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A Survey on MR Brain Image Segmentation Using SOM Based Strategies

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Abstract:
Magnetic Resonance (MR) image segmentation has greater influence in image guided surgery, therapy evaluation and diagnosis fields. Several supervised and unsupervised segmentation techniques are available for image segmentation. Supervised segmentation has less demand in medical field because it needs a priori knowledge, assistance from external entity. Whereas unsupervised segmentation yield good results without any a priori knowledge. Self Organizing Map (SOM) is an unsupervised clustering technique. The SOM is an Artificial Neural Network (ANN) which has a feed-forward structure. The SOM features are very useful in data analysis and data visualization, which makes it as an important tool in brain MR image segmentation. SOM map quality depends upon the learning parameters, map topology and map size. A comprehensive survey on SOM based automatic MR image segmentation methods are presented below.

Keywords: *Image segmentation, MR brain image, self organizing map, unsupervised segmentation.*

I. INTRODUCTION

Magnetic Resonance Imaging (MRI) is a medical imaging technique which gives detailed information about internal tissue structures. High resolution and non-invasive MR images have a crucial influence in image analysis and diagnosis field. So, the MR image segmentation has even more importance.

Segmentation is defined as the process of drawing an imaginary line in an image, making image as collection of several regions having same properties. Neuro-anatomical structures within the medical images are identified by MR image segmentation. MR brain image segmentation is used to separate the soft brain tissues like White Matter (WM), Gray Matter (GM) and Cerebral Spinal Fluid (CSF). All the non recognized tissues are considered as pathological tissues. Radiologist uses segmentation results to identify neurological diseases.

Different approaches have been developed for brain MRI segmentation. Mainly segmentation can be addressed in two ways. First one is manual segmentation technique which depends on experience and knowledge of human experts but it is a time consuming and tiring process. Later one aims to use automatic and semi automatic techniques for imaging segmentation. Some of them are based on image histogram. Histogram-based segmentation method uses intensity levels of pixel. It is a fast method, but they do not make use of the spatial information and fail under noisy conditions. On the other hand, segmentation has been addressed by edge detection and region growing methods. Edge detection methods identify edges of objects which may fail when images are blurred or too complex to identify border. Region growing algorithms focus on the spatial information but they need initial input manually.

Clustering by supervised and unsupervised learning [1] is considered as the most popular segmentation technique. In supervised segmentation, a priori knowledge about segmentation is used. On the other hand, in unsupervised technique inherent features extracted from the image is used for the segmentation. Unsupervised segmentation based on clustering includes K-means, Fuzzy C-Means (FCM) and ANN. K-means algorithm is a hard segmentation method because it assigns a pixel to a class or does not [2]. FCM uses a membership function so that a pixel can belongs to several clusters having different degree [3]. ANN can change their responses according to the environmental conditions and learn from the experience. SOM is an unsupervised ANN that uses competitive learning algorithm.

II. SELF ORGANIZING MAP

SOM developed by Kohonen [4] is a strong candidate in image processing, data mining and pattern recognition. SOM maps high dimensional input data to one or two low dimensional data grids. SOM has a feed-forward structure. It contains a set of input nodes and output nodes. Each input node is connected to the output node via adjustable weight vector and is updated in each unsupervised iterative process. During each iteration, weight vector of the unit closest to the input node becomes the winning unit or best matching unit (BMU). SOM also uses a neighbouring function, so that nodes neighbor to the BMU also gets updated.

SOM algorithm proposed by Kohonen consists of 4 phases and is summarized in Fig.1. First phase is the initialization phase, where weight vectors are initialized by random initialization or data analysis based initialization methods [5]. In competition phase, node with smallest Euclidean distance is considered as the winning unit. Winning neuron excites the neighbouring neurons in cooperation phase and the weights of neighbouring nodes are updated. For this purpose Gaussian neighborhood function is used. Last phase is known as learning process where winning unit and neighbouring units are adjusted with the input pattern.

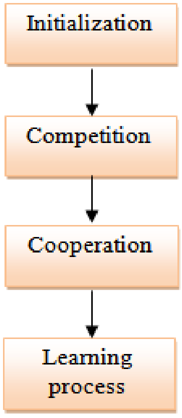

Fig.1: SOM modeling Phases

Unsupervised execution of SOM helps to identify the Alzheimer's, brain tumors, dementia and schizophrenia. SOM also used for the segmentation of mammogram images using multi-scale analysis [6]. and identifying dominant color component in medical image [7].

One of the most important features of SOM is topology preservation; nearby data in the input space is mapped onto neighbouring location in the output space. Quantization error and topological error [8] can be used to quantify goodness of the map. Quantization error measures the average distance between the data vectors and BMU and topological error measures the ratio of data vectors for which first and second BMU are not adjacent units. For an optimal quality map, quantization error and topological error need to be less. The smaller quantization error means data vectors are closer to its prototype.

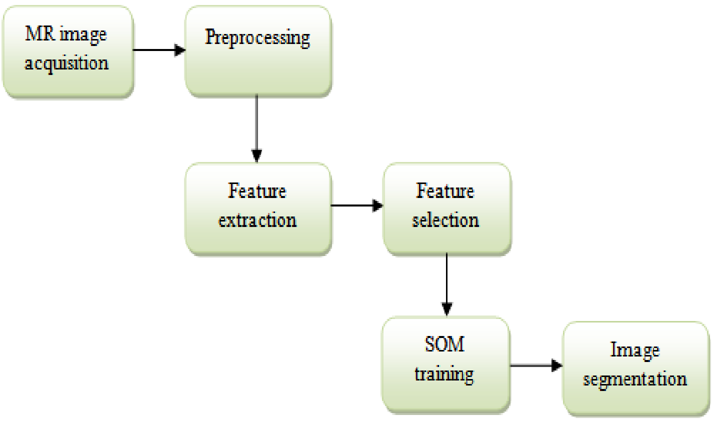

Fig.2: Steps in SOM based segmentation

MR image segmentation based on SOM follows six steps for the segmentation as shown in Fig.2. Initially MR image is acquired from an image source. The external objects in image such as noise and background are removed by using preprocessing stage. Several preprocessing algorithms have been developed such as brain surface extraction, brain extraction tool and hybrid watershed algorithm. From the preprocessed image, a set of discriminative features are extracted in order to train the SOM. Feature extraction is applied to reduce the dimensionality of the dataset used for SOM learning. In some cases, feature selection is performed after the extraction of features. To achieve good performance of SOM, small number of discriminative features is required. Genetic algorithm (GA), Principle Component Analysis (PCA) and various optimization algorithms are used in feature selection stage. These features are mapped to output nodes. SOM training gives a lower dimensional output map. Unsupervised segmentation using SOM requires, clustering the SOM output units after training. This can be addressed using the standard clustering algorithm like K-means, FCM and Learning Vector Quantization (LVQ).

III. ANALYSIS OF DIFFERENT SOM BASED SEGMENTATION TECHNIQUES

To improve the results of MR brain image segmentation several researches are being carried out by experts. Segmentation of MR brain images using SOM and performance metrics used for their evaluation are described in the following section.

3.1. Performance Metrics

Performance measurement of MR brain image segmentation is a difficult task due to the complexity of neuro-anatomical structures, quality of imaging techniques and characteristics of segmentation. Tanimoto performance index and Dice similarity metric which are associated with specificity and sensitivity used for evaluating the performance of segmentation algorithms [9].

Tanimoto coefficient measure the overlap that ground truth and segmentation results share with their attributes. Tanimoto index of value 1.0 means that results are very similar with ground truth and 0.0 means they share no similarity. Tanimoto similarity measure calculated as the size of the intersection divided by size of the union of the ground truth and segmentation result [13].

$$T = \left| \frac{A \cap B}{A \cup B} \right| \tag{1}$$

Dice similarity metric is calculated as two times the size of union divided by sum of the size of the ground truth and segmentation result.

$$D = 2 \frac{|A \cap B|}{|A| + |B|} \tag{2}$$

Where A is the automatically segmented region and B is the manually segmented brain MR image.

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3.2. SOM with Markov Random Field

Y. Li et al. [10] uses the SOM network to segment the MR brain image. To improve the segmentation results algorithm includes spatial information regarding size, shape, and orientation of regions to be segmented by using Markov Random Field (MRF) model. MRF helps to produce better results without extra data samples in the training set. MRF term is not considered as an important factor in the segmentation process instead it helps to eliminate the effect of noise and to make smoothened segmented regions. Segmentation performance is measured by using mean squared errors.

3.3. HFS-SOM and EGS-SOM

A. Ortiz et al. [11] proposed two fully unsupervised MR brain image segmentation techniques. First one is referred as Histogram based Fast Segmentation (HFS-SOM) that depends upon the features selected from the histogram of the image. Features extracted consist of intensity occurrence probabilities, the relative position regarding the intensity value, the mean of the probability values over a 3-bins window and the variance of that window. These features are used to form a feature vector and used to train the SOM. The SOM output layer is further classified using K-means, to define the border between the clusters. HFS-SOM is a faster segmentation method because it does not require any parameter setup. The second method is known as Entropy Gradient Segmentation (EGS-SOM) which depends upon the statistical features such as first order, second order and moment invariants extracted from the image slices. To reduce the number of features selected, feature selection process is performed by means of GA. The optimized output of GA is used for training the SOM. SOM outputs are further clustered using an efficient EGS algorithm. EGS-SOM is robust under noisy and bad intensity conditions and provides good segmented results with high resolution images.

Real MR brain images from Internet Brain Segmentation Repository (IBSR) are used for the segmentation. The performance evaluation is carried out by using tanimoto performance matrix. Tanimoto performance index shows that HFS-SOM has mean and standard deviation of 0.60 ± 0.1 for WM, 0.60 ± 0.15 for GM and 0.22 ± 0.08 for CSF. Corresponding value for EGS–SOM is 0.70 ± 0.04 for WM, 0.70 ± 0.04 for GM and0.1 ± 0.05 for CSF.

3.4. SOM and Knowledge Based Expert System

Knowledge based expert systems are used in the situations where experts are needed such as for analysis and diagnosis. In [12], SOM and knowledge based system are combined for medical image segmentation. In this method, feature vector elements are formed by extracting image intensities, first order features and second order features. Then a PCA is used to select the discriminative set of features from the extracted feature set. PCA is mainly used to identifying patterns in data and highlight the similarities and differences in data. The selected feature vectors are used to perform SOM modeling. After the SOM modeling, knowledge based system is used to label of the segments. The best way to construct a knowledge base is to make a rule set. Rules for the brain tissues, suspicious region and background are constructed using region properties and neighborhood function. Brain model is used to test the performance of segmentation. The brain model gives 97.46% accuracy and 11.36s working time.

3.5. SOM and Wavelet transform

A. Demirhan et al. [13] uses an anisotropic filtering in the preprocessing stage to improve the quality of the brain image without blurring the edges. Stationary Wavelet Transform (SWT) is applied to images to obtain the multi-resolution information about tissues. In this method no sub-sampling process is applied, so subimages obtained as a result of the transform is the same size as the original image. Then statistical features are extracted from the SWT subimages using spatial filtering process. The set of feature vectors formed by combining SWT coefficients and its statistical features are used to model SOM. After the training of SOM, LVQ1 and LVQ2 algorithms are used for tuning the weight vector of SOM. As a result, MR brain images are segmented into soft brain tissues and background regions.

Images obtained from the IBSR database are used for training and testing the SOM. Rough and fine tuning training of SOM require [0.5 0.05] epochs respectively. Performance measurement using tanimoto similarity metric gives an average value of 0.65 and 0.55 for GM and WM respectively. Instead Dice similarity index gives value of 0.7 and 0.78 for GM and WM respectively.

3.6. SOM-FCM and 3D Statistical Descriptors

In [14], A. Ortiz et al. proposed a segmentation technique based on 3D statistical features. In addition to 3D statistical features, local histogram features are extracted from the image. GA based selection stage is performed over the extracted features to form an optimized number of feature vectors. These feature vectors are modeled by SOM. SOM reduced the feature space to a number of prototypes, each of them representing the set of voxels. These prototypes are grouped together to define the cluster boarder in the SOM layer by using a FCM algorithm. Here the fuzzy clustering and unsupervised vector quantization does not use any a priori information. FCM addresses the problem of partial volume effect (PVE) (ie, Voxels can contain signal from several tissues at the same time) by the usage of FCM membership function. Jaccard Index used for the performance evaluation of segmentation gives mean and standard deviation of 0.83 ± 0.02 for WM and 0.82 ± 0.02 for GM.

3.7. GHSOM and Multi-objective Optimization

A. Ortiz et al. [15] improved the SOM performance by introducing Growing Hierarchical Self-Organizing Map (GHSOM) and multi-objective based feature selection technique to optimize the performance of segmentation. The main drawback of SOM is that size of the output map need to be selected before classification. GHSOM is a variant of SOM which grows dynamically and allow discovering inherent hierarchies on the data. GHSOM contains several SOM layers of variable size. During training process, the number of SOM maps and size of map is determined. The feature vectors selected from an image has greater influence in segmentation process because the odd features may cause misclassification. Selecting discriminative features may improve the performance of classifications. To improve the results of GHSOM process, multi-objective optimization is used in feature selection stage. Once GHSOM is trained, classification is performed by using probability labeling method. Labels obtained from the IBSR database is used for calculating the tanimoto coefficient.

3.8. ASGHSOM

J. Zhang et al. [16] presented an Adaptive Growing Hierarchical SOM (ASGHSOM). It is an extension of SOM. In ASGHSOM multi-scale segmentation is fused with the competitive learning clustering algorithm to overcome the problem of overlapping gray-scale intensities on boundary regions. An adaptive spatial distance is integrated with ASGHSOM to reduce the noise effect and the classification ambiguity. ASGHSOM uses multiple SOM from low resolution level to high resolution level, but number of neurons in each layer is fixed. During training stage ASGHSOM layer uses the original SOM algorithm with adaptive spatial distance. Analysis of results of ASGHSOM and GHSOM shows that when the noise level increases in the image, ASGHSOM has better performance than GHSOM. Segmentation is performed on both simulated and real MR images. The simulated image is obtained from the BrainWeb simulated brain database and the real image is taken from IBSR database. Tanimoto performance metric gives mean and standard deviation of 0.69 ± 0.08 for GM and 0.66 ± 0.07 for WM.

Table 1 shows the different SOM based segmentation techniques and their main characteristics.

Table 1: Characteristics of SOM based segmentation methods

Method	**Features extracted**	**Feature selection**	**Main characteristics**
HFS-SOM	Image histogram features (4 features)	-	Efficient and fast
EGS-SOM	Statistical image descriptors (24 features)	GA	Robust scheme under noisy and bad intensity conditions
Wavelet transform and SOM	Feature vectors formed by combining SWT and its statistical features	-	Shows better segmentation result for GM and give average result for WM
SOM-FCM	3D statistical image descriptors, local histogram features (23 features)	GA	Solves the PVE, reduce noise effect and classification ambiguity
SOM and knowledge based expert Systems	Statistical image descriptors (21 features)	PCA	Accurate labeling of tissues
GHSOM	Statistical image descriptors (24 features)	Multi objective optimization	Avoids the drawbacks of the SOM, by growing map size dynamically
ASGHSOM	Features such as intensity, average gradient, mean value of voxels	-	Solve the partial volume effect, reduce noise effect and classification ambiguity

IV. CONCLUSION

In this survey different methods for the segmentation of MR brain images using SOM are analyzed. The survey shows that SOM gives better segmentation results. Normally SOM is a hard clustering algorithm over feature vectors selected. Even though it is good for medical image segmentation, SOM shows some drawbacks. Quality of SOM depends on the feature vectors used for training. Fixed map size is another factor that affects SOM, which can be overcome by using GHSOM or ASGHSOM.

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