Segmentation of Brain MRI with Reduced Weighted Vectors Using HSOM and FCM Techniques

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Abstract: The proposed Method for automatic segmentation and detection of pathological tissues, normal tissues and CSF of human brain in Magnetic resonance image (MRI) is discussed in this paper. This method is implemented in two phases, (1) the MRI brain image is acquired from patient database, In that film artifact and noise are removed. (2) In second phase, hierarchal self organizing Map and fuzzy 'C' means algorithms are used to classify the image layer by layer. The lowest lever weight vector is acquired by the abstraction level. We also achieved a high value of pathological tissue pixels by using Hybrid Intelligence Technique. Our method does not require specific expert definition for each structure or manual interactions during segmentation process. The performance of HSOM-FCM performs more accurate and is compared with previous techniques.

Keywords: Hybrid intelligence , Image analysis , Tissue Segmentation HSOM-FCM, Segmentation.

I. INTRODUCTION

Body is made of many cells. Each cell has specific duty. The cells growth in the body and are divided to reproduce other cells. These divisions are very vital for correct functions of the body. When each cell loses the ability of controlling its growth, these divisions is done with any limitation and tumor emerges. Tumors, their self, are divided to two classes: benign and malignant. MR imaging technique, because of good ability in showing difference between soft tissues, high resolution, good contrast and noninvasive technique for using no ionization rays is very appropriate. Segmentation is the first step at quantitative analysis of medical images.Medical images analysis field [4,5,6,], because of indirect and Sophisticate structures are very complicated but interesting. Segmentation methods are very successful on normal tissues [4, 7-12] but it hasn't been done good theoretical and practical segmentation on abnormal tissues yet [4]. Computer aided tumor detection is one of the hardest index in field of abnormal tissue segmentations. There are two important problems. First, automatic tissue measurement is not very easy because of variations in the structures. Intensity distribution of normal tissues is very complicated and exist some overlaps between different types of tissues. Moreover it is probable to have some variations in the size, location and form of the brain tumor tissues and usually contains any dropsy. Other tissues that contain any dead, bloodshed or shrinkage, can be as abnormality and so abnormal tissues boundaries can be blurred. Second problem is the MR image have formed from high number of pixels (for example 256*256*128), so segmentation problem, has a high computational complexity and needs much memory. This problem can be solved by using 2D repetitive methods or semi-automatic segmentation helping human knowledge, but will lose much information such as geometry and etc [4]. MRI plays an important role in assessing pathological conditions of the ankle, foot and brain. It has rapidly evolved into an accepted modality for medical imaging of disease processes such as especially the foot and brain due to the use of non-ionizing radiation. In this paper a contribution in the detection of pathologic tissues (tumor & edema) using contrast enhancement and segmentation of images by synthesizing using "ad hoc" neurofuzzy system.MRI provides a digital representation of tissue characteristic that can be obtained in any tissue plane. On this proposal, some interesting contributions aiming at the development of diagnostic tools for automatic identification and classification of such symptoms in MRI images have already been proposed in the images produced by an MRI scanner are described as slices through the brain. It gives added advantage of being able to produce images which slice through the brain in both horizontal and vertical planes. In general MRI images are segmented using a fuzzy C-means clustering technique in order to group close pixels with similar pattern. In this case fuzzy logic reveals effective work, but the proposed algorithm is quite sensitive both to selective features and clusters obtained from MRI scanning. Segmentation of image involves in many techniques which are based on edge detection, region or surface growing, threshold level, classifier such as Hierarchical Self Organizing Map (HSOM), and feature vector clustering or vector quantization. Self organizing has proved to be a very effective model for image segmentation process [9]. Clustering vector quantization is a process of portioning an n-dimensional vector space into M regions so as to optimize a criterion function when all the points in each egion are approximated by the representation vector Xi associated with that region. Clustering involves the level of quantization with two different processes: one is the training process which determines the set of codebook vector depends on the probability of input data, the other is the encoding process which assigns input vectors to the code book. Clustering feature Vector quantization process has been implemented in terms of the competitive learning neural network (CLNN). Self Organizing Map (SOM)[10] is a member of the CLNNs using neural network. The importance of SOM is due to the similarity between the competitive learning process employed in the SOM and the vector quantization procedure.

Clustering is the process of grouping a data set in a way that the similarity between data within a cluster is aximized while the similarity between data of different clusters is maximized [5] and is used for pattern ecognition in image processing. To recognize a given pattern in an image various techniques have been utilized, but in general two broad categories of classifications have been made: unsupervised techniques and supervised techniques. In the unsupervised method, data items that are to be clustered are not preclassified while in supervised clustering the data points are preclassified. One of the well-known unsupervised algorithms that can be applied to many applications such as image segmentation [6], fuzzy c means (FCM) [11] etc.. FCM algorithm is one of the popular fuzzy clustering algorithms which are classified as constrained soft clustering algorithm. A soft clustering algorithm finds a soft partition of a given data set by which an element in the data set may partially belong to multiple clusters. Moreover, there is a constraint on the function that the membership degree of a point in all the clusters adds up to 1. Fuzzy Cmeans algorithm is one of the much used tools for the image analysis. In this paper, proposed hybrid technique combining the advantages of HSOM and FCM and implemented for the MRI image segmentation process to detect various tissues like white matter, gray matter,cst and tumor. In this paper, a new edge detection method of combining fuzzy logic and neural network is presented.

II. IMAGE ACQUISITION

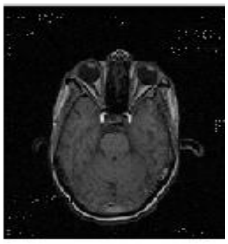
The development of intra-operative imaging system has contributed to improving the course of intracranial neurosurgical procedures. Among these systems, the 0.5T intra-operative magnetic resonance scanner of the NIMS Medical Hospital Signa SP, GE Medical Systems) offers the possibility to acquire 25*256*58 (0.86mm, 0.86mm, 2.5mm) T1 weighted images with the fast spin echo protocol (TR =400, TE=16 ms, quality of every 256*256 slice acquired intra –operatively is fairly similar to images acquired with a 1.5 T conventional scanner, but the major drawback of the intra-operative image is that the slice remains thick (2.5mm).

III. PREPROCESSING

The MRI images consist of film artifact or labels on the MRI such as patient name, age and marks. Film artifact.

Those are removed using tracking algorithm. Here, starting from the first row and the first column, the intensity value, greater than that of the threshold value is removed from MRI. The high intensity values of film artefact are removed from MRI brain image. During removal of film artifacts, the image consists of salt and pepper noise.

Before Preprocessing



After Preprocessing

The image is given to enhancement stage for the removing high intensity component and the above noise. This part is used to enhance the smoothness towards piecewise- homogeneous region and reduce the edge-blurring effects. These proposed systems Describe the information of enhancement using weighted median filter for removing high frequency Component.

IV. SOM & HSOM IMAGE SEGEMENTATION

A self-organizing map (SOM) or self-organizing feature map (SOFM) is a type of artificial neural network for unsupervised learning. SOMs operate in two modes: training and mapping, Training is a competitive process, also called vector quantization, Mapping automatically classifies a new input vector.Segmentation is an important process to extract information from complex medical images. Segmentation has wide application in medical field [2, 14, 21, and 22].

The main objective of the image segmentation is to partition an image into mutually exclusive and exhausted regions such that each region of interest is spatially contiguous and the pixels within the region are homogeneous with respect to a predefined criterion. Widely used homogeneity criteria include values of intensity, texture, color, range, surface normal and surface curvatures. During the past many researchers in the field of medical imaging and soft computing have made significant survey in the field of image segmentation [1,,7,17,25]. Several authors suggested carious algorithms for segmentation [5,3,23,27].

Image segmentation techniques can be classified as based on edge detection, region or surface rowing, threshold level, classifier such as Hierarchical Self Organizing Map(HSOM), and feature vector clustering or vector uantization. The Trained Vector quantization has proved to be a very effective model for image segmentation process [4]. Vector quantization is process of portioning n-dimensional vector space into M regions so as to optimize a criterion function when all the points in each region are approximated by the representation vector Xi associate with that region. There are two processes involved in the vector quantization: one is the training process which determines the set of codebook vector according to the probability of the input data, the other is the encoding process which assigns input vectors to the code book sectors. Vector quantization process has been implemented in terms of the competitive learning neural network (CLNN) [6,26]. Self Organizing Map (SOM) [21] is a member of the CLNNs and this can be the best choice when implementing vector quantization using neural network [19]. The importance of SOM for vector quantization is primarily due to the similarity between the competitive learning process employed in the SOM and the vector quantization procedure. The main shortcoming of the SOM is that the number of neural units in the competitive layer needs to tbe approximately equal to the number of regions desired in the segmented image. The HSOM directly address the aforesaid shortcomings of the SOM. HSOM is the combination of self organization and graphic mapping technique. The abstraction tree bears some resemblance to the major familiar quad tree data structure [20,24] used in the several image processing and image analysis algorithms. In this paper, we propose a hybrid technique combining the advantages of HSOM was implemented for the MRI image segmentation.

A. Overview Of Proposed Work

This paper describes the method of MRI brain image segmentation using Hierarchical self organizing map (HSOM). The below figure shows the flow of work in HSOM FEM and FCM image acquisition process MR brain image is loaded into MATLAB 7.0.in the form of matrix. Next initialize, the input features for the calculation of the weight vector for the HSOM with c means includes some new features, but we have achieved the lowest value of weight vector values. This is due to the fuzzy clustering technique and the abstraction level.

V. IMPLEMENTATION

In this section the implementation of the HSOM and FCM algorithm is discussed in detail. First, we describe the HSOM structure, learning procedure and then FCM with abstraction tree. The pseudo code for the above euro fuzzy technique is also presented at the end of this section. The HSOM is organized as pyramidal structure nsisting of multiple layers where each layer resembles the single layer SOM. The detailed explanations and the structure of the HSOM were presented by S.M. Bhandarkar et.al.[2]. Learning process consists of sequential corrections of the vectors representing neurons. On every step of the learning process a random vector is chosen from the initial data set and then the best-matching (the most similar to it) neuron coefficient vector is identified. The winner is selected, which is the most similar to the input vector [23]. The distance between the vectors usually measured in the Euclidean metric and is given by

$$\|x - w_C\| = \min_i \{[x - W_i]\} \qquad (1)$$

Where, x is the neuron, WC is the winning neuron vector and Wi is the weight vector. The modified weight vector coefficients can be calculate

$$Wi(t+1) = Wi(t) + hci(t) * [x(t) - w(t)] \qquad (2)$$

Where t is the epoch number (discrete-time index), x (t) is the vector and is obtained by selecting a sample randomly for iteration t. The function hci (t) is called neighborhood function and it represents a no increasing function of time and the distance between the winning neuron and its neighbors on the grid. The function hci (t) consists of two parts: the proper distance function and the learning rate function and is given by

$$h(t) = h(rc\text{-}ri)*a(t) \qquad (3)$$

Where, r determines neuron position on the grid. The result of neighborhood function h(t) is an initial luster center (centroids) for fuzzy c means algorithms. Cluster is a group of vectors with the distance between any two of them shorter than that between this group and the neighboring ones.

Fuzzy C-Means algorithm (FCM)

FCM algorithm based on the concept of fuzzy C-partition, which was introduced by various researcher in this field Ruspini[24], developed by Dunn[25] and generalized by Bezdek[26]. The aim of FCM is to find cluster centers (centroids) that minimize dissimilarity Functions [21-22]. In order to accommodate the fuzzy Partitioning technique, the membership matrix (U) is randomly initialized as

$$\sum_{i=1}^{c} U_{ij} = 1, \forall_j = 1 \ldots. n \qquad (4)$$

Where, i is the number of cluster and j is the image data points. The dissimilarity function can be computed as

$$J(U, c_1, c_2 ......c_c) = \sum_{i=1}^{c} J_i = \sum_{i=1}^{c} \sum_{j=1}^{n} u_{ij}^m d_{ij}^2 \qquad (5)$$

Where, Uij is between 0 and 1, ci is the centroid of cluster i, dij is the Euclidian distance between ith centroid (ci) and jth data point, m is a weighting exponent and the value is greater than one. The minimum of dissimilarity function can be computed as

$$U_{ij} = \frac{1}{\sum_{k=1}^{c}\left(\frac{d_{ij}}{d_{kj}}\right)^{2/(m-1)}} \qquad (6)$$

where, dij=||xi-cj||, dkj =||xi-ck||, xi is the i th of ddimensional data, cj is the d-dimension center of the cluster and ||*|| is any norm expressing the similarity between any measured data and center. This iteration will stop when Maxij{ |uij (k+1)-uij (k)| } < _, where _ is a termination criterion between 0 and 1, whereas k are the iteration steps. The steps of the FCM algorithm has been listed as follows Initialize U=[uij] matrix, U(0) At kstep:

Initialize centers vectors C(k) = [cj] taken from HSOM mapping clustering algorithm Update U(k) ,U(k+1), then compute the dissimilarity function

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

If || U(k+1) - U(k)||< _ then STOP; otherwise return to step3.

In the first step, the algorithm selects the initial cluster centers from SOM clustering algorithm. Then, in later steps after several iterations of the algorithm, the final result converges to actual cluster center. Therefore a good set of initial cluster is achieved and it

If || U(k+1) - U(k)||< _ then STOP; otherwise return to step is very important for an FCM algorithm. If a good set of initial cluster centers is chosen, the algorithm make less iterations to find the actual cluster centers. The winning neural units and their corresponding weight vectors from each layer result in a hierarchical structure termed as an abstraction tree[1]. Each node in the abstraction tree represents the region of the image at a specified level of abstraction[2]. A segmented image is generated on demand by traversing the abstraction tree in the breadth first manner starting from the root node until some criterion is met. The size of the abstraction tree (weight vector) is expanded if the sum of the variances of weight vector divided by size of the weight vector is less than element of weight vector. Otherwise the node is labeled as a closed node and none of its descendants are visited. Regions corresponding to the closed nodes constitute a segmented image and the resulting segmented image usually contains the regions from different abstraction levels.

VI RESULTS AND ANALYSIS

Table 1 show the result of image segmentation of HSOM-FCM. In any computer aided analysis, the execution time is one of the important parameter of medical image segmentation the number of pathological tissue (tumor) pixels detected by various Methods with execution time is presented. Our proposed Method for automatic tection using Hybrid intelligence based Segmentation technique provides better values. The input features for the calculation of the weight vectors for the HSOM-FCM includes some new features like energy, entropy and idm. We have used six features, but we have achieved the lowest value of weight vector. This is due to the fuzzy clustering techniques and abstraction level. The weight vector value obtained for the proposed method is less compared to existing result. The weight vector obtained by other methods is depicted in the table 1. The value tumor cells obtained with our proposed method is more as compared with others method proposed earlier. We have used the standard input features as entrophy, energy and idm in addition to mean median and standard deviation

Table 1: Weight vector value, detected tumor pixels and execution time with segmentation

Type of Segmentation	Segmentation	Value of Weight Vector	Total no. of Pixel Values	Execution Time (sec)
SOM K Means	12*12	12	2772	24.96
SOM FUZZY	8*8	8	3223.	94.93
Our Method	6*6	6	3223	98.97
HSOM K Means	12*12	12	2772	46.81

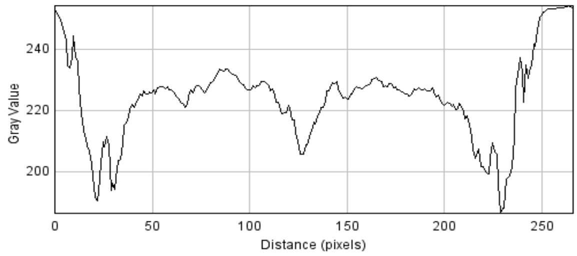
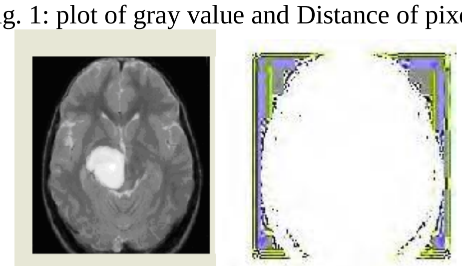
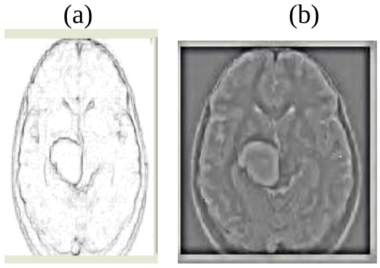


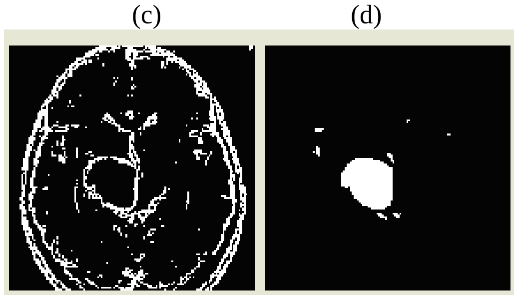
Fig. 1: plot of gray value and Distance of pixels



(a) (b)



(c) (d)



(e)

Fig. 2: (a) Input image (256x256) (b) Gray level image at level 1 (c) & (d) GW,WM,CSF, Tumour detected at level 2&3

(e) Specifically segmented tumour at level(6x6)

VII. CONCLUSION

Automatic Method for detection of Pathological tissue (tumor) normal tissues (white matter and Gray matter) and csf. Relevance of these techniques is the direct clinical application for segmentation. We have studied the performance of the MRI Image in terms of weight vectors execution time and tumor Pixels detected. We have archival a high value of detected tumor pixels than any other Segmentation techniques. achieved the weight vector value for the Neuro fuzzy is 6 x 6 with the additional input features. This paper givens more information about Pathological and healthy tissues Segmentation and this helps the doctors in diagnosis. In future the system should be improved by adapting different Segmentation algorithm to suit the different medical image Segmentations. The change of growth rate of this tumor of the same patient analyze may also be undertaken.

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