Hierarchical SOM based detection of brain tumour with segmentation as ameliorate implementation

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***Abstract*—Image segmentation denotes a process of partitioning an image into distinct regions. A large variety of different segmentation approaches for images have been developed. Among them, the clustering methods have been extensively investigated and used. In this paper, a clustering based approach using a Self Organizing Map (SOM) algorithm is proposed for medical image segmentation. This paper describe segmentation method consists of two phases. In the first phase, the MRI brain image is acquired from patient database. In that film artefact and noise are removed. In the second phase (MR) image segmentation is to accurately identify the principal tissue structures in these image volumes. A new unsupervised MR image segmentation method based on fuzzy C-Means clustering algorithm for the Segmentation is presented**

Keywords—-Image analysis, Segmentation, HSOM, Fuzzy C-Means, Tumour detection

I.INTRODUCTION

The brain is a soft, delicate, non-replaceable and spongy mass of tissue. It is a stable place for patterns to enter and stabilize among each other. A tumour is a mass of tissue that grows out of control of the normal forces that regulates growth [21]. Brain tumour is a group of abnormal cells that grows inside of the brain or around the brain. Tumours can directly destroy all healthy brain cells. It can also indirectly damage healthy cells by crowding other parts of the brain and causing inflammation, brain swelling and pressure within the skull. Over the last 20 years, the overall incidence of cancer, including brain cancer, has increased by more than10%, as reported in the National Cancer Institute statistics (NCIS) The National Brain Tumour Foundation (NBTF) for research in United States estimates that 29,000 people in the U.S are diagnosed with primary brain tumours each year, and nearly 13,000 people die. In children, brain tumours are the cause of one quarter of all cancer deaths. The overall annual incidence of primary brain tumours in the U.S is 11 to 12 per 100,000 people for primary malignant brain tumours, that rate is 6 to 7 per 1,00,000. In the UK, over 4,200 people are diagnosed with a brain tumour every year (2007 estimates). There are about 200 other types of tumours diagnosed in UK each year. About 16 out of every 1,000 cancers diagnosed in the UK are in the brain (or 1.6%). In India, totally 80,271 people are affected by various types of tumour (2007 estimates).

The Segmentation of an image entails the division or separation of the image into regions of similar attribute. The ultimate aim in a large number of image processing applications is to extract important features from the image data from which description interpretation, or understanding of the scene can be provided by the machine. The segmentation of brain tumour from magnetic resonance images is an important but time-consuming task performed by medical experts The digital image processing community has developed several segmentation methods[8], many of them ad hoc. Four of the most common methods are: 1) amplitude thresholding, 2) texture segmentation 3) template matching, and 4) region-growing segmentation. It is very important for detecting tumours, edema and necrotic tissues. These types of algorithms are used dividing the brain images into three categories (a) Pixel Based (b) Region or Texture Based (c) Structural Based.

Brain Tumours :

The majority of brain tumours have abnormalities of genes involved in cell cycle control, causing uncontrolled cell growth. These abnormalities are caused by alternations directly in the genes or by chromosome rearrangements which can be able to make a definite change the function of a gene. Patients with certain genetic conditions also have an increased risk to develop tumours of the central nervous system. There have also been some reports of people in the same family developing brain tumours that do not have any of these genetic syndromes. Research has been investigating parents of children with brain tumours and their past exposure to certain chemicals. Some chemicals may change the structure of a gene that protects the body from diseases and cancer. Workers in oil refining, rubber manufacturing, and chemists have a higher incidence of certain types of tumours. Which, if any, chemical toxin is related to this increase in tumours is unknown at this time.

If a person has symptoms that suggest a brain tumour, the doctor may perform one or more of the following procedures:

Physical exam - The doctor checks general signs of health.

Neurological exam - The doctor checks for alertness, muscle strength, coordination, reflexes, and response to pain. The doctor also examines the eyes to look for swelling caused by a tumour pressing on the nerve that connects the eye and brain.

CT scan - An x-ray machine linked to a computer takes a series of detailed pictures of the head. The patient may receive an injection of a special dye so the brain shows up clearly in the pictures. The pictures can show tumours in the brain.

MRI - A powerful magnet linked to a computer makes detailed pictures of areas inside the body. These pictures are viewed on a monitor and can also be printed. Sometimes a special dye is injected to help show differences in the tissues of the brain. The picture scan shows a tumour or other problem in the brain.

The structure and function of the brain can be studied no invasively by doctors and researchers using Magnetic Resonance Imaging (MRI). The MRI image in Figure 1 is actually a thin horizontal slice of the brain. The white area at lower left is the tumour. It looks white because MRI scans enhance tissue differences. The tumour is actually on the right side of the brain. It appears to be on the left side here because the MRI view here is from below, looking up.

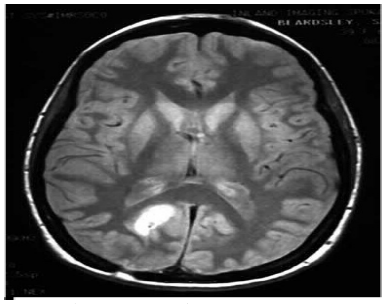


Fig. 1 MRI Brain Tumour Image

II. SELF-ORGANIZING MAP

A self-organizing map (SOM) or self-organizing feature map (SOFM) is a type of artificial neural network that is trained using unsupervised learning to produce a low-dimensional (typically two-dimensional), discretized representation of the input space of the training samples, called a map. Self-organizing maps are different from other artificial neural networks in the sense that they use a neighbourhood function to preserve the topological properties of the input space.

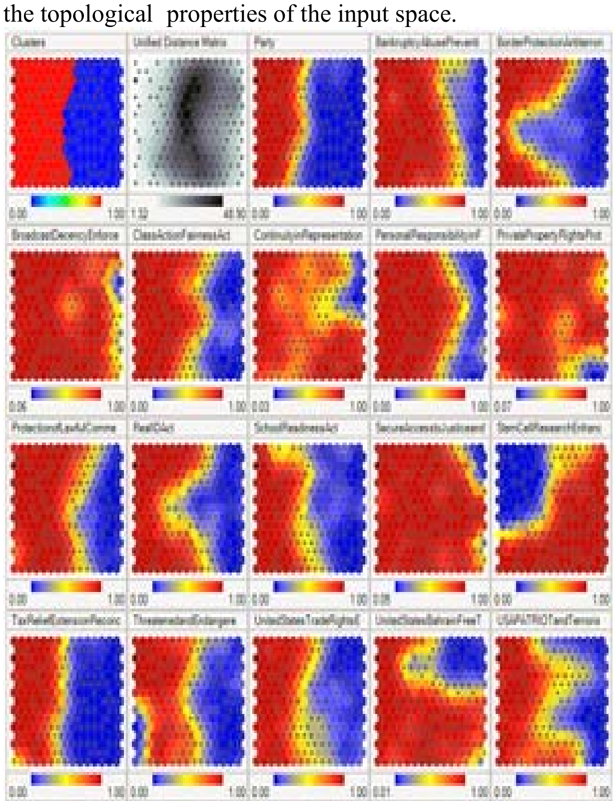


Fig. 2 A self-organizing map showing U.S. Congress voting patterns visualized in Synapse. The first two boxes show clustering and distances while the remaining ones show the component planes. Red means a yes vote while blue means a no vote in the component planes (except the party component where red is Republican and blue is Democrat).

This makes SOMs useful for visualizing low-dimensional views of high-dimensional data, akin to multidimensional scaling. The model was first described as an artificial neural network by the Finnish professor Teuvo Kohonen, and is sometimes called a Kohonen map. Like most artificial neural networks, SOMs operate in two modes: training and mapping. Training builds the map using input examples. It is a competitive process, also called vector quantization. Mapping automatically classifies a new input vector. A self-organizing map consists of components called nodes or neurons. Associated with each node is a weight vector of the same dimension as the input data vectors and a position in the map space. The usual arrangement of nodes is a regular spacing in a hexagonal or rectangular grid. The self-organizing map describes a mapping from a higher dimensional input space to a lower dimensional map space. The procedure for placing a vector from data space onto the map is to first find the node with the closest weight vector to the vector taken from data space. Once the closest node is located it is assigned the values from the vector taken from the data space. While it is typical to consider this type of network structure as related to feed_forward networks where the nodes are visualized as being attached, this type of architecture is fundamentally different in arrangement and motivation.

Useful extensions include using toroidal grids where opposite edges are connected and using large numbers of nodes. It has been shown that while self-organizing maps with a small number of nodes behave in a way that is similar to K-means, larger self-organizing maps rearrange data in a way that is fundamentally topological in character. Large SOMs display properties which are emergent. In maps consisting of thousands of nodes, it is possible to perform cluster operations on the map itself.

III. IMAGE AQUSTITATION

Images of a patient obtained by MRI scan is displayed as an array of pixels (a two dimensional unit based on the matrix size and the field of view) and stored in Mat lab 7.0.Here, gray scale or intensity images are displayed of default size 256 x 256. A gray scale image can be specified by giving a large matrix whose entries are numbers between 0 and 255, with 0 corresponding, say, to black, and 255 to white. A black and white image can also be specified by giving a large matrix with integer entries. The lowest entry corresponds to black, the highest to white. All MR images were acquired on a 0.5T open interventional MRI system (Sigma sp). MR Images were transformed on to a Linux network through LAN (KMCH Hospital, India). (All images had 1 mm slice thickness with 1×1 mm in plane resolution.

IV. PREPROCESSING

Noise presented in the image can reduce the capacity of region growing filter to grow large regions or may result as a fault edges. When faced with noisy images, it is usually convenient to pre-process the image by using weighted median filter. Weighted Median (WM) filters have the robustness and edge preserving capability of the classical median filter. WM filters belong to the broad class of nonlinear filters called stack filters. This enables the use of the tools developed for the latter class in characterizing and analysing the behaviour and properties of WM filters [23], e.g. noise attenuation capability. The fact that WM filters are threshold functions allows the use of neural network training methods to obtain adaptive WM filters.

V. HSOM WITH FCM IMAGE SEGEMENTATION

Segmentation is an important process to extract information from complex medical images. Segmentation has wide application in medical field. 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, colour, and 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 Image segmentation techniques can be classified as 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. Vector quantization has proved to be a very effective model for image segmentation process. Vector quantization is a 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 associated 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 vectors. Vector quantization process has been implemented in terms of the competitive learning neural network (CLNN). Self Organizing Map (SOM) is a member of the CLNNs and this can be the best choice when implementing vector quantization using neural network. 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. HSOM combine the idea of regarding the image segmentation process as one of data abstraction where the segmented image is the final domain independent abstraction of the input image. The hierarchical segmentation process for a hierarchical structure is called abstraction tree. The abstraction tree bears some resemblance to the major familiar quad tree data structure used in the several image processing and image analysis algorithms. The researchers in this field have used SOM or HSOM separately as one of the tool for the image segmentation of MRI brain for the tumour analysis. In this paper, we propose a hybrid technique combining the advantages of HSOM was implemented for the MRI image segmentation Clustering is the process of grouping a data set in a way that the similarity between data within a cluster is maximized while the similarity between data of different clusters is maximized and is used for pattern recognition in image processing. The below theory represents method of MRI brain image segmentation using Hierarchical self organizing map (Hsom) with FCM (Fuzzy C Means). The below illustration shows the flow of work in Hsom with FCM. In image acquisition process MR brain image is loaded into MATLAB 7.0.in the form of matrix. Next Initialize the variables sigma, weight vector and winning neuron .In that Calculate the neighbourhood function, weight vector and winning neuron .Here neuron is the input and winning neuron is the output of HSOM After that Calculate the Dissimilarity function of Maximum and Minimum, Euclidean Distance function, Cluster Points, Cluster centre of Som .Here winning neuron is the input (Acquired by Som) and adaptive threshold is the output(Obtained by FCM) if the (Current neuron>= adaptive threshold) then it is suspicious region Otherwise neglect it.

VI. IMPLEMENTATION OF HSOM AND FCM ALGORTHIM

A self-organizing map consists of components called nodes or neurons. Associated with each node is a weight vector of the same dimension as the input data vectors and a position in the map space. The usual arrangement of nodes is a regular spacing in a hexagonal or rectangular grid. The self-organizing map describes a mapping from a higher dimensional input space to a lower dimensional map space. The procedure for placing a vector from data space onto the map is to find the node with the closest weight vector to the vector taken from data space and to assign the map coordinates of this node to our vector. Euclidean to all weight vectors is computed. The neuron with weight vector most similar to the input is called the best matching unit (BMU). The weights of the BMU and neurons close to it in the SOM lattice are adjusted towards the input vector. The magnitude of the change decreases with time and with distance from the BMU. Among the wide range of possible tools, the self-organizing map (SOM) is one of the most effective.

The Self-Organizing Map as a special clustering tool provides a compact representation of the data distribution, has been widely applied in the visualization of high-dimensional data. In fuzzy clustering combined with SOM is used to project the data to lower dimensions. The most interesting approach has been presented in where a fuzzy self-organizing map is developed based on the modifications of the fuzzy c-means functional. The update formula for a neuron with weight vector Wv(i) is

Wv(i+ 1) = Wi(i+1)=wi(i)+hci(I)*[(x(i)-w(i))]---------(1)

Here hci is neighbourhood function to calculate it

h(i)=h(rc-r1)*a(i)*alpha-------- (2)

Here rc-r1=current neuron-next current neuron

a(i)=sigma 0 * exp(-i/nsm)---- (3)

Initialize the variable

Sigma = Number of neighbourhood pixels (8 or 24 or 48 or 80 or 120) if sliding window size(3*3=8), (5*5=24),(7*7=48), (9*9=80), (11*11=120).

Sigma N= Sigma 0 * exp(-i/taul)--------- (4)

Taul
= total number of pixels / log(neighbourhood number of pixel)

Similarly find the sigma value for each and every pixel This process is repeated for each input vector for a (usually large) number of cycles λ. The network winds up associating output nodes with groups or patterns in the input data set. If these patterns can be named, the names can be attached to the associated nodes in the trained net. The update formula for a neuron with winning neuron is

Step 1: The winning neuron formula is

||x-wc||=maxi{[=x-wi]} -------- (5)

X is a neuron ,wi is the weight vector

This is the winning neuron equation of HSOM giving input to the FCM Based on the previous equation, the first step of the regularized FCM-HSOM algorithm is the following:

Step 2: Calculate the cluster centres.

C = (N/2)1/2 ---------- (6)

Step 3: Compute the Euclidean distances

Dij = CCp – Cn ----------- (7)

Step 4 : Update the partition matrix

$$U_{ij}= \frac{1}{\sum_{K=1}^{c} (d_{ij}/d_{kj})^{2/(m-1)}} \quad \text{-------} \quad (8)$$

(Repeat the step 4)

Until Max[⎢Uij(k+1)-Uijk⎢] <€ is satisfied

Step 5: Calculate the average clustering points.

$$C_i = \sum_{i=1}^{c} J_i = \sum_{i=1}^{c} \sum_{j=1}^{n} U_{ij}^{n} \, d_{ij}^{2} \quad \text{----------} \quad (9)$$

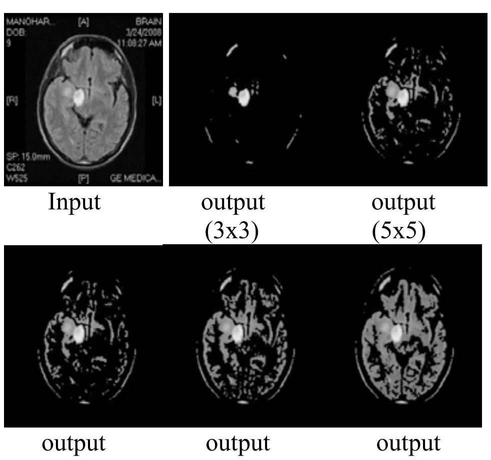
Step 6: Compute the adaptive threshold

Adaptive threshold =max (Adaptive threshold, ci) i=1...n

In the first step ,the algorithm select the initial cluster from Hsom Clustering algorithm. Then, in later step after several iteration of the algorithm, the final result converges to actual cluster centre achieved and it is very important for an FCM algorithm.

VII. EXPERIMENTAL EVALUTION

In any computer aided analysis ,the execution time is one of the important parameters of medical image segmentation .In these result, we have calculated the number of tumour cells of different neighbourhood pixel of 3×3, 5×5, 7×7, 9×9, 11×11 windows. In that 3×3 window is chosen based on the high contrast than 5×5, 7×7, 9×9, and 11×11.

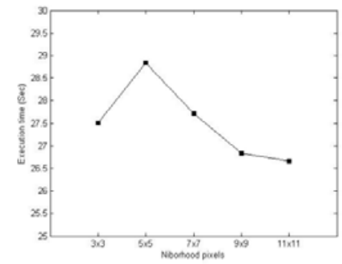


Input output (3x3) output (5x5)

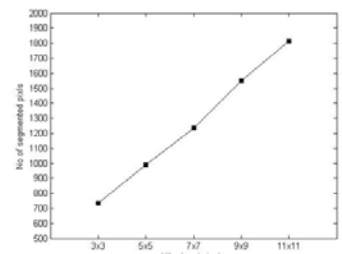
output (7x7) output (9x9) output (11x11)

Fig.3 A input image (256x256), Outpu3x3,Output 5x5 Output 7x7 Output 9x9 Output 11x11

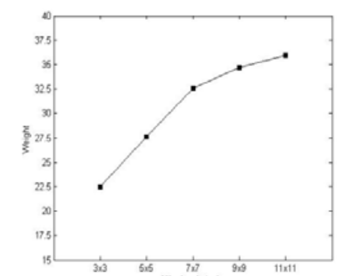
It is very difficult to measure the performance of enhancement objectively. If the enhanced image can make observer perceive the region of interest better, then we can say that the original image has been improved Here we are giving input image in that neighbourhood pixel of 3×3, 5×5, 7×7, 9×9, 11×11 windows are analysed. In that 3×3 window is chose based on the high contrast than 5×5, 7×7, 9×9, and 11×11. Figure (4c) shows the weight vector for HSOM is 3x3 is 14 , 5x5 is 8 ,7x7 is 15, 9x9 is 23 and 11x11 is 32 .Figure (4a) shows the Execution time in HSOM of 3x3 is 13.76 , 5x5 is 14.96 , 7x7 is 15.20, 9x9 is 11.05 and 11x11 is 11.53. Figure (4b) shows the number of segmented pixel in HSOM of 3x3 is 795 , 5x5 is 1073 , 7x7 is 1285, 9x9 is 1594and 11x11 is1881. (4c) shows the wining neuron for HSOM is 3x3 is 209 , 5x5 is 201 , 7x7 is 194, 9x9 is 186 and 11x11 is 177.



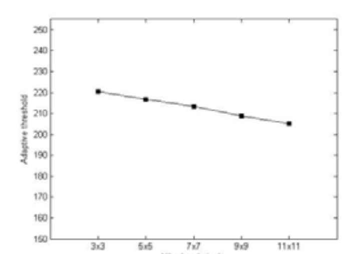
HSom with FCM type of segmentation
Fig(4a) relationship between execution time and neighbourhood pixels



HSom with FCM type of segmentation
Fig(4b) relationship between no of segmented pixel and neighbourhood pixels



HSom with FCM type of segmentation
Fig(4c) relationship between weight and neighbourhood pixels



HSOM with FCM type of segmentation
Fig(4d) relationship winning neuron and neighbourhood pixels

VIII. CONCLUSION

A fuzzy based segmentation process to detect brain tumour was implemented. In that performance of the MRI image in terms of weight vector, execution time and tumour pixels detected We have described several methods in medical image processing and discussed requirements and properties of techniques in brain tumour detection .This paper are used to give more information about brain tumour detection and segmentation of HSOM with FCM is given. In this paper various step in detection of automatic system like (a) Image capturing (b) Image segmentation (c) Performance Evaluation are discussed.

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