An Efficient Brain Tumor Detection System using Fuzzy Clustering & Neural Network

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Abstract – Segmentation of structural sections of the brain is the essential problem in medical image investigation. While surveying the previous literature, it has been found out that no work has been done in segmentation of brain tumor by using Fuzzy Neural Networks in MATLAB Environment. In this paper, a brain tumor segmentation technique has been established and validated segmentation on 2D MRI Data. This method can segment a tumor provided that the anticipated parameters are set appropriately. This method does not require any initialization while the others require an initialization inside the tumor. The visualization and quantitative evaluations of the segmentation results demonstrate the effectiveness of this approach. We are using fuzzy C-means clustering algorithm along with self-organizing MAP neural network along with thresholding and morphology for proper classification of medical data. Firstly, the work was carried over to calculate the area of the tumor of single slice of MRI data set and then it was extended to calculate the area of the tumor from multiple image MRI data set.

Keywords – Medical Image Segmentation, MRI analysis, Brain tumor detection, Fuzzy Clustering, Neural Networks.

I. INTRODUCTION
Brain cancer is one of the greatest deadly and obstinate diseases. Tumors may be set in areas of the brain that are critical to run the body’s vital tasks, this tumor cells infect other parts of the brain, establishing additional tumours that are too minor to spot with the usual imaging techniques. Sometimes, it’s a hard to identify the Brain cancer’s position such complications make it a difficult task to cure it for those people who has to fight with their life.

In Current years we have observed that the growth in cancer patient has outstripped the previous facts. The tumor in the primary phase is certainly hard to recognise however once it gets recognised we can move towards its treatment and is treatable with methods like chemotherapy. But certainly late recognition of tumour is lethal. Cancer is a type of infection in which signs are recognised late. But the usage of computer supported technology have taken a wise step in recognizing the tumour, like used in Neuro surgery.

II. LITERATURE REVIEW
Kovacevic et al. [1] propose a segmentation method for brain images that performs a basic segmentation process comprising three steps. The training algorithm is relatively simple as compared to the back-propagation iterative algorithm used with MLP. But the proposed algorithm does not perform well on trained data. Zhang et al. [2], suggest employing the Hidden Markov Random Field (HMRF) model for segmenting Brain MRI by using Expectation-Maximization algorithm. Technique possesses ability to encode both spatial and statistical properties of an image. The proposed framework employs unsupervised classification using iterative updating. The method requires estimating threshold which is heuristic in nature. This method does not produce accurate results most of the time and is computationally expensive. Ahmed et al. [3] present customized algorithm for estimation of intensity in homogeneity using fuzzy logic that supports fuzzy segmentation of MRI data. The proposed algorithm is articulated by altering the objective function used in the standard FCM algorithm. The alteration of the objective function compensates intensity in homogeneities and allows labeling of a pixel (voxel) to be influenced in its immediate neighbourhood. Such a scheme is effective in segmenting scans corrupted by salt and pepper noise. Efficiency and effectiveness are proven through experiments on both synthetic and MR data. Major contribution of their work is the introduction of a BCFCM algorithm which is faster to converge to generate accurate classification. The drawback of this technique is that it is limited to a single feature input. Tolba et al. [4] in their paper presented a new algorithm proposed for MR brain image
segmentation, which is based on EM algorithm and the multi-resolution analysis of images, namely Gaussian multi-resolution EM algorithm. Methodology is lesser sensitive to noise and utilizes strong spatial correlation between neighbouring pixels. But has complications with the edges. Li et al. [5] use Discrete Wavelet frame transform method for edge detection. This method is enhanced version of DWT and is relatively easy to implement. Sing et al. [6] propose fuzzy adaptive RBI based neural network for MR brain image segmentation. The technique removes noise from medical images without losing sharpness of the objects. Bayro-Corrochano et al. [7] assert that medical image segmentation approach involves combination of texture and boundary information. This method use less number of primitives to model volumetric data in this way it makes registration process faster. But has limitation with image from CT scan. In Yu et al [8] proposed 3 level image segmentation using QGA. This methodology is used for optimal combination of parameters. This approach do not provide us the computation of each possible value. In the same year DiBono [9] proposed the SVR Kernel-based approach for extremely complex regression problem, this method use statistical techniques but sometime it proves inaccurate for virtual environment. Luts et al. [10] propose a technique to create nosologic brain images based on MRI and MRSI data. This technique uses color coding scheme for each voxel to differentiate distinctive tissues in a single image. This technique is a combination of MRI and MRSI this improves the classifiers’ performance. This method gives only one dimensional image feature. Shi et al. [11] employed neural networks for medical image processing, including the key features of medical image pre-processing, segmentation, and object detection and recognition. The study employed Hopfield and feed-forward neural networks. The feed-forward and Hopfield neural networks are simple to use and easy to implement. Roy and Bandyopadhyay [12] propose automatic brain tumor detection approach using symmetry analysis. They have suggested multi-step and modular approached to solve the complex MRI segmentation problem. The authors claim that MRI segmentation is one of the essential tasks in medical area but boring and time consuming if it is performed manually, so visually study of MRI is more interesting and fast. Padole and Chaudhari [13] proposed an efficient method for brain tumor detection. Combination of two standard algorithm, mean shift and normalized cut is performed to detect the brain tumor surface area in MRI. T.Logeswari and M.Karnan [14] this paper describes segmentation method consisting of two phases. In the first phase, the MRI brain image is acquired from patients’ database. In that film artifact and noise are removed. After that Hierarchical Self Organizing Map (HSOM) is applied for image segmentation.

III. PROPOSED ALGORITHM

A. Image acquisition

Images are obtained using MRI scan and these scanned images are displayed in a two dimensional matrices having pixels as its elements. These matrices are dependent on matrix size and its field of view. Images are stored in MATLAB and displayed as a gray scale image of size 256*256. The entries of a gray scale image are ranging from 0 to 255, where 0 shows the total black colour and 255 shows the pure white colour. Entries between this ranges vary in intensity from black to white. For experimental purpose 30 female and 30 male patients were examined, all patients have ages ranging from 20 to 60 years. Their MRI scans were stored in the database of images in JPEG image formats.

B. Pre-processing

The first phase is to get the MRI image and application of pre-processing steps. There are various methods which come under this step; we will be dealing with only grey scale and filters. Basically pre-processing is done to remove noise and blurring as well as a ringing effect in order to get the enhanced and much clear image for our purpose. The filter which we have used is median filter but as we are working on image samples that are required for the medical purpose. The median filter has to be passed with mask for better image, to achieve this we are using a sobel operator.

C. Self-Organizing Maps

Self-organizing maps (SOMs) are a data visualization technique invented by Professor Teuvo Kohonen which reduce the dimensions of data through the use of self-organizing neural networks. The problem that data visualization attempts to solve is that humans simply cannot visualize high dimensional data as is so techniques are created to help us understand this high dimensional data. The way SOMs go about reducing dimensions is by producing a map of usually 1 or 2 dimensions which plot the similarities of the data by grouping similar data.
items together. So SOMs accomplish two things, they reduce dimensions and display similarities. As you can see in the figure below, like colours are grouped together such as the greens are all in the upper left hand corner and the purples are all grouped around the lower right and right hand side.

Self-organizing maps are dissimilar from other artificial neural networks in the sense that they use a neighbourhood function to preserve the topological properties of the input space. This makes SOMs valuable for imagining low-dimensional views of high-dimensional data, akin to multidimensional scaling. The model was first labelled as an artificial neural network by the Finnish professor Teuvo Kohonen, and is also known as a Kohonen map or network.

Like most artificial neural networks, SOMs operate in two modes: training and mapping. “Training” builds the map using input examples (a competitive process, also called vector quantization), while “Mapping” automatically classifies a new input vector.

Algorithm: SOM

Step 1: Randomize the map’s nodes weight vectors.
Step 2: Grab an input vector.
Step 3: Traverse each node in the map
Step 4: Use Euclidean distance formula to find the similarity between the input vector and the map’s node’s weight vector.
Step 5: Track the node that produces the smallest distance (this node is the best matching unit, BMU)
Step 6: Update the nodes in the neighbourhood of BMU by pulling them closer to the input vector.

\[ W(t + 1) = W(t) + \alpha(D(t) - W(t)) \]

Increment \( t \) and repeat from 2.

\( \alpha \rightarrow \) Monotonically decreasing learning coefficient. It is 1 for neurons close to BMU and zero for others.

\( D(t) \rightarrow \) input vector

Neighbourhood function shrinks with time. At the beginning, when the neighbourhood is broad, the self-organizing takes place on a global scale. When the neighbourhood has shrunk to just a couple of neurons, the weights are converging to local estimates.

D. Fuzzy c-means clustering

In fuzzy clustering, each point has a degree of belonging to clusters, as in fuzzy logic, rather than belonging completely to just one cluster. Thus, points on the edge of a cluster, maybe in the cluster to a lesser degree than points in the centre of cluster. An overview and comparison of different fuzzy clustering algorithms are available.

With fuzzy c-means, the centroid of a cluster is the mean of all points, weighted by their degree of belonging to the cluster:

\[ c_k = \frac{\sum_{x} w_k(x) x}{\sum_{x} w_k(x)} \]

The degree of belonging, \( w_k(x) \), is related inversely to the distance from \( x \) to the cluster center as calculated on the previous pass. It also depends on a parameter \( m \) that controls how much weight is given to the closest center. The fuzzy c-means algorithm is very similar to the k-means algorithm:

1. Choose a number of clusters.
2. Assign randomly to each point coefficients for being in the clusters.
3. Repeat until the algorithm has converged (that is, the coefficients’ change between two iterations is no more than the given sensitivity threshold) :
   - Compute the centroid for each cluster, using the formula above.
   - For each point, compute its coefficients of being in the clusters, using the formula above.

The algorithm minimizes intra-cluster variance as well, but has the same problems as k-means; the minimum is a local minimum, and the results depend on the initial choice of weights. Using a mixture of Gaussians along with the expectation-maximization algorithm is a more statistically formalized method which includes some of these ideas: partial membership in classes.

Algorithmic steps for Fuzzy c-means clustering
Let $X = \{x_1, x_2, x_3, \ldots, x_n\}$ be the set of data points and $V = \{v_1, v_2, \ldots, v_c\}$ be the set of centers.

1) Randomly select ‘c’ cluster centers.

2) Calculate the fuzzy membership $\mu_{ij}$ using:

$$\mu_{ij} = 1 / \sum_{k=1}^{c} (d_{ij} / d_{ik})^{(2/(m-1))}$$

3) Compute the fuzzy centers $v_j$ using:

$$v_j = \frac{\sum_{i=1}^{n} \mu_{ij}^m x_i}{\sum_{i=1}^{n} \mu_{ij}^m} \quad \forall j = 1, 2, \ldots, c$$

4) Repeat step 2) and 3) until the minimum $J$ value is achieved or $||U^{(k+1)} - U^{(k)}|| < \beta$.

Where,

‘$k$’ is the iteration step.

‘$\beta$’ is the termination criterion between [0, 1].

‘$U = (\mu_{ij})_{n \times c}$’ is the fuzzy membership matrix.

‘$J$’ is the objective function.
Fig. 6. Image after Morphological Operation on threshold Operation on Main MRI data

Fig. 7. shows 3D variations in Self-Organizing MAP of Pre-processed MRI data

Fig. 8. Value of membership function in Fuzzy C-means Clustering

Fig. 9. Value of Intensity variation in tumor region in Medical image taken

Fig. 10. 3D plotting of extracted tumor region in MRI patient data

Fig. 11. Extracted Final Output of tumorous region in 2D from medical data
Table 1. below shows the tumor area calculated from different patients data input

<table>
<thead>
<tr>
<th>Patient data</th>
<th>Tumor area (in pixel square)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Patient 1</td>
<td>5683</td>
</tr>
<tr>
<td>Patient 2</td>
<td>4276</td>
</tr>
<tr>
<td>Patient 3</td>
<td>6631</td>
</tr>
<tr>
<td>Patient 4</td>
<td>8525</td>
</tr>
<tr>
<td>Patient 5</td>
<td>4965</td>
</tr>
</tbody>
</table>

V. CONCLUSION

The results show that Fuzzy Clustering Classification can successfully segment a tumor provided the parameters are set properly in MATLAB environment. Our Hybrid approach algorithm performance is better for the cases where the intensity level difference amongst the tumor and non-tumor regions is higher. It can also segment non homogenous tumors providing the non-homogeneity is within the tumor section. This paper proves that methods aimed at general purpose segmentation tools in medical imaging can be used for automatic segmentation of brain tumors. The quality of the segmentation was similar to manual segmentation and will speed up segmentation in operative imaging. Among the clustering methods investigated, the fuzzy c-means clustering is marked out best out of all others. The user interface in the main application must be extended to allow activation of the segmentation and to collect initialization points from a pointing device and transfer them to the segmentation module. Finally the main program must receive the segmented image and present the image as an opaque area. It has only one limitation that the method is semi-automatic. Further work can be carried out to make this method automatic so that it can compute the dimensions of the segmented tumor automatically.

REFERENCE


