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BRAIN TUMOUR SEGMENTATION IN MEDICAL IMAGES USING SOFT COMPUTING - A REVIEW

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ABSTRACT

Analysis of tumour images is very exhausting and a complicated process. Many different techniques have been proposed for segmentation of tumours in brain images. In Recent times, mostly researchers have been paying close attention to tumour image processor techniques, in which the tumour image segmentation technology is regarded as the absolutely research focus. The goal of the segmentation is to sub-divides an image into its constituent regions or objects. The objective of this study is to identify suitable segmentation techniques for distinguishing different types of brain tumour by using Fuzzy C-Means, K-mean, NN, and ANFIS to be efficient in segmenting all the brain tumours.

Keywords: K-mean, Fuzzy C-mean, NN, feed-forward NN, ANFIS

I. INTRODUCTION

Brain tumours have a prevalence of <1 %, but they are among the most fatal cancers. Brain tumours based on the degree of aggressiveness can be classified as benign or malignant (Al-Tamimi Mohammed *et al.*, 2014). Generally benign tumours are characterized by distinct borders, can usually be completely removed, are unlikely to recur and they rarely spread. On the other hand malignant tumours usually characterized by rapid growth will be life threatening. Considering the benign tumours, based on location it can also be life threatening. If a tumour is identified as benign then without further consideration a doctor will prescribe for a successful surgery. Hence identification of benign tumors plays a vital role in coping up with brain tumor. Moreover there are specific brain tumour shapes for identification of benign from malignant brain tumours [3]. A group of cells or tissues (mass) which are under uncontrolled division and cannot be stopped by normal forces can be defined as Tumour. Now days more well founded algorithms are developed for real time analysis and diagnosis of tumour. The main focus in latest development in medical imaging is to detect brain tumours in MR images and CT scan images. The separation of the cells and their nuclei from the rest of the image content is one of the main problems faced by most of the medical imagery diagnosis systems [9].

II. TECHNIQUES

2.1 K-Mean

K-means clustering is an algorithm to group objects based on attributes/features into k number of groups where k is a positive integer. The grouping (clustering) is done by minimizing the Euclidean distance between the data and the corresponding cluster centroid. Thus the function of k-means clustering is to cluster the data [1].K-mean used for extracted tumour from MRI images.

Given a set of observations ($\mathbf{x}_1$, $\mathbf{x}_2$, …, $\mathbf{x}_n$), where each observation is a d-dimensional real vector, K-Means clustering aims to partition the n observations into k ($\leq$ n) sets $\mathbf{S} = \{S_1, S_2, \ldots, S_k\}$ so as to minimize the within-cluster of squares (WCSS) [3]:

$$\underset{\mathbf{S}}{\arg\min} \sum_{i=1}^{k} \sum_{\mathbf{x} \in S_i} \left\| \mathbf{x} - \boldsymbol{\mu}_i \right\|^2 \quad \ldots\ldots\ldots\ldots\ldots(1)$$

where μ_i is the mean of points in S_i

In color-based segmentation method that uses the K-means clustering technique to track tumour objects in magnetic resonance (MR) brain images. The key concept in this color-based segmentation algorithm with K-means is to convert a given gray-level MR image into a color space, image and then highlight the position of tumour objects from other items of an MR image by using K means clusteringFIG2.1 [2].

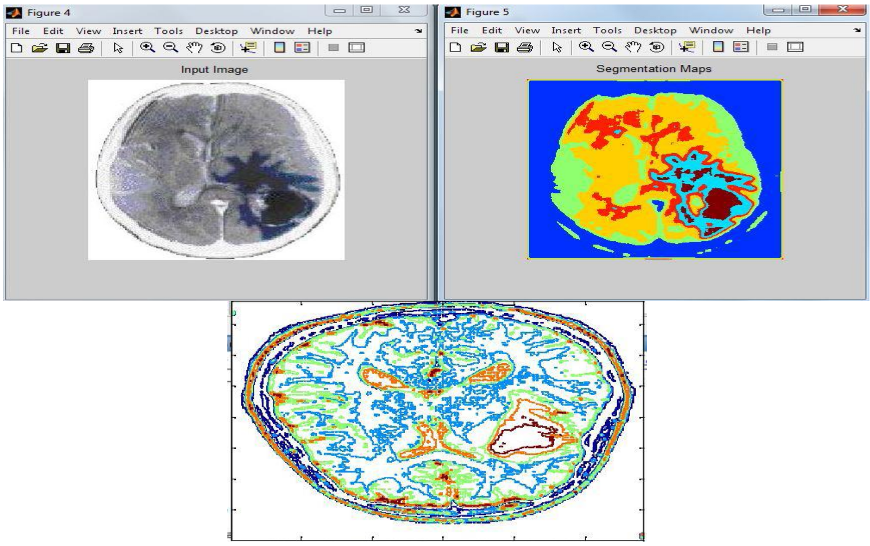

Fig. 1: Segmentation Result of Tumour Image [2] (Sunita Singh)

2.2 Fuzzy C-Mean

Fuzzy C-Mean (FCM) is an unsupervised clustering algorithm. In segmentation process, the most common method for pixel classification is Fuzzy C-means (FCM) clustering. The FCM algorithm assigns pixels to each category by using fuzzy memberships. In terms of segmentation efficiency fuzzy C-mean algorithm is better than other clustering approaches but the major drawback is huge computational time which is necessary for convergence. The computational rate is improved by modifying the cluster centre and membership value updating criterion.

Fuzzy C-Means, the centroid of a cluster is the mean of all points, weighted by their degree of belonging to the cluster. 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 centre.[3]

It is based on minimization of the following objective function [3]:

$$J_m = \sum_{i=1}^{N}\sum_{j=1}^{C} u_{ij}^{m}\left\|x_i - c_j\right\|^2 , \quad 1 \le m < \infty \qquad \text{....................(2)}$$

where m is any real number greater than 1, u_{ij} is the degree of membership of x_i in the cluster j, x_i is the i^{th} of d-dimensional measured data, c_j is the d-dimension center of the cluster, and ||*|| is any norm expressing the similarity between any measured data and the center[3].

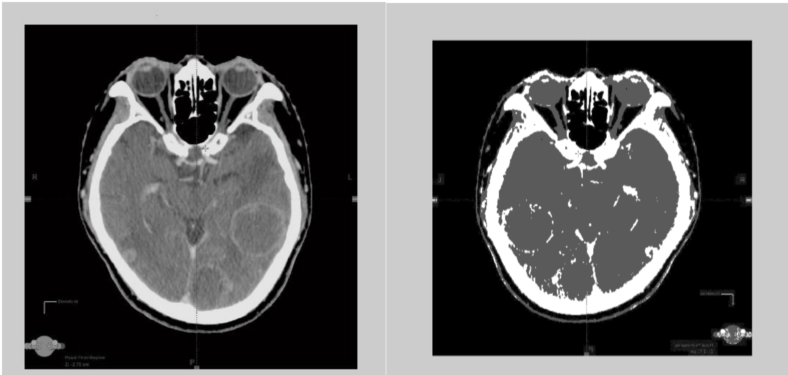

Fig. 2: (a) the original brain image (b) the result after fuzzy clustering segmentation
(Jianning Han, Quan Zhang, Peng Yang and Yifan Gong,[13].)

2.3 Adaptive Neuro-Fuzzy Inference System (ANFIS)

An adaptive neuro-fuzzy inference system (ANFIS) is a fuzzy system whose membership function parameters have been tuned using neuro-adaptive learning methods similar to those used in training neural networks. Fuzzy Logic Toolbox™ software provides command-line functions and an app for training Sugeno-type fuzzy inference systems using given input/output training data. ANFIS integrates both neural networks and fuzzy logic principles, it has potential to capture the benefits of both in a single framework for identification purpose [11 and 12]. A fuzzy inference system is implied through the structure and neurons of the feed forward adaptive neural network. The ANFIS architecture could be utilized to model nonlinear functions, recognize nonlinear parts on-line in a control system, and forecast a disordered time series was reported by J.S. Roger Jang who was introduced ANFIS [9]. Learning capabilities of neural networks is reveal to fuzzy inference systems by this hybrid neuro-fuzzy technique. The training input output data is used by the learning algorithm to adjust the membership functions [6].

Typical membership function:

$$\mu A(x) = \frac{1}{1 + |x - ci\ ai\,|2bi}$$

2.3.1 Architecture of ANFIS

The conservative architecture of ANFIS is shown in figure1, where a fixed node is represented as circle and an adaptive node is represented as square [6].

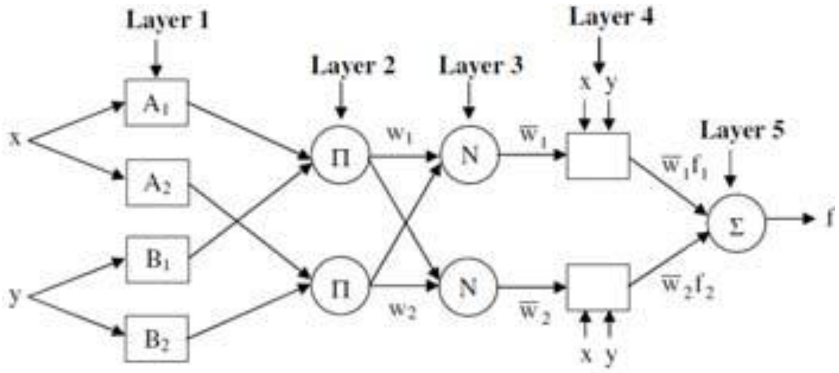

Fig. 3: Anfis Architecture [6] (G.Thamarai Selvik, K.Duraisamy)

Layer 1 Every node *i* in this layer is an adaptive node with a node function:

$$O_{1,i} = \mu_{A_i}(x), \qquad \text{for } i = 1, 2, \text{ or}$$
$$O_{1,i} = \mu_{B_{i-2}}(y), \qquad \text{for } i = 3, 4,$$

Where, x & y are the input to node i and A_i (or B_{i-2}) is a linguistic label associated with this node. In other words, $O_{1,i}$ is the membership grade of a fuzzy set $A= (A_1 , A_2 , B_1 , B_2)$ and it specifies the degree to which the given input x (or y) satisfies the quantifier A, where $\{a_i, b_i, c_i\}$ is the parameter set.[6]

Layer 2 Every node in this layer is a fixed node, whose output is the product of all the incoming signals:

$$O_{2,i} = w_i = \mu_{A_i}(x)\mu_{B_i}(y), \ i = 1, 2.$$

Each node output represents the **firing strength** of a rule. [6]

Layer 3 Every node in this layer is a fixed node labelled N. The i_{th} node calculates the ratio of the i_{th} rule's firing strength to the sum of all rules' firing strengths:

$$O_{3,i} = \overline{w}_i = \frac{w_i}{w_1 + w_2}, \ i = 1, 2.$$

Output of this layer are called **normalized firing strength**.[6]

Layer 4 Every node i in this layer is an adaptive node with a node function. [6]:

$$O_{4,i} = \overline{w}_i f_i = \overline{w}_i(p_i x + q_i y + r_i),$$

$\{p_i, q_i, r_i\}$ is the parameter set of this node. Parameters in this layer are referred to as **consequent parameters**.

Layer 5 The single node in this layer is a fixed node, which computes the overall output as the summation of all incoming signals. [6]:

$$\text{overall output} = O_{5,1} = \sum_i \overline{w}_i f_i = \frac{\sum_i w_i f_i}{\sum_i w_i}$$

2.4 Neural network

Artificial neural networks (ANNs) are non-linear data driven self-adaptive approach as opposed to the traditional model based methods. An extremely important characteristic of these networks is their adaptive character, where "learning by example" replaces "programming" in solving problems. This feature makes such computational models very appealing in application domains where partial knowledge of the problem to be solved but where training data can be easily obtain. The intensity, shape deformation, symmetry, and texture characters were extracted from all the images. The Ada Boost classifier was used to choose the selective character and to segment the tumour region. [7]

2.4.1 MRI Image Classification using Neural Network:

The FFNN was the first and affably in complex type of artificial NN devised. In this network, the information moves in only one direction, forward, from the input nodes, through the hidden nodes and to the output nodes.

In FFNN, the neurons of the initial layer drive their output to the neurons of the second layer in a unidirectional mode. Multilayer Perceptron Neural Networks (MLPNN) or Multilayer Feed-forward Neural Network (MFNN) is one such FNN mechanism. A general structure of MLPNN comprising three layers is described. The only task of the neurons in the input layer is the sharing of the input signal x_{i} to neurons in the hidden layer. Each neuron j in the hidden layer sums up its input signals x_i after weighting them with the strengths of the respective connections w_{ji} from the input layer and computes its output y_j as a function f of the sum, given by:

$$Y_j = f\,(\Sigma Wji\ X_i)$$

Here, f can be a simple threshold function such as a sigmoid, or a hyperbolic tangent function. The output of neurons in the output layer is calculated in the same way. Following this calculation, a learning algorithm is used in adjusting the strengths of the connections so as to allow a network to achieve a desired overall behavior. In neural network, the deformity of the brain image can be detected. To evaluate the classification efficiency, two metrics have to be computed:

a) The training performance (i.e. the proportion of cases which are correctly classified in the training process).

b) The testing performance (i.e. the proportion of cases which are correctly classified in the testing process).

Basically, the testing performance provides the final check of the NN classification efficiency, and thus is explained the diagnosis accuracy using the neural networks. Remember that the testing performance, similar to the NN based diagnosis accuracy, involves only cases with unknown diagnosis for the NN classifier. [8]

III. CONCLUSION

There are various types of tumours. They may be as mass in brain or malignant over the brain. Suppose if it is a mass then K- means algorithm is enough to extract it from the brain cells. If the noise is present in the MR image it is removed before the K-means process. The noise free image is given as a input to the k-means and tumor is extracted from the MRI image. And then segmentation using Fuzzy C means for accurate tumour shape extraction of malignant tumour. By using the techniques of ANFIS for classification we have obtained the tumour detection. NN based brain tumour detection technique with MRI images. The efficiency is achieved with brain tissue and tumour segmentation, feature extraction of the segmented regions and the classification based on NNs.

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