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MR Brain Image Segmentation Based on Principle Component Analysis and Self-Organizing Map

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Abstract— ***In this paper, a fully unsupervised segmentation of Magnetic Resonance (MR) brain image is presented, which is based on a competitive learning algorithm-Self Organizing Map (SOM). We tried to address the problem of segmentation of MR brain images using Principle Component Analysis (PCA) and unsupervised classifier. The proposed technique contains number of steps such as pre-processing using Brain Extraction Tool (BET), feature extraction (first and second order features), feature selection using PCA and segmentation using SOM clustering. Our proposed method is performed over real MR data provided by Internet Brain Repository (IBSR) database. Performance evaluation using Tanimoto performance index shows that the proposed method has good segmentation results. Tanimoto performance index gives mean and standard deviation of 0.59±0.06 for white matter (WM) and 0.58±0.05 for gray matter (GM). Algorithm offers 86.74% and 70.2% sensitivity for WM and GM respectively and 96.49% and 96.44% specificity for WM and GM. This fully unsupervised method can be used to identify the brain disorders such as brain tumours, dementia Alzheimer's disease and other neuro anatomical disorders.***

Keywords— ***Feature Selection, Segmentation, Self Organizing Map, Principle Component Analysis***

I. INTRODUCTION

Magnetic Resonance Imaging (MRI) technique is used to get detailed view of brain and is a viable option to study the abnormal brain tissues. MRI has no known side effects related to radiation exposure which make it as a valuable tool in quantitative brain imaging studies.

Segmentation is the method used to partition an image into several regions of homogeneous characteristics. Segmentation of MR images is a complex task because the image contains intensity inhomogeneity, noise and Partial Volume Effect (PVE) due to voluntary and involuntary movement of the patients and equipments. MR brain image segmentation separates the three main soft tissues such as WM, GM and Cerebrospinal Fluid (CSF). Accurate segmentation of brain tissues helps to analyse the tissue volume, detection of tumors and measuring tumor volumes.

Several approaches are used for the segmentation of MR brain images can be categorized as supervised and unsupervised. Supervised segmentation requires external support or need human intervention. Unsupervised segmentation is performed without any support; fully depending upon the image features. Clustering techniques plays a major role in image segmentation field. SOM [1] is a clustering technique that is used for unsupervised segmentation of MR brain images. It is the one of the most popular neural network algorithms, that have the advantages like automatically form similarity diagrams according to input data. SOM maps high dimensional data to a low dimensional discrete lattice of neurons. Several studies have been performed that uses SOM for the segmentation of brain MR images.

To automatically segment MR brain images SOM and knowledge based expert system is used in [2]. This method has high segmentation and labeling accuracies for most of the brain tissues. A. Ortiz et al. [3] developed two

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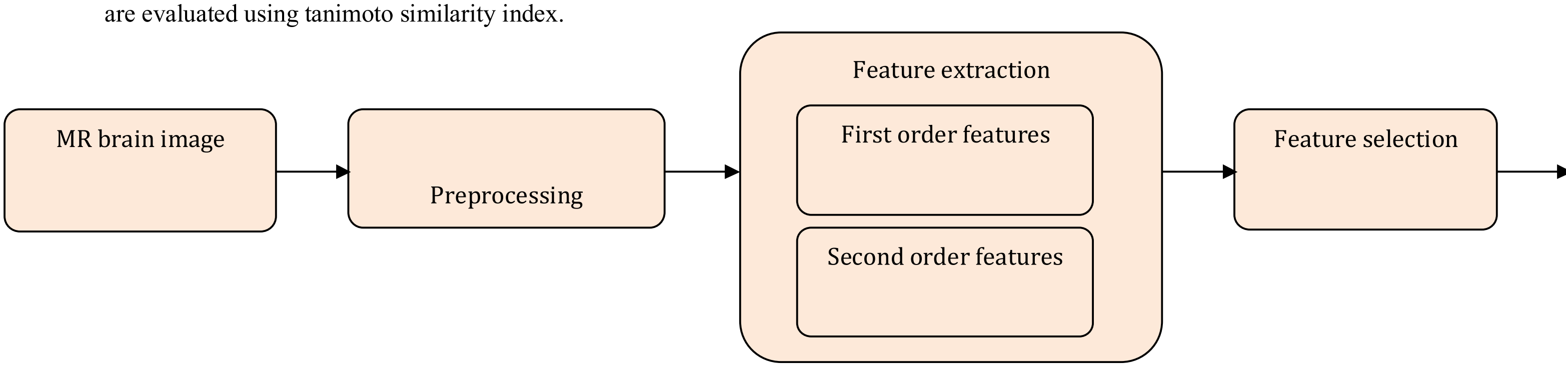
fully unsupervised segmentation methods for MR image segmentation using SOM. First one is a fast and efficient method for segmentation that depends upon the histogram developed from the image. Second one depends on the inherent features extracted from the image and it is a robust scheme under noisy and bad intensity image conditions. In order to addresses the problem of PVE, segmentation based on SOM-Fuzzy C Means method is proposed in [4].This method uses the 3D statistical descriptors extracted from the image for SOM training. Demirhan et al. [5] combined the stationary wavelet transform and SOM to segment the MR brain images, that gives better segmentation results for GM and average results WM.

In this paper BET is used in the preliminary stage of segmentation for the purpose of preprocessing the image. Then image is divided into small windows and diverse features are extracted from the subimages. Feature set is reduced by using the PCA selection method. These reduced feature vectors is given to SOM for clustering and the results are evaluated using tanimoto similarity index.



Rest of the paper is organized as follows. Section II presents the methods and the model used in the proposed method. It is divided into 5 subsections; section A describes the database used in this work; section B describes the preprocessing stage; section C describes feature extraction technique; section D explains feature selection method; and section F describes the SOM clustering. Section III covers the experimental results obtained from the evaluation of the proposed method. Finally conclusion is included in section IV.

II. Methods and Model

Fig 1. Summarizes the segmentation method proposed in this work.

A. *MR Brain Images*

Proposed algorithm is performed over IBSR brain images from Massachusetts general Hospital and are available at http://www.cma.mgh.harvard.edu./ibsr [6]. IBSR provides brain MR images as well as segmentation results that are performed by the trained experts in a manually guided manner. Manually segmented images are treated as ground truth to compare the results of segmentation. IBSR 2.0 set provides 18 T1 weighted volumetric images that have been spatially normalized and processed by the Center for Morphometric Analysis (CMA) at the Massachusetts General Hospital with the bias field correction routines already applied. Images are spatially and intensity normalized, but skull and scalp are not removed from the image. The images have the thickness of 1.5mm and size of 256x256.

B. *Image Preprocessing*

Preprocessing is considered as the first step in image segmentation. Because the image acquired from the database contains non-brain structures such as skull and scalp, these parts have to be removed before the start of segmentation. In this paper, we used the BET [7] to remove non brain structures. This method is very fast and requires no preregistration or other pre-processing before being applied on the image. Bet can also estimate the inner and outer skull surfaces, and outer scalp surface.

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C. Feature Extraction

The main purpose of feature extraction phase is to extract some properties from the data set that can be used to classify and recognize the patterns in the image. As a result, a feature vector whose dimension is equal to the number of extracted features can be used for further phases. Feature extraction plays a decisive role in segmentation because selected feature set contains the discriminative characteristics that can be used as a basis for classification.

In order to extract features from the image whole image is divided into small window of size $w_x x w_y$. Then a feature set is computed from each window. The feature descriptors include the first order features, textural features and moment invariants. First order features are derived from the intensity level of the central pixel in a window and mean and variance of intensity of the pixels in the window. Second order features are derived from spatial relationship among pixels in a window. Haralick et. al [8] proposed 14 features computed using Gray Level Co-occurrence Matrix (GLCM). GLCM is a structure that describes the co-occurring intensity values at a given offset. GLCM is defined over an image *I*, parameterized by an offset $(\Delta x\, \Delta y)$ as:

$$C\Delta_x\Delta_y(i,j) = \sum_{p=1}^{n}\sum_{q=1}^{m}\begin{cases}1, & if\ I(p,q)=i\ and\ I(p+\Delta x,q-\Delta y)=j\\ 0, & otherwise\end{cases} \tag{1}$$

where *i* and *j* are the image intensity values of the image *I*, *p* and *q* are the spatial positions in the image *I*. In addition to this moment invariants computed from each window are used to form the feature vector. Moment invariants are invariant under scaling and rotation. Seven moment invariants defined in [10] are included here.

Once the features are extracted, a feature vector is constructed. This feature set is contained in R^D, where D is the number of features. Here, totally 24 features are extracted, therefore the feature space is contained in R^{24}. Features extracted are shown in Table 1.

Fig. 1. Block diagram of the segmentation

Table 1: Feature set extracted

Feature Index	Features	Feature Type
1	Intensity	First order features
2	Intensity mean	
3	Intensity variance	
4	Energy	Textural features
5	Entropy	
6	Contrast	
7	Homogeneity	
8	Sum Average	
9	Autocorrelation	
10	Matlab correlation	
11	Correlation	
12	Angular second moment	
13	Cluster prominence	
14	Maximum probability	
15	Cluster shade	
16	Dissimilarity	
17	Variance	
18	Humoment(1)	Moment invariants
19	Humoment(2)	
20	Humoment(3)	
21	Humoment(4)	
22	Humoment(5)	
23	Humoment(6)	
24	Humoment(7)	

D. Feature selection

Feature selection is the process of selecting the relevant and useful features from the dataset by removing the redundant, irrelevant and noisy features. To improve the segmentation results, it is important to select best features from the image. Feature selection provides a smaller but more distinguishing subset compared with the starting data. Feature

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selection helps to improve the performance of learning models by:

- Alleviating the effect of the curse of dimensionality.
- Enhancing generalization capability.
- Speeding up learning process.
- Improving model interpretability.

In this work, to improve the selection process, PCA is used. PCA [10] is one of the most widely used multivariate data analysis techniques and is employed primarily for dimensional reduction and visualization. PCA extracts a lower dimensional feature set that can explain most of the variability within the original data. Principal Components (PC) are the projection of the original features onto the eigenvectors and correspond to the largest eigenvalues of the covariance matrix of the original feature set. PC provides linear representation of the original data using the least number of components with the mean squared error minimized. PCA can be used to approximate the original data with lower dimensional feature vectors.

E. Self Organizing Map

SOM signifies unsupervised learning class of neural network algorithms [7]. SOM makes a projection of high level data manifold to a low level data grid by preserving topology. SOM has much application in data exploration especially in data visualization and dimension reduction.

SOM consists of components called nodes or neurons. Each input node connected to every output through an adjustable weight vector. SOM uses neighborhood function for the learning process. Feature set selected from the feature selection process are used to train SOM.

SOM clustering can be described as follows:

1.Initialization stage: An initial weight is assigned to all nodes.

2.Competition: All input node compete for the ownership of input pattern. Node with minimum Euclidean distance is considered as the winning node or Best Matching Unit (BMU). BMU is found by using the equation 2.

$$U_w(t) = argmin_i \{\|x(t) - w_i(t)\|\} \quad (2)$$

where $x(t)$, $x \varepsilon X$, the input vector at time t and $w_i(t)$is the prototype vector associated to unit *i.*

3.Cooperation: Winning neuron makes the neighboring nodes to change their weight. Gaussian neighborhood function is,

$$h_{ui}(t) = e^{\left(\frac{-(\|r_u - r_i\|^2)}{2\sigma(t)^2}\right)} \quad (3)$$

Where $\|r_u - r_i\|$ represents the distance between winning unit and unit i on the outer space and $\sigma(t)$ controls the reduction of Gaussian neighborhood in each iteration according to a time constant τ_1.

$$\sigma(t) = \sigma_0 e^{(-t/\tau_1)} \quad (4)$$

4.Learning process: The winning neuron and neighbors are adjusted with the rule,

$$W_i(t) = w_i(t) + \alpha(t)h_{ui}(t)\left(x(t) - w_i(t)\right) \quad (5)$$

Where $\alpha(t)$ exponential decay learning factor and $h_{ui}(t)$ is the neighborhood function. Neighborhood function shrinks in each iteration.

SOM map quality is measured by considering two criteria: Quantization error and topological error. Quantization error is the mean distance between every data vector and its BMU [11]. Topological error is the ratio of first and second BMUs that is not in the neighborhood of each other [12]. The output map that gives lower quantization and topological error is considered as the quality one.

Quantization error, $$qe = \sum_{i=1}^{N} \|x_i - b_{xi}\| \quad (6)$$

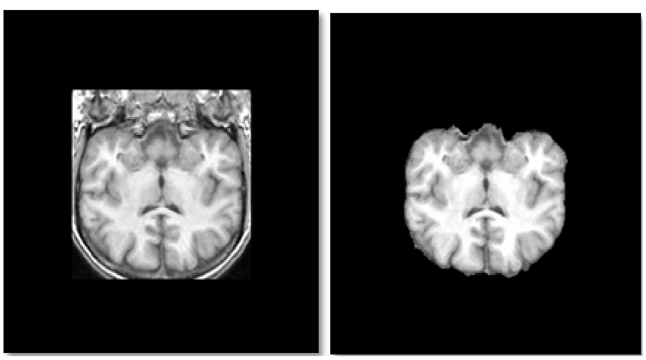
Topological error, $$te = \frac{1}{N} \sum_{i=1}^{N} u(x_i) \quad (7)$$

It quantizes the input feature space by a number of prototypes and each prototype can be considered as the most representative of a class.

III. RESULTS AND DISCUSSION

In this section we present the results of the experiments conducted to select the most discriminative features and segmentation results over IBSR images. IBSR database contains 18 T1 weighted MR images of size 256x256 pixels. Images are preprocessed using BET tool to extract the brain and remove undesired parts. Fig. 2.a shows the MR brain image and Fig. 2.b shows the corresponding preprocessed image. BET removes the skull and scalp from the image.

Preprocessed image is divided into window of size 3X3 and 24 features (first order and second order features) are extracted from each window. These feature set is given as input to PCA. Feature selection using PCA is performed by computing PCs of feature space. PCA finds the eigenvalues of the covariance matrix of feature set and maximizes the variance of the data set. PC are the projection of the original features onto the eigenvectors and correspond to the largest eigenvalues of the covariance matrix of the original feature set. SOM is trained using the selected set of PCs and map quality is evaluated by computing quantization and topological error. Features that give minimum topological and quantization error are selected for further step.



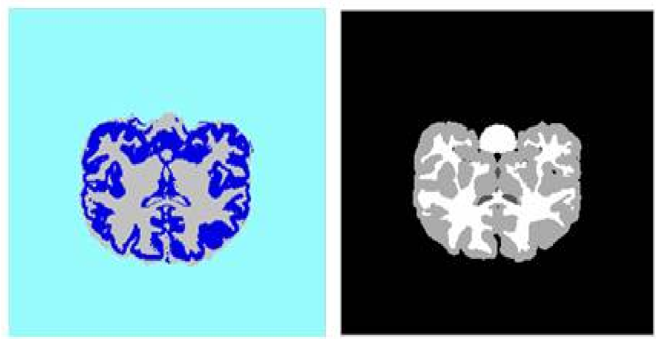
(a) (b)

Fig. 2 (a) MR brain image IBSR_01_ana from IBSR database and (b) Corresponding preprocessed image

Once the number of features is reduced, those vectors are used to train the SOM. Hexagonal lattice is used on the SOM layer. SOM classification performance depends upon the map size. SOM map size (the number of map units) is determined by the formula 'map_units = 5*d^0.5', where d is the number of training samples. Then the SOM weight vectors are linearly initialized by computing the eigenvectors and eigenvalues of training data. SOM was trained using 2000 iterations. SOM training parameters are shown in table 2. Fig. 3a shows the segmentation results for the IBSR brain image using the proposed algorithm and Fig. 3b shows the segmentation results performed by expert radiologists provided by IBSR database.

Table 2: Training parameters of SOM network

Parameter	**Value**
Number of neurons	5x d^0.5
Initialization	Linear
Lattice	Hexagonal
Neighborhood function	Gaussian
Learning rate function	Exponential



(a) (b)

Fig. 3. Segmentation of the IBSR_01_ana MR brain image (a) using the proposed PCA-SOM algorithm (b) Ground truth

It is difficult to evaluate the performance of MR brain segmentation due to the complexity of neuro-anatomic structures and quality of images. Tanimoto similarity coefficient used here to evaluate the segmentation results. Tanimoto index is a region based coefficients that is a measure of spatial overlap between segmentation result and ground truth for each tissue.

$$\text{Tanimoto metric} = \frac{|A_i \cap B_i|}{|A_i \cup B_i|} \quad (8)$$

Where $A_i \cap B_i$ denotes the number of pixels classified as class i by both the ground truth and the segmentation result and $A_i \cup B_i$ denotes number of pixels classified as class i either the ground truth or the segmentation result. Tanimoto coefficient 1.0 represents perfect overlap, whereas an index of 0.0 represents no overlap. Tanimoto give

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perfect measure for the brain tissue segmentation Table 3 shows the tanimoto index values obtained from the system while analyzing various images.

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

Data set	**WM**	**GM**
Img_01_ana	0.5968	0.5794
Img_03_ana	0.5922	0.5918
Img_08_ana	0.5872	0.5931
Img_12_ana	0.6014	0.5887
Img_18_ana	0.5843	0.5896

In order to evaluate the overall performance of segmentation method, sensitivity, specificity and accuracy values for each tissue is computed and is shown in Table 4.

Table 4: Sensitivity, specificity and accuracy achieved by PCA-SOM algorithm

Images	**Brain tissues**	**Sensitivity**	**Specificity**	**Accuracy**
Img_01_ana	WM	0.8826	0.9448	0.9403
	GM	0.6640	0.9774	0.9231
Img_03_ana	WM	0.8644	0.9661	0.9591
	GM	0.6751	0.9829	0.9497
Img_08_ana	WM	0.8287	0.9761	0.9674
	GM	0.7882	0.9422	0.9278
Img_12_ana	WM	0.8864	0.9720	0.9665
	GM	0.7095	0.9467	0.9249
Img_18_ana	WM	0.8752	0.9657	0.9587
	GM	0.6732	0.9430	0.9264

The proposed method has good segmentation accuracies for brain tissues as can be seen in Table 4. Mean and standard deviation of tanimoto index for different segmentation algorithms are presented in Table 5. Average performance for different segmentation method is shown as graph in Fig.4.

Table 5: Mean and standard deviation of Tanimoto index for different segmentation methods

Segmentation algorithm	**Ref**	**WM index**	**GM index**
Proposed method (PCA-SOM)	-	0.59±0.06	0.58±0.05
Adaptive map(amap)	[6],[11]	0.57±0.13	0.58±0.17
Biased map(bmap)	[6],[11]	0.56±0.17	0.58±0.21
Fuzzy c-means	[6],[14]	0.47±0.11	0.58±0.19
Tree structure k-means	[6],[15]	0.48±0.12	0.58±0.19
Maximum posteriori probability	[6],[16]	0.55±0.16	0.57±0.20

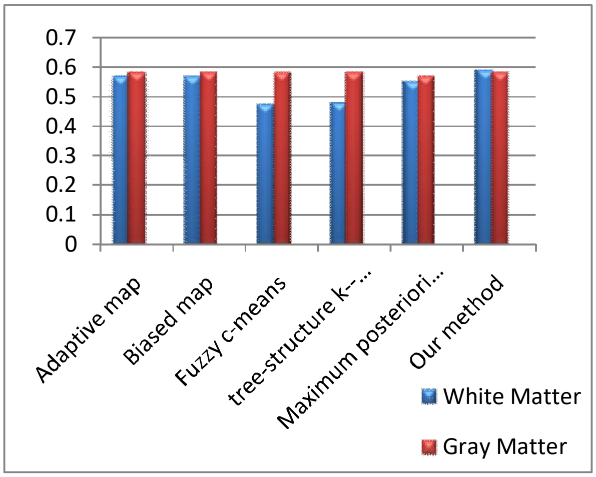

Fig. 4. Average segmentation performance of different segmentation method

IV. CONCLUSION

In this paper we used an unsupervised segmentation algorithm for MR brain image segmentation based on PCA and SOM classifier. Feature selection plays an important role in segmentation. PCA algorithm is used for feature selection process to improve the segmentation results which reduce the computation time and give optimum results. SOM is trained by different number of features and map quality (quantization and topological error) computed to evaluate the performance of SOM. 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 V2image gives mean and standard deviation of 0.59±0.06 for WM and 0.58±0.05 for GM. Algorithm offers 86.74% sensitivity for WM and 70.2% sensitivity for GM and 96.49% specificity for WM and 96.44% specificity for GM.

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