Un-Supervised MR Images Segmentation Using SOM and Anisotropic Diffusion Filter

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Abstract--The primary aim in brain image segmentation is to perform partition a given brain image into different regions which are homogeneous with some criterion. Magnetic resonance image (MRI) segmentation plays crucial role in accurate representation of white matter (WM), grey matter (GM) and cerebrospinal fluid (CSF) provides a way to identify many brain disorders, such as Alzheimer's disease, schizophrenia or dementia. In this paper presents a unsupervised method for MR image segmentation based on Self Organizing Maps (SOMs). the proposed method is consist of five stages these are image acquisition, pre-processing step contain anisotropic diffusion filter and contrast limited adaptive histogram equalization(CLAHE), feature extraction using haralick features, feature selection using principle component analysis(PCA) and tissue classification using SOM. Our proposed method is performed over real MR data provided by Internet Brain Repository (IBSR 2.0) database. Performance evaluation using Tanimoto performance index indicate that the proposed method has good segmentation results. Tanimoto performance index gives mean and standard deviation of 0.66 ± 04 for white matter and 0.59 ± 06 for gray matter.

Keywords- Feature Selection, Principle Component analysis, Self organizing Map, Anisotropic Diffusion filter, CLAHE

I. Introduction

Magnetic Resonance Imaging (MRI) is a medical imaging technique which gives detailed information about internal tissue structures using magnetic field utilization. They provide Good resolution and non-invasive procedure to identify tissues. These images have a crucial impact in medical image analysis and diagnosis field before and after surgical treatment. Therefore the MR image segmentation has even more importance. Image segmentation refers to the process of partitioning an image into groups of pixels which are homogeneous with some criterion. These criterions can be based on region, boundary and edge. MR brain image segmentation is used to separate the soft brain tissues white Matter, grey Matter and cerebrospinal fluid. All the non recognized tissues are considered as pathological tissues. Magnetic resonance imaging is well suited for studying disease of nervous system due to the high spatial resolution; Different techniques have been developed for brain MRI segmentation. Mainly segmentation can be demonstrated in two ways. First one is manual segmentation technique which depends on experience and knowledge of human experts. It requires prior knowledge with human intervention but it is a time consuming and tiring process. It varies from expert knowledge and interpretation. Another one is automatic and semi-automatic techniques

DOI- 10.18486/ijcsnt.2015.4.3.01
ISSN-2053-6283

for image segmentation. These are less human intervention and there is no requirement of prior knowledge. Self-organizing map (SOM) maps high dimension data to a low dimensional discrete lattice of neurons. The accurate segmentation of the brain images has become one of the most important issues in MRI application; Segmentation can be based on the image voxel attributes, neighbourhood information, or geometric characteristics. The difficulties to obtain accurate image segmentation arise from noise, partial volume effects, inhomogeneities, and the highly convoluted geometry of the cortex. In this paper, a novel MR image segmentation method is presented based on Kohonen self organizing map neural network that uses competitive learning algorithm for image segmentation.

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

II. Model and Method

A. Anisotropic Diffusion Filter

Anisotropic diffusion can be used to remove noise from digital images without disturbing edges. Perona and malik proposed this powerful multi scale smoothing and edge detection filter. This anisotropic diffusion filtering method is mathematically formulated as a diffusion process and preserves smoothing within a region in preference to smoothing across the boundaries [6].

The anisotropic diffusion is defined as

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

Where ∇ denotes the gradient, c(x,y,t) is the diffusion coefficient and div(..) denotes the divergence operator. The (x,y) represents spatial coordinates of pixel in image and t is enumerating iteration steps. I represent the intensity function of an image. c(x,y,t) controls the rate of diffusion process and it 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 location of high gradient. The function for the diffusion coefficient is

$$C(||\nabla||) = \frac{`1}{1+(\frac{(||\nabla I||)}{k})^2} \qquad (2)$$

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

B. Haralick feature

Haralick [2] proposed set of features for discriminate pixels and texture of an image. Feature extraction is used to minimize the dimensionality of the data set used for the SOM learning. Therefore minimum feature will help SOM to execute fast. In the few cases, first performed the extraction of features then feature selection is performed, for better performance and results, minor amount of discriminative features is required for training in SOM.
Some Haralick features are

Contrast: it is a measurement of the intensity contrast between a pixel and its neighbour over the whole image.

$$\sum_{i,j} |i-j|^2 p(i,j) \qquad (3)$$

Where p (i,j) is gray level co-occurrence matrix(GLCM) [3].

Correlation: it is a measurement of how correlated a pixel is to its neighbour over the whole image

$$\sum_{i,j} \frac{(i-\mu i)(j-\mu j)p(i,j)}{\sigma_i \sigma_j}$$

(4)

Where μ *is mean* and σ *is* variance.

Energy: Energy is the sum of squared elements in the gray-level co-occurrence matrices (GLCM)

$$\sum_{i,j} p(i,j)^2 \qquad (5)$$

Homogeneity: Homogeneity measures the closeness of the distribution of elements in the GLCM to the GLCM diagonal.

$$\sum_{i,j} \frac{p(i,j)}{1+|i-j|} \qquad (6)$$

C. Self Organizing Map

SOM developed by Kohonen [1] is a strong approach in image processing for segmentation, pattern recognition and data mining. SOM has a feed-forward structure. It

contains a set of large input nodes and output nodes. All input node is associated to the output node through adjustable weight vector and it is updated in every process of unsupervised iterative. SOM also uses a neighbouring function, so that node's neighbour of the best matching unit also gets updated.

Kohonen proposed an algorithm which is the SOM algorithm mainly 4 stages consists of initialization, competition, co-operation and learning

SOM clustering can be described as follow:

1. Initialization stage: An initial weight is assigned to all nodes using random, linear and other method for initialization.

2. Competition: All input node compete for the winner of input patter. Node with minimum Euclidean distance is considered as the winning node or best matching unit (BMU). BMU is found by using the equation 7.

$$U_w(t) = argmin_i\{||x(t) - w_i(t)||\} \quad (7)$$

Where x(t), x∈X, the input vector at time t and $w_i(t)$ is the prototype vector association to unit i.

3. Cooperation: winning neuron makes the neighbouring nodes to change their weight.

Gaussian neighbourhood function equation is

$$h_{ui}(t) = e^{\frac{-||r_u - r_i||^2}{2\sigma(t)^2}} \quad (8)$$

Where $||r_u - r_i||$ represent the distance between winning unit and unit i on the outer space and σ(t).

Controls the reduction of Gaussian neighbourhood in each iteration according to a time constant τ_1. $\sigma(t) = \sigma_0\, e^{(\frac{-t}{\tau 1})}$ (9)

4. Learning process: the winning neuron and its neighbours are adjusted with the given rule,

$$w_i(t) = w_i(t) + \alpha(t) h_{ui}(t)\big(x(t) - w_i(t)\big) \quad (10)$$

Where α(t) exponential decay learning factor and $h_{ui}(t)$ is the neighbourhood function, neighbourhood function shrinks in each iteration

III. Proposed Method

The flow of the proposed method is shown in the Fig.1.

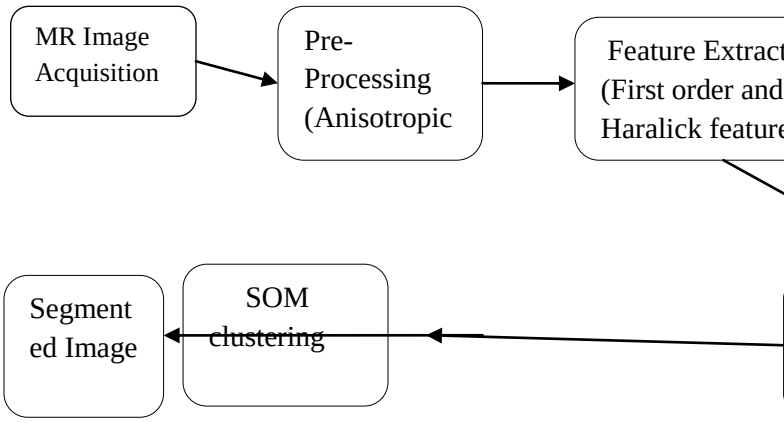


Fig.1: Block diagram of the Segmentation

Proposed algorithm is performed over Internet brain segmentation repository (IBSR) images. IBSR provides MR brain images as well as segmentation results that are performed by the trained experts in a manually guided manner. Manually segmented images are considered as ground truth to compare the results of segmentation. IBSR 2.0 set provides T1 weighted volumetric images that have been spatially normalized with bias field correction routines already applied. Images are spatially and intensity normalized but skull and scalp are not removed from the images. The images have the thickness of 1.5mm and size of 256*256.

The procedure is as follows

Step 1: Pre-processing step including noise removal by anisotropic diffusion filter, contrast enhancement by adapthisteq (CLAHE) and skull striping using brain extraction tool (BET).

Step 2: extract features from the image, whole image is divided into small window of size $w_x * w_y$. Features extraction is performed by first and second order features. First order feature are central pixel of window, mean and variance. Second order features are extracted from Haralick features that are consider as textual feature.

DOI- 10.18486/ijcsnt.2015.4.3.01
ISSN-2053-6283

Step 3: Feature selection is the process of selecting the discriminative feature that are able to distinguishing subset compared with the starting data. Feature selection is performed by principle component analysis (PCA). PCA extract lower dimensional feature set from large data that can explain most of the variability within the original data.

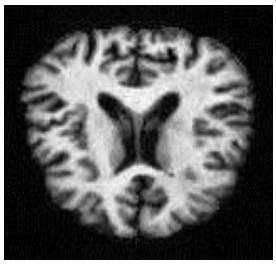
Step 4: Reduced feature sets are used to train SOM for clustering.

IV. Experimental Results

The images are downloaded from IBSR with the size of 256*256. An anisotropic filtering pre-process is applied before segmentation to remove the noise from the MR brain images. In that stage the k value selected as 5 in equation (2). Haralick features are used to extract the features that distinguish different tissue types in the brain from the MR brain images. PCA are used for feature selection, it finds the Eigen values of the covariance matrix of feature set and maximizes the variance of the data set. This feature set is applied to the SOM network. SOM is used to segment images in a competitive unsupervised approach.
SOM training parameters are shown in table 1. Fig 2a, 2b shows the input image and referenced segmentation results for the IBSR brain image using the proposed algorithm and Fig 2c and 2d shows the segmentation results performed by proposed method.

Table 1: Training parameters of SOM networks

Parameter	Value
Initialization	Linear
Lattice	Hexagonal Topology
Neighbourhood function	Gaussian
Learning rate function	Exponential
Distance function	Euclidean
Epoch(iteration)	1000



(a)

(b)

(c)

(d)

Fig2. Segmentation of the IBSR_13_ana MR Brain image (a) Original image (b) Reference output image (c) white matter and (d) grey matter are segmented through proposed method. It is difficult to analysis the performance of MR brain segmentation due to the complexity of neuro-anatomic tissue structures and quality of images. Tanimoto similarity coefficient used here to analysis the segmentation results. Tanimoto index is a region based coefficients that is a measure of spatial overlap between segmentation results and ground truth for each tissue.

DOI- 10.18486/ijcsnt.2015.4.3.01

ISSN-2053-6283

Tanimoto similarity index= $\frac{|A_i \cap B_i|}{|A_i \cup B_i|}$ (11)

Where $A_i \cap B_i$ represent the number of pixels classified as class i by both the ground truth and the segmentation results and $A_i \cup B_i$represent number of pixels classified as class i either the ground truth or the segmentation results. Tanimoto coefficient 1.0 denotes perfect overlap between segmented results and ground results. Whereas an index of 0.0 denote no overlap between segmented and ground results.

Tanimoto similarity index give perfect measure for the brain tissue segmentation performance. Table 2 shows the tanimoto index values obtained from the system while analyzing various MR brain images.

Table 3. Tanimoto similarity metrics obtained for the segmentation method over IBSR v2 images

Data set	WM	GM
Img_01_ana	0.6035	0.5936
Img_03_ana	0.6534	0.5929
Img_08_ana	0.6756	0.5956
Img_12_ana	0.7082	0.5805
Img_18_ana	0.7032	0.5961

The proposed method has good segmentation results for different brain tissue as can be seen in table 2. Mean and standard deviation of tanimoto similarity index for different segmentation algorithms are presented in table 4. Average performance for segmentation method is shown as graph in fig 3 and fig 4.

Table 4. Mean and standard deviation of Tanimoto index for segmentation methods

Segmentation algorithm	WM index	GM index
Proposed Method	0.66±0.04	0.59±0.06
PCA+SOM [13]	0.59±0.06	0.58±0.05

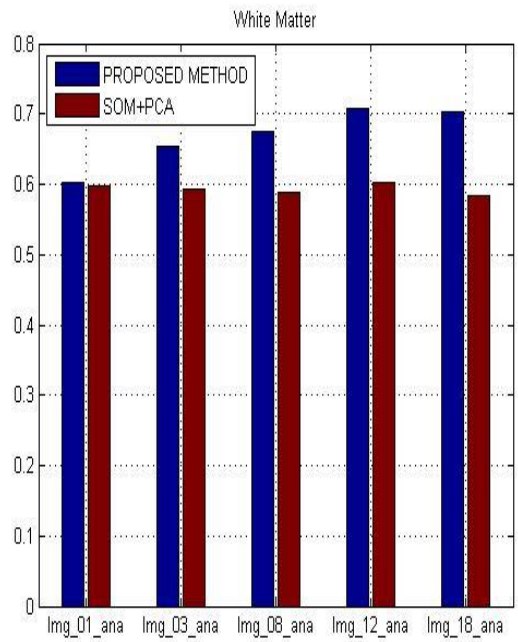


Fig 3. Average White Matter Segmentation Performance Of Different Segment Method

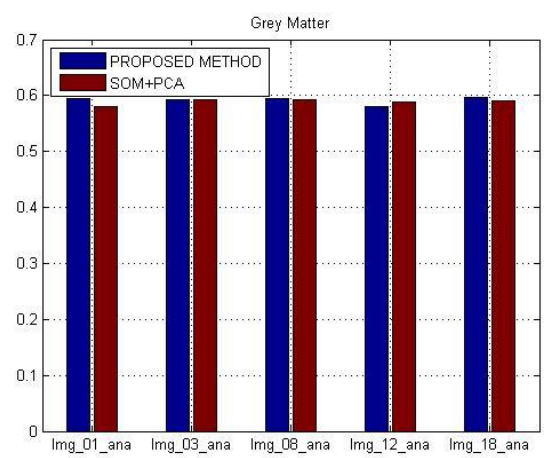


Fig 4. Average Grey Matter Segmentation Performance Of Different Segment Method

V. Conclusion

DOI- 10.18486/ijcsnt.2015.4.3.01
ISSN-2053-6283

In this paper we used an unsupervised segmentation algorithm for MR brain image segmentation based on Anisotropic Diffusion filter, principle component analysis and SOM classifier. Feature extraction is performing by haralick features along with first and second order feature. Feature selection plays crucial part in segmentation. PCA algorithm is used for feature selection process to improve the segmentation results which reduce the computation time and provide optimum results. SOM is trained by different number of features vectors. PCA selection reduces the processing time and the overall segmentation time is less. Our proposed segmentation method is validated by real MR data. Tanimoto performance index over IBSR 2.0 images gives mean and standard deviation of 0.66±0.04 for WM and 0.59±0.06 for GM.

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