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Analysis of Brain Tumor Detection of Fuzzy Algorithm Using C Cluster

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Abstract- *Segmentation is a difficult and challenging problem in the MRI images, and it is very important in computer application and artificial intelligence. Image segmentation is the partition of an image into several regions of interest such that the contents of each region have similar characteristics. This paper presents a survey of latest image segmentation techniques using fuzzy clustering. Fuzzy clustering techniques have been widely used in automated image segmentation.*

Keyword: Segmentation, Fuzzy clustering, fuzzy c-mean, membership function.

I. INTRODUCTION

Image segmentation is one of the most widespread means to classify correctly the pixels of an image in decision oriented applications. Image segmentation is a technique that partitions an image into uniform and non-overlapping regions based on some likeness measure. This technique has a variety of applications including computer vision, image analysis, medical digital image processing, distant sensing and geographical system. Image segmentation is based on two basic properties of image 1) *intensity* values involving discontinuity that refers to sudden or abrupt changes in intensity as edges and 2) *similarity* that refers to partitioning a digital image into
regions according to some pre-defined likeness criterion.

A particularly important concern in practice is to construct membership functions from a given set of data via unsupervised or supervised learning approaches. In general, membership functions may be constructed from available data when adequate amount of data is already collected in a database or a data warehouse. It is necessary to build Medical Imaging Support Decision Systems (MISSD)[5] able to extract the salient information embedded in the multivariate medical image, removing redundancies and noise. It is made up by an interactive graphical system supporting the full analysis sequence: extraction of features,reduction of spaciality, unsupervised agglomeration, voxel classification, and post-processing refinements. The core of the system was a segmentation technique based on an unsupervised clustering neural network named ”capture effect”.

II. SEGMENTATION THROUGH CLUSTERING

Multivariate volumes can be built from a number of different diagnostic volumes with complementary information (both structural and functional) provided by medical imaging technology, for absolutelycorrelating info regarding constant patient. An efficient analysis of multivariate medical imaging volumes is an inherently complex task in every part of the information structure, that is the spatial distribution of the values of one feature, should be thought of besides the other components. Such an analysis may be helpful in the clinical oncological environment to delineate volumes to be treated in radiotherapy and surgery and to assess quantitatively (in terms of tumor mass or detection of metastases)[3] the effectof oncological treatments. All these applications involve the extraction of objects or other entities of interest from the imaging data, usually by defining sets of voxels with similar features within the entire multivariate volume. This task is a possible definition of image segmentation and is usually accomplished, either by methods of edge detection (e.g. gradient operators), or by methods of similarity detection (e.g. thresholding and region growing techniques).

Actually, volumes of interest in medical imaging are not strictly bounded and the application of similarity methods to multivariate data is complex and often very time consuming with complex geometries. Let us consider a multivariate volume resultingfrom the spatial registration of a set of *s* different imaging volumes.We may notice that its voxels are associated to an array of *s* values, each one representing the intensity of a single feature in that voxel. In other words, the *s* different intensity values related to each voxel in such multivariate volumes can be viewed as the coordinates of the voxel within a*s*-dimensional feature space where multivariate analysis can be made. Two different spaces have therefore to be considered for a more complete description of the segmentationproblem:an image space (usually 3D)[4] outlined by the abstraction coordinates of the information set, and a third dimensional feature space as delineate before. The principal steps in segmenting of multivariatevolumes is the definition of clusters within the *s*- dimensional feature space and the classification of all the voxels of the volume in the resulting classes.These two goals can be attained both by supervised and unsupervised methods. Supervised methods has been largely employed in medical imaging segmentation studies but provide for conditions hardly satisfied in the clinical environment. First of all, they require the labelling of prototypical samples needed by the generalization process to be applied. Even if the number of clusters is predefined, careful labeling of voxels in the training set belonging with certainty to the different clusters is not trivial especially when concerning multivariate data sets. Moreover, bias can be introduced by users due to the large inter-user variability generally observed when manual labelling is performed. On the contrary, unsupervised approaches self organize the implicit structure of data and make clustering of the feature space independent from the user definition of the training regions.

III. TYPES OF CLUSTERING

Suppose that it has N objects (e.g. pieces of fruit). Of each of these objects, we make n measurements (e.g. size, weight, etcetera). These measurements are also called features or attributes. The set of measurements of one object, $z_k = [z_{1k}, \dots, z_{nk}]^T$, is called a sample, a pattern or simply an object. We can also put all measurements in a matrix. We then get the data matrix $Z = [z_1 \dots z_N]$. To divide objects into clusters, we often make use of (dis)similarity measures. One well-known example of a dissimilarity measure is the Euclidian distance $\|z_j - z_i\|$, but we'll consider more later. Based on the supported measures, objects square measure divided into clusters.

A. Hard clustering

There is an important distinction between hard clustering and fuzzy clustering. In hard clustering it make a hard partition of the data set Z. In other words, itdivide them into c > 2 clusters (with c assumed known). With a partition, it mean that

$$\bigcup_{i=1}^{c} A_i = Z \text{ And } A_i \cap A_j = \phi \text{ for all } i \neq j$$

Also, none of the sets Ai may be empty.To indicate a partitioning, itmake use of membership functions μ_{ik}. If $\mu_{ik} = 1$, then object i is in cluster k. Alternatively, if $\mu_{ik} = 0$, then object i is not in cluster k. Based on the membership functions, it can assemble the partition matrix U, of thatμ_{ik}suare measure the elements. In other words, every object is only part of one cluster. Thus, every column of U has solely a single 1. The set of all hard clusterings U that can be obtained with hard clustering is now denoted as M_{hc}.

B. Fuzzy clustering

Hard clustering has a drawback. Once associate in nursing an object roughly falls between 2 clusters Ai and Aj, it has to be put into one of these clusters. Also, outliers ought to be place in some cluster. This is undesirable. But it can be fixed by fuzzy clustering. In fuzzy clustering, we make a fuzzy partition of the data[7]. Now, the membership function μ_{ik} can be any value between 0 and 1. This implies that associate in nursing object z_k can be for 0.2 part in Ai and for 0.8 part in A_j . However, requirement still applies. So, the total of the membership functions still has to be 1. The set of all fuzzy partitions that can be formed in this way is denoted by M_{fc}.Fuzzy partitioning again has a downside. When we have an outlier in the data.That is, the sum of its membership functions still must equal one.

IV. THE FUZZY C-MEANS CLUSTERING ALGORITHM

Numerous methodologies have been proposed and a dense literature is available for extracting information from an image and to partition it into different regions. But all suffer from different limitations in terms of time complexity, accuracy. This is due to not well defined boundaries of clusters within the image, so techniques other than fuzzy result in disambiguates in segmented images, on the other hand fuzzy image segmentation methodologies yield good results. Clustering methods[6] use information like brightness and spatial location of pixels. These methods lack the ability to separate image regions having similar pixels intensities by considering only their pixel intensity. The pixels on an image are highly correlated, that is the pixels in the immediate neighborhood possess nearly the same feature data. Therefore, the spatial correlation of adjacent pixels is an important characteristic that can be of great aid in image segmentation. The objective function basedfuzzy clustering algorithms includes Fuzzy C-Means (FCM) algorithm, Gustafson-Kessel algorithm (GK),Fuzzy C-Varieties (FCV) algorithm, Adaptive Fuzzy C Shell (FCS) algorithm, Fuzzy C-Spherical Shells (FCSS) algorithm, Fuzzy C-Quadric Shells (FCQS) algorithm.Among these above mentioned fuzzy clustering methods FCM is the most accepted means of image segmentation since it has robust characteristics for ambiguity and can preserve much more information than hard clustering approaches. FCM assigns pixels to eachclass by means of fuzzy membership function. Lets suppose $X=(x_1, x_2, x_3 \dots x_N)$ denotes an image with N pixels to becategorized into C clusters. FCM is the iterative minimization(1)of the following objection function:

$$J = \sum_{j=1}^{N} \sum_{i=1}^{C} u_{ij} \| x_j - v_i \| \quad (1)$$

where$u_{ij}$is the membership of pixel $x_j$in i^{th}cluster, $v_i$is the i^{th} clustercenter, *m* is the fuzzifier that controls the fuzziness of resulting partitions and occurs between $1<m\leq\infty$ and ||.|| are norm metric. Sometimes Euclidean distance between pixel $x_j$andthe center of i^{th}cluster v_i, is used as norm metric. The membership function and cluster centers are updated as(2):

$$u_{ij} = \frac{1}{\sum_{k=1}^{c} \left(\frac{\| x_j - v_i \|}{\| x_j - v_i \|} \right)^{2/(m-1)}} \quad (2)$$

$$vi = \frac{\sum_{j=1}^{N} u_{ij}{}^{m} x_j}{\sum_{i=1}^{N} u_{ij}{}^{m}} \quad (3)$$

The cluster centers will either be initialized byan approximation method. On noisy images, FCM does not incorporate spatialinformation which makes it sensitive to noise and other imageartifacts. Furthermore, as FCM cluster assignment is basedexclusively on the distribution of pixel intensity, that makes itsensitive to intensity variations in the illumination or thegeometry of the object[4].

V. BIAS CORRECTED FUZZY C MEAN ALGORITHM

In this method novel algorithm for fuzzy segmentation of magnetic resonance imaging(MRI) data and estimation of intensity inhomogeneities exploitation fuzzy logic[6]. MRI intensity inhomogeneities may be attributed to imperfections in the radio-frequency coils or to problems associated with the acquisition sequences. The result is a slowly varying shading artefact over the image that can produce errors with conventional intensity-based classification. The algorithm is formulated by modifying the objective function of the standard fuzzy c-means (FCM) algorithm to compensate for such inhomogeneities and to allow the labelling of a pixel (voxel) to be influenced by the labels in its immediate neighborhood. The neighborhood result acts as a regularizer and biases the answer toward piecewise-homogeneous labelling. Such a regularization is useful in segmenting scans corrupted by salt and pepper noise. Spatial intensity inhomogeneity induced by the radio-frequency coil in magnetic resonance imaging (MRI)[9]is a major problem in the computer analysis of MRI data. Such inhomogeneities have rendered conventional intensity-based classification of MR images very hard, even with new techniques like statistic, multichannel methods. This is due to the fact that the intensity inhomogeneities appearing in MR images produce spatial changes in tissue statistics, i.e., mean and variance.The removal of the spatial intensity inhomogeneity from MR images is difficult because the inhomogeneities could change with different MRI acquisition parameters from patient to patient and from slice to slice. So, the correction of intensity inhomogeneities is generally required for each new image.The observed MRI signal is modeled as a product of the true signal generated by the underlying anatomy, and a spatially variable issue known as gain field.

$$Y_k = X_k G_k \ \forall k \varepsilon \{1, 2, \ldots N\}$$

Where X_k andY_k are the square measure actuality and discovered intensities at the K^{th} voxel, respectively, $G_k$is the gain field at the K^{th} voxel, and is the total number of voxels in the MR images volume. The applying of a index transformation to the intensities permits the artifact to be modeled as an additive bias field.

$$y_k = x_k + \beta_k \ \forall k \in \{1, 2, \ldots N\}$$

Where x_k and y_k are the true and observed log-transformed intensities at the k^{th} voxel, respectively, and β_k is the bias field at the k^{th} voxel. If the gain field is known, then it is relatively easy to estimate the tissue class by applying a conventional intensity-basedsegmenter to the corrected knowledge. Similarly, if the tissue categories square measure illustrious, then we will estimate the gain field[10]. The standard FCM objective function(4) for partitioning $\{x_k\}_{k=1}^{N}$ into clusters is given by

$$J = \sum_{i=1}^{C} \sum_{K=1}^{N} u_{ik}{}^{p} \| x_k - v_i \|^2 \quad (4)$$

where $\{\beta_k\}_{k=1}^{N}$ square measure the prototypes of the clusters and also the array $[\mu_{ik}] = U$ represents a partition matrix(5),

$$u\{u_{ik} \in [0,1] \mid \sum_{i=1}^{c} u_{ik} = 1 \forall k \quad (5)$$

The parameter may be coefficient exponent on every fuzzy membership and determines the quantity of fuzziness of the ensuing classification. The FCM objective perform is decreased once when high membership values are alloted to voxels whose intensities are near to the center of mass of its explicit category, and low membership values are alloted when the voxel data is far from the centroid. It propose a modification by introducing a term that allow the labeling of a pixel (voxel) to be influenced by the labels in its immediate neighborhood. As mentioned before, the neighborhood effect acts as a regularizer and biases the answer toward piecewise-homogeneous labeling. Such a regularization is beneficial in segmenting scans corrupted by salt and pepper noise. The changed objective function is given by(6)

$$Jm = \sum_{i=1}^{c} \sum_{k=1}^{N} u^{p}{}_{ik} \| x_k - v_i \|^2 + \frac{\alpha}{N_R} \sum_{i=1}^{c} \sum_{k=1}^{N} u^{p}{}_{ik} \left(\sum_{x_r \in N_k} \| x_r - v_i \|^2 \right) \quad (6)$$

Where N_k stands for the set of neighbors that exist in a window around x_k and N_R is the cardinality of N_k . The effect of the neighbors term is controlled by the factor α. The importance of the regularizing term is reciprocally proportional to the signal-to-noise ratio (SNR) of the MRI signal. Lower SNR would need a higher value of the parameter α.

$$Jm = \sum_{i=1}^{c}\sum_{k=1}^{N} u^{p}{}_{ik} \| y_k - \beta_k - v_i \|^2 + \frac{\alpha}{N_R}\sum_{i=1}^{c}\sum_{k=1}^{N} u^{p}{}_{ik} (\sum_{y_r \in N_k} \| y_r - \beta_r - v_i \|^2) \quad (7)$$

Formally, the optimization problem comes in the form U, $\{v_i\}_{i=1}^{C}$, $\{\beta_k\}_{k=1}^{N}$ subjected to $U \in u$

A. Parameter Estimation

The objective function J_m can be minimized in a fashion similar to the standard FCM algorithm. Taking the first derivatives of J_m with respect to u_{ik}, v_i, and β_k and setting them to zero results in three necessary but not sufficient conditions for J_m to be at a local extrema[8]. In the following subsections, these three conditions are derived.

B. Membership Evaluation

The constrained optimization will be solved using one Lagrange multiplier

$$Fm = \sum_{i=1}^{c}\sum_{k=1}^{N} (u_{ik}^{p} D_{ik} + \frac{\alpha}{N_R} u_{ik}^{p} \gamma_i) + (1 - \sum_{i=1}^{c} u_{ik}) \quad (8)$$

Where $D_{ik} = \| y_k - \beta_k - v_i \|^2$ and

$$\gamma i = (\sum_{yr \in Nk} \| y_r - \beta_r - v^i \|^2)$$

Taking the derivative of F_m with respect to u_{ik} and setting the result to zero, we have, for p>1.

$$[\frac{\delta F_m}{\delta u_{ik}} = p u_{ik}^{p-1} D_{ik} + \frac{\alpha p}{N_R} u_{ik}^{p} \gamma_i - \lambda]_{u_{ik} = u_{ik}^{*}} = 0$$

Resolution for u_{ik} we get

$$u_{ik}^{*} = \frac{\lambda}{p(D_{jk} + \frac{\alpha}{N_R}\gamma_j)})^{1/(p-1)} \quad (9)$$

Since $\sum_{j=1}^{c} u_{ik} = 1 \forall k$

$$\sum_{j=1}^{c} (\frac{\lambda}{p(D_{jk} + \frac{\alpha}{N_R}\gamma_j)})^{1/(p-1)} = 1$$

$$\lambda = \frac{p}{(\sum_{i=1}^{c} (\frac{1}{(D_{jk} + \frac{\alpha}{N_R}\gamma_j)})^{1/(p-1)}))^{p-1}}$$

zero-gradient condition for the membership computer may be newly written as:

$$u_{ik}^{*} = \frac{1}{\sum_{j=1}^{c} (\frac{D_{ik} + \frac{\alpha}{N_R}\gamma_i}{D_{ik} + \frac{\alpha}{N_R}\gamma_j})^{1/(p-1)}} \quad (10)$$

C. Cluster Prototype Updating

In the following derivation, the standard Eucledian distance is used. Taking the derivative of F_m with respect to v_i and setting the result to zero, it gives

$$\left[\sum_{k=1}^{N} u_{ik}^{p} (y_k - \beta_k - v_i) + \sum_{k=1}^{N} u_{ik}^{p} \frac{\alpha}{N_R} \sum_{y_r \in N_k} (y_r - \beta_r - v_i) \right]_{v_i = v_i^{*}} = 0$$

Solving for v_i, it gives

$$v_i^{*} = \frac{\sum_{k=1}^{N} u_{ik}^{p} ((y_k - \beta_k) + \frac{\alpha}{N_R} \sum_{y_r \in N_k} (y_r - \beta_r))}{(1+\alpha)\sum_{k=1}^{N} u_{ik}^{p}} \quad (11)$$

D. Bias-Field Estimation

In a similar fashion, taking the derivative of F_m with respect to β_k and setting the result to zero, it gives

$$\left[\sum_{i=1}^{c} \frac{\delta}{\delta \beta_k} \sum_{k=1}^{N} u_{ik}^{p} (y_k - \beta_k - v_i)^2 \right]_{\beta_k = \beta_k^{*}} = 0 \quad (12)$$

Since only the k^{th} term in the second summation depends on β_k ,it gives(13)

$$\left[\sum_{i=1}^{c} \frac{\delta}{\delta \beta_k} \sum_{k=1}^{N} u_{ik}^{p} (y_k - \beta_k - v_i)^2 \right]_{\beta_k = \beta_k^{*}} = 0 \quad (13)$$

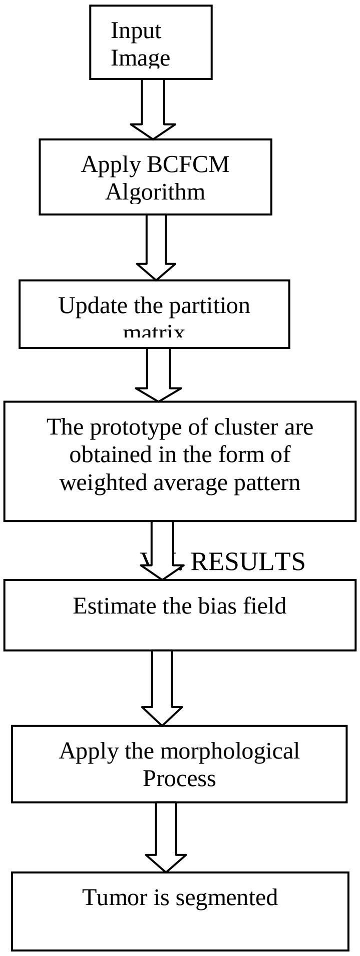
Differentiating the distance expression(14), it gives

$$\left[y_k \sum_{i=1}^{c} u_{ik}^{p} - \beta_k \sum_{i=1}^{c} u_{ik}^{p} - \sum_{i=1}^{c} u_{ik}^{p} v_i \right]_{\beta_k = \beta_k^{*}} = 0 \quad (14)$$

Thus, the zero-gradient condition for the bias-field estimator is expressed as

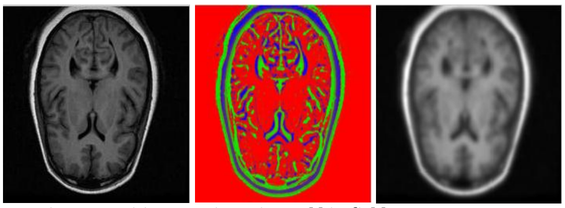
$$\beta_k^* = y_k - \frac{\sum_{i=1}^{c} u_{ik}^p v_i}{\sum_{i=1}^{c} u_{ik}^p}$$

VI. FLOW CHART



In this paper the brain MRI real images are used as input images. As these images are MRI images it contains spatial intensity inhomogeneity (Bias field) because of RF coil. This bias field is estimated by updating the partition matrix. It also separate the 1)white matter, 2)gray matter and 3)CSF(cerebrospinal fluid). By applying the morphological processes the tumor is segmented. These results are explained step by step as follows.

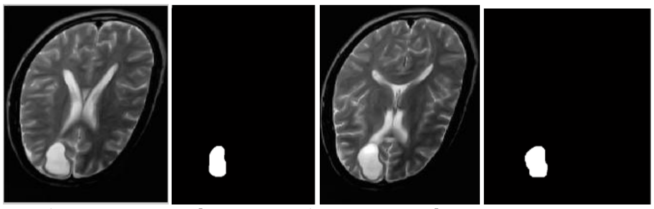
(Normal Brain MR Image)



Input imagePartition Matrix Estimated biasfield

Corrected image white matter gray matter CSF

(Abnormal Brain MR Images)



Input image segmented tumorInput imagesegmented tumor

VII. CONCLUSION AND FUTURE DIRECTIONS

Segmentation is an important step in advance image analysis and computer vision and therefore is an ongoing research area although a dense literature is available. The incorporation of spatial information in to the objective function of standard FCM yields successful results for robust and effective image segmentation of noisy images and the techniques like, ISFCM and NFCM can beapplied to segment colored images. The techniques reviewed in this survey are applicable to analysis of MRI images and in future can be applied to other medical image types like CT and PET for better analysis. 3D volume of MR data based on segmentation using fuzzy clustering can be reconstructed and lesion volume can also be analyzed quantitatively. Furthermore in future a hybrid technique based on clustering algorithms and classifiers like Neural Networks and etc can be combined to work on input data set for better results and previously designed algorithm can be modified to work for color image segmentation.

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