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ANALYSIS OF MS USING GLCM

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Abstract:-

Automated MRI (Magnetic resonance Imaging) brain tumor segmentation is a difficult task due to the variance and complexity of tumors. In this paper, a statistical structure analysis based tumor segmentation scheme is presented, which focuses on the structural analysis on both tumorous and normal tissues. The basic concept is that local textures in the images can reveal the typical 'regularities' of biological structures. Thus, textural features have been extracted using co-occurrence matrix approach. By the analysis of level of correlation we can reduce the number of features to the only significant component .An artificial neural network and SVM are used for classification. This approach is designed to investigate the differences of texture features among macroscopic lesion white matter (LWM), normal appearing white matter (NAWM) in magnetic resonance images (MRI) from patients with MS and normal white matter (NWM).

Keywords: MRI; Texture Analysis; Feature Selection; Texture Classification; SVM

Methods:- MRI of any number of MS patients & healthy subjects were selected & that much ROI were chosen from MS patients MRI & healthy subject MRI(magnetic resonance imaging) for LWM(lesion white matter),NAWM(Normal appearing white matter) & NWM(Normal white matter) respectively. All of the ROI were analysed by gray-level difference statistics & contrast, angular second moment, mean & entropy those 4 texture features were extracted .Finally statistic significance was tested among three groups. An ANN & SVM are used for classification. This approach is designed to investigate the differences of texture features among macroscopic LWM, NAWM in & MRI from patients with MS & NWM.

Keywords:- MS, Gray level difference statistics, T.A.(texture analysis),MRI ,LWM,NAWM,NWM.

Introduction:-Multiple sclerosis is a chronic idiopathic disease resulted in multiple areas of inflammatory demyelination in the CNS(Central nervous system).MS lesion formation often leads to unpredictable cognitive decline & Physical disability.Due to the sensitivity in detecting MS lesions,MRI has become an important tool for diagnosing MS & monitoring its progression.

Over the past decade, the demand for accurate detection & quantification of MRI abnormalities increase rapidly.Thus it is crucial to use image analysis techniques to extract diagnostically significant image features[3].

Texture analysis refers to a set of processes applied to characterize spatial variations of pixel's gray levels in an image.Texture analysis which is used to quantify pathological changes that may be undetectable by conventioalMRI techniques,has the potential to detect the subtle changes in tissues & supports early diagnosis of MS.

In this paper,texture analysis was performed on brain MRI of MS patients & normal controls.Texture features from gray-level difference statistics were extracted,& statistical analysis method GLCM(Gray-level co-occurance matrix) was applied between LWM,NAWM & NWM.

1. Prior Work:-

All the previous methods are classified into 4 types.

1) Thresholding method:-

This method is frequently used for image segmentation,simple & effective method for images with different intensities. It has the drawback of generating only two classes therefore this method fails to deal with multichannel images. It also ignores the spatial characteristics due to which an image becomes noise sensitive which corrupts the histogram of the image.

2) Region growing method:-

This technique is not fully automatic.It is also noise sensitive therefore extracted regions might have holes or even some discontinuitites.

3) Shape based method:-

This method has limited degree of freedom & semi-automatic.

4)Supervised & unsupervised segmentation methods:-

2. Proposed work:-

In this paper texture analysis method using SVM & ANN is presented & applied to MRI brain MS segmentation.Firstly sample MR images will be selected & then the MR image is divided into small elements to extract the different kinds of features which quantify the intensity,symmetry & texture properties of different tissues as shown in Fig.1.We used gray-level co-occurrence matrix approach introduced by Harlick [7] which is well-known statistical method for extracting second-order texture information for images. The assumption is that local texture of tumor cells is highly different from local texture of other biological tissues. From GLCM we extracted the textures features like contrast, angular second moment, mean & entropy.

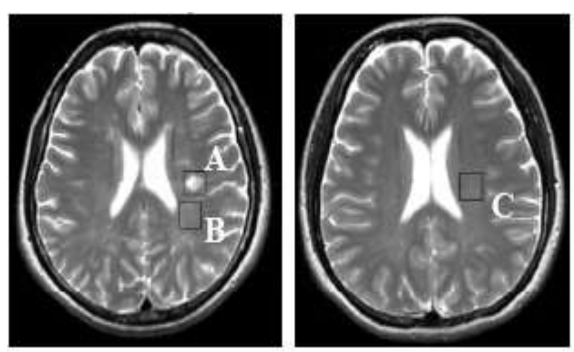

Fig. 1. ROI selection from MRI of MS patients and normal controls.
Left: MRI from a MS patient; Right: MRI from a healthy subject.
A: ROI of LWM ; B: ROI of NAWM; C: ROI of NWM

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For segmentation & classification we used ANN & SVM to detect various tissues like white matter,Gray matter & MS.

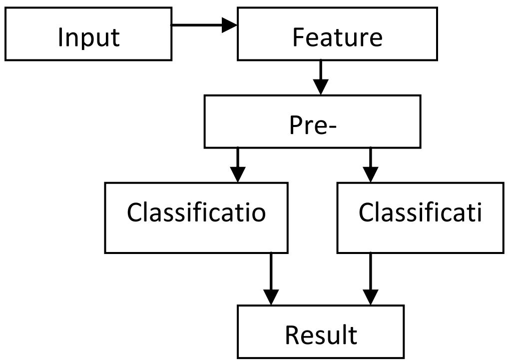

Fig.2 Block diagram of proposed work

3. Methods:-

3.1Need for Texture Analysis:-

In the early Multiple sclerosis (MS) stages when only subtle pathological changes occur,it is very hard to detect MS damage in MRI by visual examination or conventional measures such as lesion volume & number[5].Thus tissue discrimination between Lesion white matter(LWM) & Normal White Matter(NWM) is of critical importance to the early detection of MS.Texture analysis on MRI in essence is the analysis of Gray-level variations between image pixels in ROIs which capture the spatial & intensity information from the possible microscopic MS lesions.Texture features that are extracted by texture analysis techniques quantify both macroscopic lesions & microscopic abnormalities that may be undetectable to conventional measures.

3.2 Terms used in Texture Analysis:

Gray-level difference statistics is commonly used in texture analysis. Suppose g(x,y) is a pixel point of image, the gray difference between this pixel and its neighborhood pixel $g(x+\Delta x, y+\Delta y)$ is as below:

$$g\Delta(x,y)=g(x,y)-g(x+\Delta x,y+\Delta y) \quad (1)$$

$g\Delta(x,y)$ in (1) is defined as gray difference. $g\Delta(x,y)$ of each pixel is caculated by moving (x,y) throught the image.Suppose gray difference level is m , the number of each $g\Delta(x,y)$ is counted up,and histogram of $g\Delta(x,y)$ is drawn.Finally occurred probability $P\Delta(i)$ of each $g\Delta(x,y)$ is caculated based on histogram Texture characteristic is closely related to $P\Delta(i)$. If $P\Delta(i)$ changes rapidly along with variation of i, texture of image is coarse, whereas it is fine if $P\Delta(i)$ distributes smoothly. In this study , texture features including contrast,angular secondmoment, mean and entropy were extracted from the graylevel difference statistics. Their mathematical expressionsare as below

1.Contrast:- $CON=\sum_i i^2 P\Delta(i)$

2. Angular second moment:-

$$ASM=\sum_i (P\Delta(i))^2$$

3.Mean:- $Mean=1/m \sum_i iP\Delta(i)$

4. Entropy:- $Ent= - \sum P\Delta(i) \log P\Delta(i)$

i

These 4 texture features describe the texture characteristics of image from 4 different texture analysis aspects.

4. Artificial Neural Network

The Neural networks [3] developed from the theories of how the human brain works. Many modern scientists believe the human brain is a large collection of interconnected neurons. These neurons are connected to both sensory and motor nerves. Scientists believe, that neurons in the brain fire by emitting an electrical impulse across the synapse to other neurons, which then fire or don't depending on certain conditions. Structure of a neuron is given in fig.3

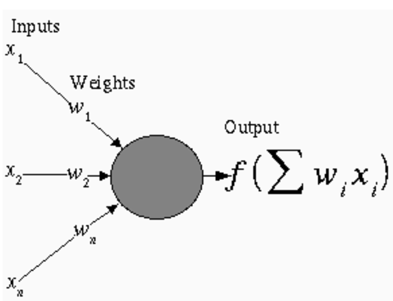

Fig-3 Structure and functioning of a single neuron

The Artificial neural network [3] is basically having three layers namely input layer, hidden layer and output layer. There will be one or more hidden layers depending upon the number of dimensions of the training samples. Neural network structure used in our experiment is consist of only two hidden layers having 14 neurons in the input layer and 1 neuron in the output layer as shown in Figure 4.

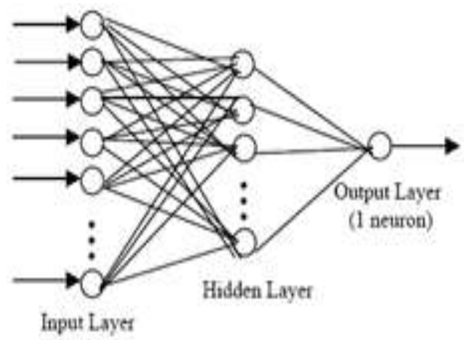

Fig-4 Simple Neural network Structure

A learning problem with binary outputs (yes / no or 1 / 0) is referred to as binary classification problem whose output layer has only one neuron. A learning problem with finite number of outputs is referred to multi-class classification problem whose output layer has more than one neuron. The examples of input data set (or sets) are referred to as the training data. The algorithm which takes the training data as input and gives the output by selecting best one among hypothetical planes from hypothetical space is referred to as the learning algorithm. The approach of using examples to synthesize programs is known as the learning methodology. When the input data set is represented by its class membership, it is called supervised learning and when the data is not represented by class membership, the learning is known as unsupervised learning. There are two different styles of training i.e., Incremental Training and Batch training. In incremental training the weights and biases of the network are updated each time an input is presented to the network. In batch training the weights and biases are only updated after

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all of the inputs are presented. In this experimental work; back propagation algorithm is applied for learning the samples, Tan-sigmoid and log-sigmoid functions are applied in hidden layer and output layer respectively, Gradient descent is used for adjusting the weights as training methodology.

In this paper, each pixel together with a small square neighborhood is defined as a structure element, which is called „block‟. Further steps are all based on the blocks. For training process, firstly different features are extracted block by block in one image. When a new image comes, only those selected features are extracted and the trained classifier is used to categorize the tumor in the image. The training and detection process flow of the proposed method is shown in figure 5. It should be noticed that the input images are preprocessed beforehand, including skull stripping which eliminates the skull from the brain image and scale normalization to adjust the intensity scale of the input images.

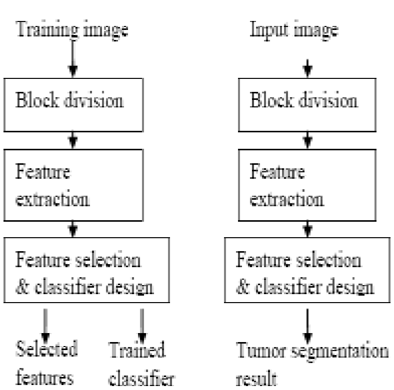

Fig-5 (Left) the training process flow (Right)The tumor segmentation process flow

4. Support vector Machine:-

MS slices based on visual examination by radiologist/physician may lead to missing diagnosis when a large number of MRIs are analyzed. To avoid the human error, an automated intelligent classification system is proposed which caters the need for classification of image slices after identifying abnormal MRI volume, for MS identification. In this research work, advanced classification techniques based on MATLAB Support Vector Machines(SVM) are proposed and applied to brain image slices classification using features derived from slices.Support vector machines are a set of related supervised learning methods which analyze data and recognize patterns.In this paper we are using it only to train the algorithm to recognize the lesions as well as the clean white cells.We use only the in built MATLAB svm functions to train and classify.

G. Conclusion

In this study, texture analysis using SVM & ANN based on Gray-level co-occurance matrix was performed on brain MRI of MS patients and normal controls. The results suggested that texture features of NAWM with MS patients were significant difference from LWM and nomal controls, which is valuable in supporting early diagnosis of MS.

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