Volume 6, Issue 6, June 2016 ISSN: 2277 128X
International Journal of Advanced Research in Computer Science and Software Engineering
Research Paper
Available online at: www.ijarcsse.com

MRI Segmentation Using Clustering Algorithm

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***Abstract-** In this study, unsupervised clustering methods are examined to develop a medical diagnostic system and fuzzy clustering is used to assign patients to the different clusters of brain tumor. We present a novel algorithm for obtaining fuzzy segmentations of images that are subject to multiplicative intensity inhomogeneities, such as magnetic resonance images. The algorithm is formulated by modifying the objective function in the fuzzy algorithm to include a multiplier field, which allows the centroids of each class to vary across the image. Magnetic resonance (MR) brain section images are segmented and then synthetically colored to give visual representation of the original data. The results are compared with the results of clustering according to classification performance. This application shows that fuzzy clustering methods can be important supportive tool for the medical experts in diagnostic.*

***Index Terms-** Image segmentation, intensity inhomogeneities, fuzzy clustering, magnetic resonance imaging.*

I. INTRODUCTION

According to rapid development on medical devices, the traditional manual data analysis has become inefficient and computer-based analyses are indispensable. Statistical methods, fuzzy logic, neural network and machine learning algorithms are being tested on many medical prediction problems to provide a decision support system.

Image segmentation plays an important role in variety of applications such as robot vision, object recognition, and medical imaging. There has been considerable interest recently in the use of fuzzy segmentation methods which retain more information from the original image than hard segmentation methods. The fuzzy c means algorithm (FCM), in particular, can be used to obtain segmentation via fuzzy pixel classification. Unlike hard classification methods which force pixels to belong exclusively to one class, FCM allows pixels to belong to multiple classes with varying degrees of membership. The approach allows additional flexibility in many applications and has recently been used in the processing of magnetic resonances (MR) images.

In this work, unsupervised clustering methods are to be performed to cluster the patients brain tumor. Magnetic resonance (MR) brain section images are segmented and then synthetically colored to give visual representation of the original data. This study fuzzy c means algorithm is used to separate the tumor from the brain and can be identified in a particular color. Supervised and unsupervised segmentation techniques provide broadly similar results. Unsupervised fuzzy algorithm were visually observed to show better segmentation when compared wit raw image data for volunteer studies. Clustering is the process of partitions a data set into several groups such that the similarity within a group is larger than that among groups.

II. PROPOSED METHODOLOGY

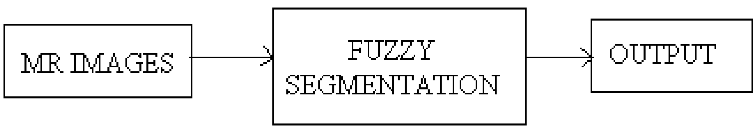

Figure1 Block Diagram

Figure1. shows the proposed methodology of segmentation of images. Magnetic resonance (MR) brain section images are segmented and then synthetically colored to give visual representation of the original data wit three approaches: the literal and approximate fuzzy c means unsupervised clustering algorithms and a supervised computational neural network, a dynamic multilayered perception trained with the cascade correlation learning algorithm. Supervised and unsupervised segmentation techniques provide broadly similar results. Unsupervised fuzzy algorithm were visually observed to show better segmentation when compared wit raw image data for volunteer studies.

In computer vision, 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. Image segmentation is typically used to locate objects and boundaries (lines, curves, etc.) in images.

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 (see edge detection). 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). Some of the practical applications of image segmentation are:

- Medical Imaging
    - Locate tumors and other pathologies
    - Measure tissue volumes
    - Computer-guided surgery
    - Diagnosis
    - Treatment planning
    - Study of anatomical structure
- Locate objects in satellite images (roads, forests, etc.)
- Face recognition
- Fingerprint recognition
- Automatic traffic controlling systems
- Machine vision

III. FUZZY C - MEANS CLUSTERING

Fuzzy C-means Clustering (FCM), is also known as Fuzzy ISODATA, is an clustering technique which is separated from hard k-means that employs hard partitioning. The FCM employs fuzzy partitioning such that a data point can belong to all groups with different membership grades between 0 and 1.

FCM is an iterative algorithm. The aim of FCM is to find cluster centers (centroids) that minimize a dissimilarity function.

To accommodate the introduction of fuzzy partitioning, the membership matrix (U) is randomly initialized according to Equation

$$\sum_{i=1}^{c} u_{ij} = 1, \forall j = 1,...,n \qquad (1)$$

The dissimilarity function which is used in FCM is given Equation

$$J(U, c_1, c_2, ..., c_c) = \sum_{i=1}^{c} J_i = \sum_{i=1}^{c}\sum_{j=1}^{n} u_{ij}{}^{m} d_{ij}{}^{2} \qquad (2)$$

Uij is between 0 and 1;

Ci is the centroid of cluster i;

Dij is the Euclidian distance between i_{th} centroid (c_i) and j_{th} data point;

m ϵ [1,∞] is a weighting exponent.

To reach a minimum of dissimilarity function there are two conditions. These are given in Equation (3) and Equation (4).

$$c_i = \frac{\sum_{j=1}^{n} u_{ij}{}^{m} x_j}{\sum_{j=1}^{n} u_{ij}{}^{m}} \qquad (3)$$

$$u_{ij} = \frac{1}{\sum_{k=1}^{c} \left(\frac{d_{ij}}{d_{kj}} \right)^{2/(m-1)}} \qquad (4)$$

3.1 ALGORITHM

This algorithm determines the following steps.

Step1. Randomly initialize the membership matrix (U) that has constraints in Equation (1).

Step 2. Calculate centroids (c_i) by using Equation (3).

Step 3. Compute dissimilarity between centroids and data points using equation (2). Stop if its improvement over previous iteration is below a threshold.

Step 4. Compute a new U using Equation (4). Go to Step 2.

FCM does not ensure that it converges to an optimal solution. Because of cluster centers (centroids) are initialize using U that randomly initialized (Equation (3)).

IV. FAST FUZZY CLUSTERING

The fuzzy c-means (FCM) clustering algorithm has been extensively used for pattern recognition and data clustering. It has also been used in the process of generating fuzzy rules from data. Due to (1) the iterative nature of the algorithm and (2) the large number of feature vectors often involved in the calculations, it is computationally intensive. We mitigate this time problem by reducing the number of iterations required to converge. The idea is to use a small (representative) subset of the full data set to obtain an initial approximation of the cluster centers, which can then be used for approximating cluster centers of the full data set. This initial approximation helps to reduce the number of iterations needed to process the full data set. This approach is distinct from the AFCM algorithm, which is really an algorithm similar to FCM without the convergence properties of FCM.

Our algorithm is based on the assumption that a small subset of a data set of feature vectors can be used to approximate the cluster centers of the complete data set. Under this assumption FCM is used to compute the cluster centers of an appropriate size (randomly selected) subset of the full data set. After obtaining the cluster centers of this small subset, the subset of data is merged with an additional small randomly selected subset of the remaining unprocessed feature vectors to form a larger subset which is processed by FCM.

4.1 ALGORITHM

The Multistage Random Sampling FCM algorithm is divided into two phases, where Phase I is a multistage iterative process of modified FCM and Phase II is standard FCM with the cluster centers initialized by the final cluster center values from Phase I. There are four factors that must be determined prior to execution. First is the size of the subsamples, which will be Δ% of the n samples in X and is denoted by $X_{(\Delta\%)}$. Second is the number of stages n. The final size of data set for rnrFCM Phase I will be n * Δ% samples denoted by X (n*Δ %). The final two factors are the stopping condition for first stage of mrFCM Phase I, $\epsilon_{\text{first stage}}$ and the stopping condition for the last stage of mrFCM Phase I, $\epsilon_{\text{last stage}}$. The following steps make up the algorithm,

Phase I

Randomly initialize the cluster center matrix v in the range of the data.

Step 1: Select $X_{(\Delta\%)}$. from the set of feature vectors matrix. Set s = 1.

Step 2: Initialize the fuzzy partition matrix U with $X_{(s*\Delta\%)}$.

Step 3: Compute the stopping condition

$$\epsilon_{sub} = \epsilon_{\text{first stage}} - s*((\epsilon_{\text{first stage}} - \epsilon_{\text{last stage}}) / n) .$$

Step 4: Set k = 0.

Step 5: Set k=k + l.

Step 6: Compute the cluster center matrix $V_{(s*\Delta\%)}$.

Step 7: Compute the $U^k_{(s*\Delta\%)}$.

Step 8: If $\|U^k_{(s*\Delta\%)} - U^{k-1}_{(s*\Delta\%)}\| \geq \epsilon_{sub}$ then go to Step 5

Else If s < = n then select another $X_{(\Delta\%)}$ and merge it with the existing $X_{(s*\Delta\%)}$.

Set s = s+ 1.

Go to Step 2 of Phase I.

Else begin Phase II.

Phase II

Step 1: Initialize the fuzzy partition matrix U by using the results from Phase I, $V_{(s*\Delta\%)}$, with functions (5) and (6), for X, the full data set. Note this is equivalent to initializing the cluster centers with the previously found v's.

Step 2: Follow Step 3 to Step 5 in regular FCM, using the stopping condition of $\epsilon_{\text{last stage}}$.

V. IMPLEMENTATION

The set of MR images consist of 256*256 12 bit images. The fuzzy segmentation was done in MATLAB software. There four types of brain tumor used in this study namely astrocytoma, meningioma, glioma, metastase.

Table 1. Types and number of datas

DATA TYPES	NUMBER OF IMAGES
Astrocytoma	15
meningioma	25
glioma	20
metastase	10
TOTAL	70

VI. EXPERIMENTAL RESULTS

Fuzzy c means algorithm is used to assign the patients to different clusters of brain tumor. This application of fuzzy sets in a classification function causes the class membership to become relative one and an object can belong to several classes at the same time but with different degrees. This is important feature for medical diagnostic system to increase the sensitivity. The four types of datas were used. One sample is shown as above. Figure 3. shows the input image of the brain tumor and Figure 4. Shows the fuzzy segmentated output image.

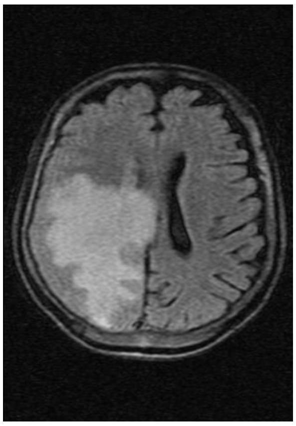

Figure 3. Input image

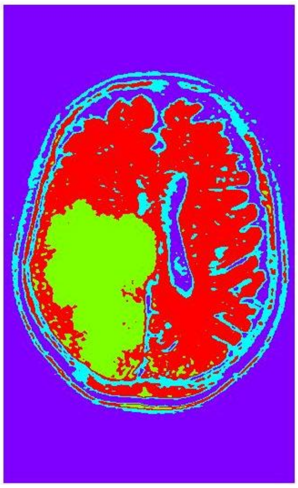

Figure 4. Output image

Table 2. Segmentation results

Count	20
threshold	0.0085
Time period	78.500000 seconds
Centroid	67.3115 188.9934 120.2793 13.9793

VII. CONCLUSION AND FUTURE WORK

In this study, we use fuzzy c means algorithms to cluster the brain tumor. In medical diagnostic systems, fuzzy c means algorithm gives the better results according to our application. Another important feature of fuzzy c means algorithm is membership function and an object can belong to several classes at same time but with different degrees. This is a useful feature for a medical diagnostic system. At a result, fuzzy clustering method can be important supportive tool for the medical experts in diagnostic.

Future work is fuzzy c means result is to be compared with fast fuzzy segmentation. Then with adaptive fuzzy c-mean clustering. Reduced time period of fuzzy segmentation is used in medical.

ACKNOWLEDGMENT

We would like to thank M/S Devaki Scan Center Madurai, Tamil nadu for providing MR brain tumor images of various patients and datas.

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