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Brain MR Image Segmentation Using Self Organizing Map

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Abstract*:* In this paper a novel brain MR image segmentation method is presented based on self organizing map (SOM) neural network. An accurate segmentation of brain tissues provides a way to identify many brain disorders. This paper presents unsupervised approaches for brain image segmentation. The proposed method consists of four stages. Initially an anisotropic diffusion filtering is used as a pre-processing step to eliminate bias field and random noise. Then Stationary wavelet transform (SWT) is applied to the images to obtain multi-resolution information for distinguishing different tissues. Statistical information of the different tissues is extracted by applying spatial filtering to the coefficients of SWT. These features are combined together with the raw wavelet transform coefficients to obtain a feature vector. This feature vector is applied to the SOM network. SOM is used to segment images in a competitive unsupervised training methodology. The output images show that the proposed method generated more segmented details of the input images.

Keywords*:* Anisotropic diffusion filter, Stationary Wavelet Transform, Feature Vector, Self Organizing Map.

I. INTRODUCTION

This Magnetic resonance imaging is the one of the popular medical imaging technique that has proven to be an effective tool in the study of the human brain. It is used in radiology to visualize detailed internal structures, for diagnosis of many diseases and gives high quality informative images about inside structure of brain. It provides the anatomy of the brain in terms of spatial and contrast resolution [1].

The purpose of image segmentation is to partitioning a digital image into meaningful regions with respect to some criterion such as color, intensity or texture. Image segmentation plays a crucial role in many medical imaging applications and is an important but inherently difficult problem. In medical image segmentation, different image components are used for analysis of different structures and tissues, spatial distribution of functional activities and pathologic regions [2, 3].

The brightness and contrast of the screen can affect the segmentation accuracy and the following analyses. The automatic segmentation need overcome the problems of manual segmentation, it not only requires less time from human experts, but can also provide less variable results [4].

Neural networks are one of the classification based segmentation methods [5]. They perform classification by a method that learns from data, instead of using a given rule set. They organize themselves in a data driven manner. Neural network methods attract more and more attentions for its abilities of self-learning, fault tolerance, and optimum search. In this paper, a novel MR images segmentation method is presented based on Kohonen self organizing map (SOM) neural network. SOM is an unsupervised neural network that use competitive learning algorithm.

The rest of the paper is organized as follows: section 2 explains anisotropic diffusion filter, stationary wavelet transform and self organizing map. Section 3 explains the proposed method. Section 4 is the discussion on the experimental results.

II. METHOD AND MODEL

A. *Anisotropic Diffusion Filter*

Anisotropic diffusion can be used to remove noise from digital images without blurring edges. Perona and Malik developed this powerful multiscale smoothing and edge detection filter. This anisotropic diffusion filtering method is mathematically formulated as a diffusion process, and encourages smoothing within a region in preference to smoothing across the boundaries. In their filtering method the estimation about local image structure is guided by knowledge about the statistics of the noise degradation and the edge strengths [6].

The anisotropic diffusion is defined as

$$\frac{\partial I}{\partial t} = div(c(x,y,t)\nabla I) = \nabla c.\nabla I + c(x,y,t)\Delta I \quad (1)$$

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Where ∇ denotes the gradient, div (…) denotes is the divergence operator and c(x,y,t) is the diffusion coefficient. The (x,y) represents spatial coordinates and t is used for enumerating iteration steps. I represent the intensity function of an image. c(x,y,t) controls the rate of diffusion and is usually chosen as a function of the image gradient so as to preserve edges in the image. This function c(x,y,t) is a monotonically decreasing function. This function diffuses within regions and does not affect region boundaries that are at locations of high gradients. The function for the diffusion coefficient is

$$c(\|\nabla I\|) = \frac{1}{1+\left(\frac{\|\nabla I\|}{k}\right)^2} \qquad (2)$$

The constant K controls the sensitivity to edges and is usually chosen experimentally or as a function of the noise in the image [7].

B. Stationary Wavelet Transform

The stationary wavelet transform (SWT) is an improvement of the discrete wavelet transform (DWT). It is designed to overcome the lack of translation-invariance of the DWT. The process of the SWT is very similar describing the DWT process. The only difference is that the SWT does not perform down-sampling after every filtering step, and instead up-samples the filters at every step which is shown in Fig.1. [8]. Since the outputs do not get down-sampled, the SWT produces two outputs with the same amount of coefficients as components in the input signal at each step. This gives a redundant result where no valuable information is lost, which can be necessary for sensitive data [9].

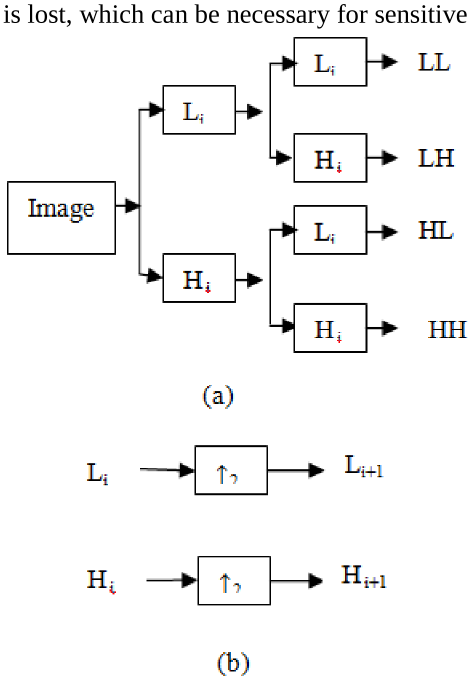

Fig.1. Frames of SWT: (a) decomposition frame of SWT and (b) upsampling operation of filters.

SWT is defined by Unser [10], for the characterization of texture properties at multiple scales using the wavelet transform. The multiresolution properties of the wavelet transform are beneficial for texture discrimination. It is proven that this translation-invariance representation constitutes a tight frame and it has a fast iterative algorithm. For application of the decomposition, the filter used in decomposition is upsampled for each iterations using Equation (3) and convolved with the signal to obtain the subsignals of the next level using Equation (4), instead of applying downsampling process to the signal like in traditional transform methods.

$$h_{i+1}(k) = [h]_{\uparrow 2^i} h_i(k)$$

$$g_{i+1}(k) = [g]_{\uparrow 2^i} g_i(k) \qquad (3)$$

Here the arrow marks $[.]_{\uparrow m}$ denotes the upsampling by a factor of m. The effects of one iteration means dilating the filters h_i and g_i by a factor of 2:

$$s_{i+1}(k) = h_{i+1}(k) s_i(k)$$

$$d_{i+1}(k) = g_{i+1}(k) s_i(k) \qquad (4)$$

Each proceeding step involves convolution with the basic filters h and g that are expanded by inserting appropriate number of zeros between filter taps. The complexity of this algorithm is proportional to the number of samples. The subsignals obtained from the SWT have the same length with the original signal and the results are translation invariant. Nonetheless they contain information of the middle frequency region which is very useful for segmenting images.

C. Self Organizing Map

The SOM introduced by Kohonen [11], is an unsupervised learning neural network. They perform classification by a method that learns from data, instead of using a given rule set. SOM projects a high dimensional space to a one or two dimensional discrete lattice of neuron units. Each node of the map is defined by a vector W_{ij} whose elements are adjusted during the training. An important feature of this neural network is its ability to process noisy data. The map preserves topological relationships between inputs in a way that neighbouring inputs in the input space are mapped to neighbouring neurons in the map space [12].

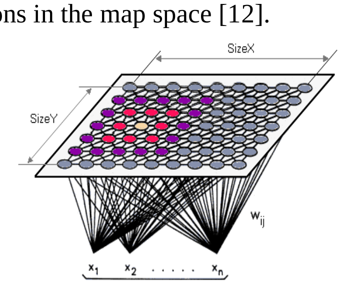

Fig.2. Mapping of feature vector to the output

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In an SOM, the neurons are arranged into the nodes of a lattice that is shown in Fig.2 [13]. It consists of two layers. First layer includes input nodes and second layer includes output nodes. Output nodes are in a two-dimensional grid view. Every input is connected to every output with adjustable weights [14].

Best matching unit and finding the winner neuron determined by the minimum Euclidean distance to the input. Let x be the input and W_{ij} be the weight vector to the nodes. Vector x is compared with all the weight vectors. The smallest Euclidian distance (d_{ij}) is defined as the best-matching unit (BMU) or winner node.

$$d_{ij} = min\|x(t) - w_{ij}(t)\| \qquad (5)$$

Adjustment of the weight vector for the winning output neuron and its neighbours are calculated as

$$w_{ij}(t+1) = w_{ij}(t) + \alpha(t)[x(t) - w_{ij}(t)], \; i \in N_C$$

$$w_{ij}(t+1) = w_{ij}(t), \quad i \notin N_C \qquad (6)$$

Where, for time t, and a network with n neurons: α is the gain sequence ($0< \alpha <1$) and N_c is the neighbourhood of the winner ($1< N_c <n$).

The basic training algorithm is quite simple:

1. Each node's weights are initialized.

2. Vector is chosen at random from the set of training data.

3. Every node is examined to calculate which one's weights are most like the input vector. The winning node is commonly known as the Best Matching Unit (BMU).

4. Then the neighbourhood of the BMU is calculated. The amount of neighbours decreases over time.

5. Update weights to node and neighbours according to equation (6).

6. If $N_c \neq 0$ then repeat step 2.

To evaluate the SOM quality two indexes were calculated. The first, the *average quantization error* (q) is the weighted average distance from each data vector to its best matching unit. It is an index of "memorization" of the map. The second, the *topological error*, (t) represents the percentage of the data vectors for which the BMU and the second BMU is not neighbouring map. These indexes are strictly dependent from the input training set.

III. PROPOSED METHOD

The flow of the proposed method is shown in the Fig.3.

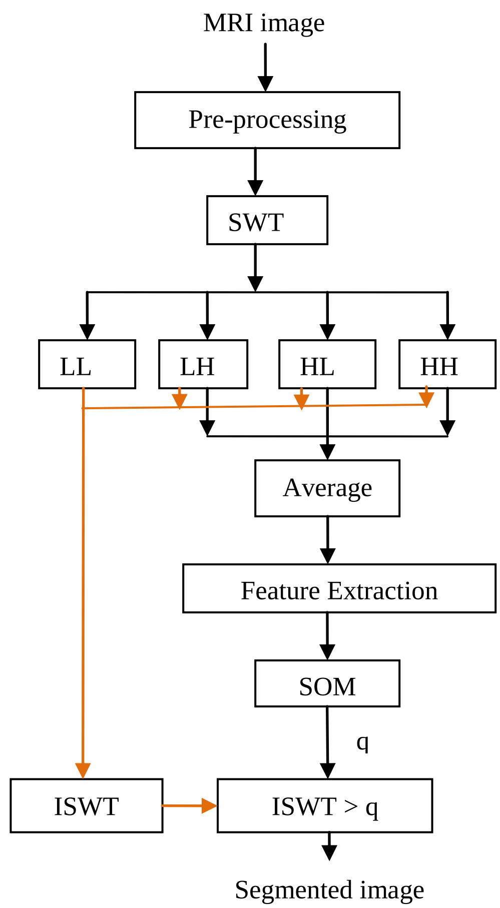

Fig.3. Proposed method flow chart

The procedure is as follows

Step 1: Pre-processing Apply anisotropic diffusion filter on input image.

Step 2: Decompose the step 1 output using SWT to obtain multiresolution information.

Step 3: *Feature Vector*-- The features of the images, that represent local statistical information of the regions extracted from the images by sliding a 3x3 sized window along the average image of higher sub bands of SWT [i.e., HL, HH, and LH]. These features are as follows [17]:

Mad is defined as the median of the absolute deviations of data from the data's median.

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$$MAD = \frac{1}{N}\sum_{i=1}^{N}|x_i - \bar{x}| \qquad (7)$$

Entropy (E) is a statistical measure of randomness that can be used to characterize the texture of the input image.

$$Entropy = -\sum_{i} x_i^2 \operatorname{Log}(x_i^2) \qquad (8)$$

Energy (En) is used to describe a measure of information used for representing textural features.

$$Energy = \frac{1}{N}\sum_{i}|x_i|^2 \qquad (9)$$

Standard deviation (SD) shows how much variation or dispersion exists from the average or expected value.

$$\sigma = \sqrt{\frac{1}{N}\sum_{i}^{N}(x_i - \bar{x})^2} \qquad (10)$$

The variance (V) is a measure of how far the numbers lie from the mean (expected value).

$$Variance = \sum_{i=1}^{m-1}\sum_{j=1}^{n-1}(1 - \bar{x})^2 \; x(i,j) \qquad (11)$$

Contrast (C) is the difference between bright and dark values in the display or printout of a continuous tone (usually grayscale) image

$$Contrast = \sum_{i=1}^{m-1}\sum_{j=1}^{n-1}(i - j)^2 \; x(i,j) \qquad (12)$$

Where x_i represents a data sample and $\bar{x}$ is the mean of the data set.

The feature vector (FV) is constructed by combining the all above features. It is represented as

$$FV = \{MAD; E; En; SD; V; C\} \qquad (13)$$

Step 4: The SOM network is trained with the above feature vector to generate *quantization error* (q) and *topological error* (t).

Step 5: Finally the segmented output is generated with the comparison of q value and ISWT of the image.

IV. EXPERIMENTAL RESULT

The images are downloaded from [15] [16] with the size of 256x256. An anisotropic filtering preprocess is performed before segmentation to remove the noise from the brain MR images. In that stage the k value selected as 10 in equation (2). SWT is used to extract the features that distinguish different tissue types of the brain from the brain MR images. The subimages obtained as a result of the transform are the same size as the original image. One level SWT is applied to the images using the Daubechies 2 wavelet from the Daubechies wavelet family. As a result of the transform, one approximate and 3 detailed (horizontal, vertical and diagonal) subimages are obtained. Wavelet coefficients alone are insufficient for describing tissue properties exactly, therefore a spatial filtering operation is applied to the wavelet coefficients by [3x3] sliding a window through the coefficients. These features are combined as a feature vector. The feature vector size with all considered features is [256x6]. This feature vector is applied to the SOM network. SOM is used to segment images in a competitive unsupervised approach.

In order to evaluate the effectiveness of the proposed method, the segmented outputs are compared with existing method [14]. The obtained segmented results are shown in Fig.4. The comparison between existing and proposed method with respect to q (*quantization error*) and t (*topological error*) values are tabulated in table1.

Image 1

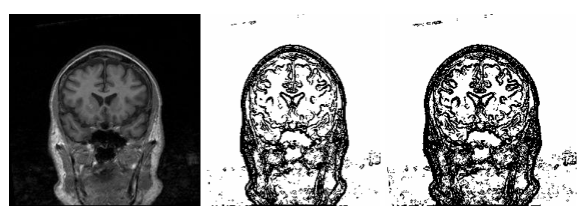

Image 2

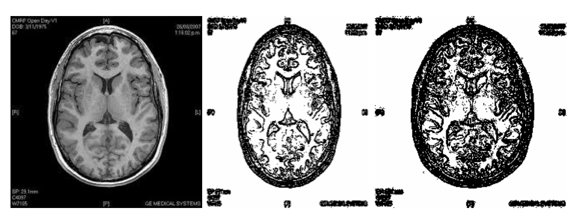

Image 3

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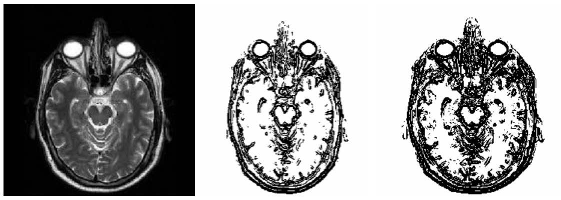


Image 4

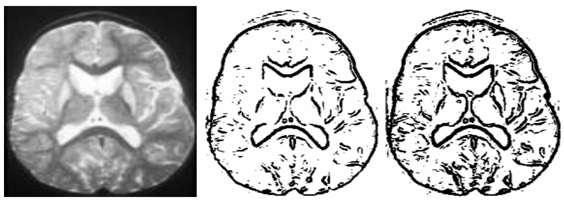


Image 5

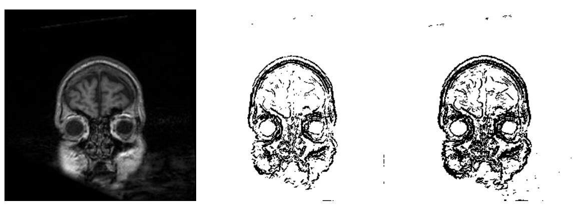
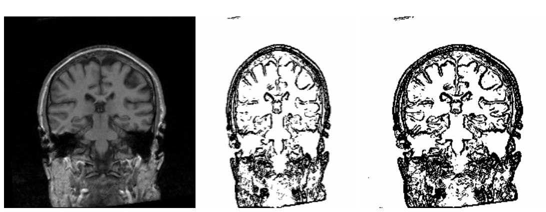


Image 6



(a) (b) (c)

Fig.4. (a) Original image, Segmented Images- (b) Existed method, (c) Proposed method

TABLE I
RESULT OF EXISTED METHOD AND PROPOSED METHOD

Images	Existed method		Proposed method	
	q	t	q	t
Image1	0.5132	0.0314	**0.6305**	**0.0314**
Image2	0.3286	0.0353	**0.5738**	**0.0157**
Image3	0.2051	0.0314	**0.3781**	**0.0196**
Image4	0.3441	0.1059	**0.4825**	**0.1569**
Image5	0.2335	0.0314	**0.3312**	**0.0039**
Image6	0.3434	0.0196	**0.4567**	**0.0118**

V. CONCLUSION

This paper proposes an automatic brain MRI segmentation method. The proposed method contains preprocessing, SWT, feature extraction and segmentation. An anisotropic filtering preprocess is performed before segmentation to improve the quality of the brain MR images. Then SWT is applied to the images to obtain subimages that contain multiresolution information for distinguishing different tissues. Statistical features are extracted from the subimages using spatial filtering process. A multidimensional feature vector is formed by combining SWT coefficients and their statistical features. This feature vector is used as input to the SOM. SOM is trained using unsupervised training methodology. The output results shows that the segmented image of proposed method contains more edges of the input image. The tabulated q and t values are higher than existing method [14].

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BIOGRAPHY

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