuzzy set theory in medical imaging, namely the segmentation of brain images. We propose a fully automatic technique to obtain image clusters. A modified fuzzy c-mean (FCM) classification algorithm is used to provide a fuzzy partition. Our new method, inspired from the Markov Random Field (MRF), is less sensitive to noise as it filters the image while clustering it, and the filter parameters are enhanced in each iteration by the clustering process. We applied the new method on a noisy CT scan and on a single channel MRI scan. We recommend using a methodology of over segmentation to the textured MRI scan and a user guided-interface to obtain the final clusters. One of the applications of this technique is TBI recovery prediction in which it is important to consider the partial volume. It is shown that the system stabilizes after a number of iterations with the membership value of the region contours reflecting the partial volume value. The final stage of the process is devoted to decision making or the defuzzification process.**

Keywords— **Fuzzy c-mean, Image Segmentation, Fuzzy clustering, Adaptive filter.**

I. Introduction

TODAY medical imaging technology provides the clinician with a number of complementary diagnostic tools such as x-ray computer tomography (CT), magnetic resonance imaging (MRI) and positron emission tomography (PET). Routinely these images are interpreted visually and qualitatively by radiologists. Advanced research requires quantitative information, such as the size of the brain ventricles after a traumatic brain injury or the relative volume of ventricles to brain. It is important to have a faithful tool to help with viewing and measuring various structures in the brain. This requires the study of theories and algorithms for getting a precise description of the regions of interest. One of such algorithms is the segmentation of images to isolate objects and regions. One of the main problems in image segmentation is uncertainty. Some of the sources of this uncertainty include additive and non-additive noise, imprecision in computations and vagueness in class definitions. Traditionally, probability theory was the primary mathematical model used to deal with uncertainty problems; however, the possibility concept introduced by the fuzzy set theory has gained popularity in modeling and propagating uncertainty in imaging applications. This paper describes in details the implementation of a modified fuzzy c-mean algorithm in the brain image segmentation, and is organized as follows. Section II gives an overview of the existing segmentation techniques. In section III the FCM algorithm is explained and our modified method is explained in section IV. Section V and VI present the implementation, results and conclusions.

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II. Image Segmentation

Much past work on medical image segmentation relied strictly on human graphical interaction to define regions, using methods such as manual slice editing, region painting and interactive thresholding. Rajapakse[1] classified the different methods of Image Segmentation as four main categories. (1)The classical methods such as thresholding, region growing and edge based techniques. (2)The statistical methods such as the maximum-likelihood-classifier (MLC). These methods are basically supervised and depend on the prior model and its parameters. Vannier et. al.[2] reported satisfactory preliminary results with Bayesian MLC. Ozkan et. al.[3] made a comparison between the MLC and the neural network classifier which showed the superiority of the N.N. New methods of segmentation that could be classified as statistical methods have been introduced in the past few years. Hansen[4] used a probabilistic supervised relaxation technique for segmenting 3-D medical images. The method introduced the use of cues to guide the segmentation. Those cues marked by the user have the mean and standard deviation as description parameters. (3)The neural networks methods, one example of which is the work of Ahmed et. al.[5] who used a two-stage neural network system for CT/MRI image segmentation. The first stage is a self-organized principal component analysis (SOPCA) network and the second stage consists of a self-organizing feature map (SOFM). The results obtained compare favorably with the classical and statistical methods. (4) The Fuzzy Clustering methods. In [6] a comparison between the fuzzy clustering and neural network techniques in segmenting magnetic resonance images of the brain debated for the need of unsupervised technique in segmentation which was provided using the unsupervised fuzzy c-mean algorithm. However, the long time taken by the fuzzy c-mean algorithm was documented. Lawrence et. al.[6] stated that the fuzzy algorithm exhibited sensitivity to the initial guess with regard to both speed and stability. The fuzzy c-mean showed sensitivity to noise. In this paper we propose a method that filters the image during the clustering process. The method, borrowed from Markov Random Field (MRF), is based on the consideration of the neighbors as factors that attract pixels into their cluster.

III. The Fuzzy c-mean Algorithm

The structure of partition spaces for clustering algorithms can be described as follows [7]: let c be an integer, such that $1 < c < n$ and let$\{x_1, x_2, x_3, ..., x_n\}$ denote a set of n unlabeled column vectors in R^p where p represents the number of features in each vector. The notation used is as follows: for the vector x_j its numerical representation x_{js} represents the sth characteristic of the vector $j, 1 < s < p$. Given X, we say that c fuzzy subsets $\{X \to [0,1]\}$ are a fuzzy c-partition of X if the following conditions on the membership value u_{ik} for the cluster i and the feature vector x_k are satisfied:

$$u_{ik} = u_i(x_k), 1 \leq i \leq c \; and \; 1 \leq k \leq n, \quad (1)$$

$$where \; 0 \leq u_{ik} \leq 1 \; \forall i, k. \quad (2)$$

$$\textstyle\sum_{i=1}^{c} u_{ik} = 1 \; \forall k. \quad (3)$$

$$0 < \textstyle\sum_{k=1}^{n} u_{ik} < n \; \forall i \quad (4)$$

The set of values satisfying the above conditions can be arranged in a matrix form $U[c \times n]$. Column j of which represents membership values of x_j in the c fuzzy subsets of X. Raw I of U exhibits values of a membership function u_i on X where $u_{ik} = u_I(x_k)$ denotes the grade of membership of x_k in the ith fuzzy subset of X. The objective of fuzzy segmentation is to convert image feature values into class membership numbers. Furthermore, if we define a uniformity predicate $P(\mu_{ij})$ that it assigns the value true or false to the sample point x_k based on its membership value, we will have parallel crisp segmentation. The fuzzy c-mean algorithm attempts to cluster feature vectors by searching for local minima of the following objective function [8]

$$J_m(U, v; X) = \sum_{i=1}^{c} \sum_{k=1}^{n} (u_{ik})^m D_{ik} \quad (5)$$

where the real number m $\in [0, \infty)$ is a weighting exponent on each fuzzy membership, $v = (v_1, v_2, ..., v_c)$ are geometric cluster prototypes, $v_i \subset R^p$; D_{ik} is some measure of similarity between v_i and x_k or the attribute vectors and the cluster centers of each region. Minimization of J_m is based on the suitable selection of U and V using an iterative process through the following equation :

$$U_{ik} = \left(\sum_{j=1}^{c} \left(\frac{D_{ik}}{D_{jk}}\right)^{\frac{2}{(m-1)}} \right)^{-1} \forall i, k \quad (6)$$

$$v_i = \frac{\sum_{k=1}^{n} {U_{ik}}^m X_k}{\sum_{k=1}^{n} {U_{ik}}^m} \forall i. \quad (7)$$

If m is set to 1 then

$$u_{ik} = 1, D_{ik} = min(D_{sk}) \; for \; 1 \leq s \leq c \quad (8)$$

$$u_{ik} = 0, \; otherwise \; for \; 1 \leq i \leq c; 1 \leq k < n \quad (9)$$

which results in the crisp set. Necessary conditions for minimizing J_m is that U is positive definite. The algorithm stops when $u_{ik(\alpha)} - u_{ik(\alpha-1)} < \epsilon$. The fuzzy c-mean has several advantages. 1)It is unsupervised, 2) it can be used with any number of features and any number of classes and 3) it distributes the membership values in a normalized fashion. However, being unsupervised, it is not possible to predict ahead of time what type of clusters will emerge from the fuzzy c-means algorithm (FCM).

IV. The Modified FCM Algorithm

In the FCM algorithm for a pixel $x_k \in I$ where I is the image, the clustering of x_k with class i depends on the membership value $u_{i,k}$. If we consider a noisy image, the FCM does not have a method to overcome this problem. Consider $D_{i,k}$ as the resistance of pixel p_k to be clustered with class i. This resistance can be tolerated by the neighboring pixels p_j. The neighboring pixels work to decrease the pixel's resistance by a fraction that depends on the membership value of p_j with cluster i, u_{ij}. The membership value was chosen to tolerate the resistance. As the system converges to its minimum the membership value reaches its meaningful value, and the neighboring effect robustify the result.

$$D_{ik} = D_{ik} \left(1 - \alpha \frac{\sum_{j \in neighbors} U_{ij} * p_{kj}}{\sum_j p_{kj}} \right) \quad (10)$$

where α is a constant that satisfies the condition $0 \leq \alpha \leq 1$. If $\alpha = 0$ it gives the original FCM algorithm without considering the neighbors. If α was set to 1 and the membership values $u_{ij} = 1$ for all $j \in neighbors$ then $D_{ik} = 0$ meaning that $u_i(p_k) = u_{ik} = 1$. We tried several values for α

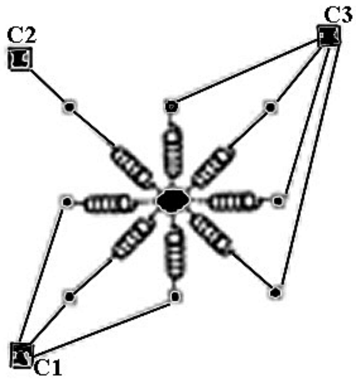

Fig. 1. Modeling the effect of neighbor pixels in the modified FCM. The neighbor pixels attract the pixel to their clusters. This makes the method less sensitive to noise while enhancing the edges.

and found that a value of $\alpha = 0.5$ gives a convenient result. p_{kj} measures the proximity of pixel k to its neighbor pixel j. The proximity here is measured with respect to the relative locations between the two pixels $p_{kj} = ||k-j||$. So the total effect of the neighboring pixels is that each surrounding pixel tries to pull its neighbor toward its class without neglecting the effect of the pixel itself as shown in Fig[1]. This works as an adaptive filter applied during the segmentation. Each iteration enhances the filtering effect while emphasizing the edges.

The FCM Algorithm

Step 1) The initial cluster centers are distributed uniformly over the scale. In CT scans the background and the gray level of the ventricles are very low. Thus having one cluster center of value zero would cluster those regions into one cluster. Considering the skull, a "255" cluster center value would cluster those into one region. In between is the gray-matter and white-matter.

Step 2) Determining a value for m. The FCM was developed here by considering $m = 2$.

Step 3) Defining the number of clusters. In the CT scans it is desirable to classify the brain into ventricles and brain tissue (either white-matter or gray-matter). The number of clusters in this case is three. In the case of the MRI scan, we applied the algorithm several times using a different number of clusters each time.

Step 4) Obtaining D_{ik}, using the new method, from which U matrix is calculated. As the non-descriptive initial centers would enlarge the processing time, we considered applying the neighbors effect after approaching the final centers. In our case, we found that after three iterations the system starts to stabilize. Therefore we applied the neighbors effect after the third iteration.

Step 5) The process continues until the minimization condition is fulfilled.

Step 6) The defuzzification process then takes place in order to achieve the crisp clusters. We tried using a weighted measure from each region depending upon the membership function (for example the $clusteri = \sum_{i=1}^{c} u_{ik} i$) and using the maximum value $clusteri = argmax(u_{ik}) \forall i \in c$. The argmax method was found more reliable.

V. Implementations and Results

First we developed an image of multiple regions where the gray level inside each region varies within certain limits. Then we added gaussian noise with different signal to noise ratio, using the values 5, 10 and 20. As shown in Fig[2], we applied the FCM algorithm without considering the neighboring pixels. For the image with $SNR = 20$, the FCM successfully segmented the image. Applying the FCM on the image with $SNR = 10$ did not totally recover from the noise, but successfully segmented the image into the desired regions. Segmenting the image with $SNR = 5$ gave the same regions but the result suffered from the noise. We used a preprocessing step in which a hybrid median filter was applied on the images. Then we applied the FCM algorithm. The filter enhanced the results but it deformed the boundaries. We applied the modified FCM algorithm with $\alpha = 0.75$, and the results show superiority over that of the FCM algorithm even with the preprocessing step. We applied the FCM algorithm and the modified FCM algorithm with $\alpha = 0.5$ on a noisy CT brain scan. The results are shown in Fig[3]. To get the accurate size of a segmented region, we calculated the partial volume using the membership value. Fig[3] shows the points that have a membership value less than the threshold (0.8) The figure shows that those points are either near the regions' boundaries or noise. In this case, we calculated the membership value of the surrounding pixels without the neighbor effect so that the resulting float would be a faithful value of the partial volume. For the single channel MRI image shown in Fig[4], we over-segmented the image into four regions in order to overcome the textured effect of the MRI image. In a further process those segments could be joined into the final clusters.

VI. Conclusions

In this paper, an application of the fuzzy set theory in image segmentation was presented. The volumetric measurements for structures can be accurately determined using the membership value as a guideline to get the partial volume at the boundaries. Using the neighbors to enhance the clustering with the FCM

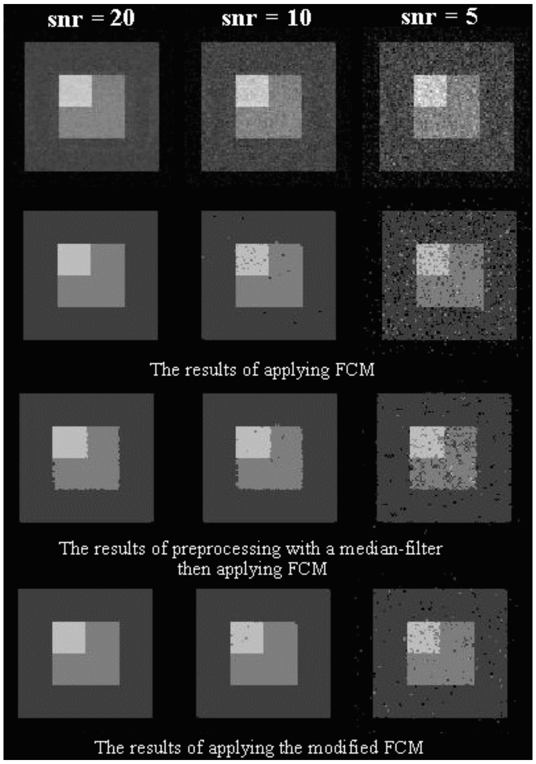

Fig. 2. Comparison between the FCM and the Modified FCM in a noisy synthetic image

algorithm corrects for noisy images without affecting the edges. The effect of the neighboring pixels at the boundaries in a narrow real region could affect the region size after clustering; however, considering the partial volume around it can compensate for the region loss.

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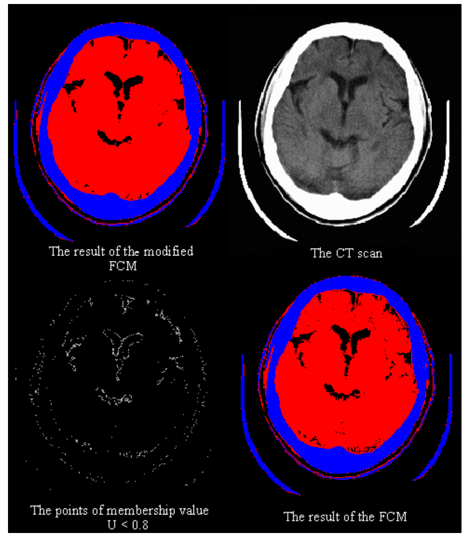

Fig. 3. Application to a CT image

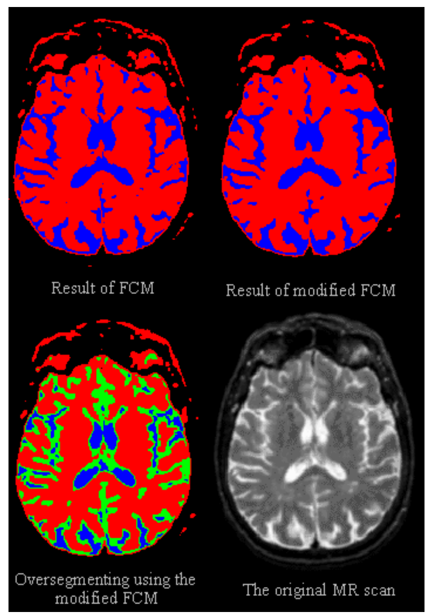

Fig. 4. Application to an MRI image

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