MR Brain Image Segmentation Based on Self-Organizing Map Network

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Abstract

Magnetic resonance imaging (MRI) is an advanced medical imaging technique providing rich information about the human soft tissue anatomy. The goal of magnetic resonance (MR) image segmentation is to accurately identify the principal tissue structures in these image volumes. A new unsupervised MR image segmentation method based on self-organizing feature map (SOFM) network is presented. The algorithm includes spatial constraints by using a Markov Random Field (MRF) model. The MRF term introduces the prior distribution with clique potentials and thus improves the segmentation results without having extra data samples in the training set or a complicated network structure. The simulation results demonstrate that the proposed algorithm is promising.

Keyword: Magnetic resonance imaging, Self-organising feature maps, Markov random field, White matter, Grey matter, Cerebrospinal fluid.

I. Introduction

Magnetic resonance imaging is an advanced medical imaging technique providing rich information about the human soft tissue anatomy [1]. It has several advantages over other imaging techniques. MRI can provide three-dimensional (3D) data with high contrast between soft tissues. However, the amount of data is far too much for manual interpretation and analysis, and this has been one of the biggest problems in the effective use of MRI.

In the specific case of brain MRI, the problem of segmentation is particularly critical for both diagnosis and treatment purposes. In these cases, the accurate location of a lesion is directly related to an early detection of a potential pathology, as well as to minimizing the damage to healthy tissues that can be caused by therapy procedures such as radio-surgery. The brain MRI offers a valuable method to perform pre-and-post surgical evaluations, which are keys to define procedures and to verify their effects. Therefore, it is necessary to develop algorithms to obtain robust image segmentation such that the following may be observed:

- Automatic and semi-automatic delineation of areas to be treated to radio-surgery.
- Delineation of tumours before and after surgical or radio-surgical intervention.

- Tissue classification: Volumes of white matter(WM), Grey matter(GM), Cerebrospinal fluid (CSF), Skull, Scalp and abnormal tissues.

Tissue classification is also of importance in the study of neuro degenerative diseases such as Alzheimer's disease and multi-infarct dementia.

MRI is unique among diagnostic imaging modalities because it employs several independent parameters which determine the image scale. The image intensity permits the detailed visualisation of the internal anatomical structures in living human subjects. MR image parameters include tissue relaxation times: the spin-lattice relaxation time (T1) and the spin-spin relaxation time (T2), and the proton density (PD). The goal of MR image segmentation is to accurately identify the principal tissue structures in these image volumes.

There are several typical MRI segmentation approaches as follows:

1. Threshold techniques: where the classification of each pixel depends on its own information such as intensity and colour information. Those techniques are efficient when the histograms of objects and background are clearly separated.
2. Edge-based methods are focused on detecting contour. They fail when the image is blurry or too complex to identify a given border.
3. Region-based segmentation: in which the concept of extracting features (similar texture, intensity levels, homogeneity or sharpness) from a pixel and its neighbours is exploited to derive relevant information for each pixel.
4. Cooperative hierarchical computation approach: Use pyramid structures to associate the image properties to an array of father nodes, selecting iteratively the point that average or associate to a certain image value.
5. Statistical approaches: This type of method labels pixels according to probability values, which are determined based on the intensity distribution of the image. With a suitable assumption about the distribution, statistical techniques attempt to solve the problem of estimating the associated class label, given only the intensity for each pixel. Such an estimation problem is necessarily formulated from an established criterion.
6. ANN image segmentation techniques: originated from clustering algorithms and pattern recognition methods. They usually aim to develop unsupervised segmentation algorithms

Sometimes, the above segmentation approaches are overlapped and can be combined. Several brain MRI segmentation techniques using neural networks are reviewed in literature [2]-[6]. The most famous unsupervised approach using ANN, the self-organizing feature maps (SOFM), developed by Kohonen [7] is a strong candidate for continuous valued unsupervised pattern recognition.

We develop a new unsupervised MRI segmentation method based on the SOFM network in this paper. The algorithm includes spatial constraints by using a Markov Random Field (MRF) model. Many researchers have applied the MRF to model the spatial constraints in supervised and semi-supervised segmentation algorithms [1], [8]-[10]. In this paper, we model the contextual information in the brain MRI with MRF and add the model in the SOFM learning. The MRF term introduces the prior distribution with clique potentials and thus improves the segmentation results.

The rest of the paper is organised as follows: The proposed algorithm is described in the next section. Experimental results are presented in Section 3. Finally, the paper is concluded in Section 4.

II. The Algorithm

MR images are large data sets with an important number of independent variables and complex relationships. They usually show a nonlinear character that makes classical statistical methods particularly inappropriate for their analysis. It is suggested that neural networks are good approaches to analyse such MR data and classify different tissues of texture, intensity or contrast.

A. The Self-organizing Feature Map

The basic SOFM model consists of two layers. The first layer contains the input nodes and the second one contains the output nodes. The output nodes are arranged in a two dimensional grid as shown in Figure 1.

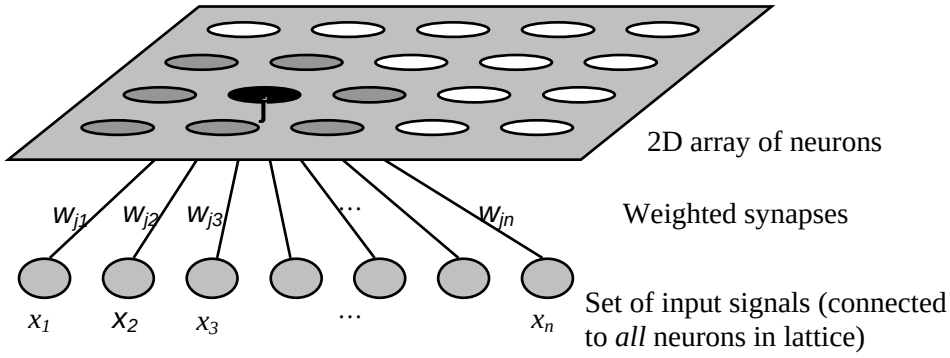


Figure 1 The Self-Organising Map Network

Every input is connected extensively to every output node via adjustable weights. Let $X=[x_0, x_1, x_2, \ldots, x_{N-1}]^T$ be a set of N inputs in R^N such that each x_i has N dimensions (or features). Let P be the number of output node and $W_j = [w_{0j}, w_{1j}, \ldots, w_{(N-1)j}]^T$ denote the weights or reference vectors. x_i denotes the input to output node j and w_{ij} is the weight from input node i to the output node j. W_j is the vector containing all of the weights from N input nodes to output node j. Updating weights for any given inputs in SOFM form is done only for output units in a localized neighbourhood. The neighbourhood is centred on the output node whose distance d_{ij} is minimum. The measurement of d_{ij} is an Euclidean distance, defined as:

$$d_{ij} = \min_j \| x_i - w_{ij} \|^2 \quad (1)$$

The neighborhood decreases in size with time until only a single node is inside its bounds. A learning rate, $\alpha_{ij}(t)$, is also required which decreases monotonically in time. The weight updating rule is as follows:

$$w_{ij}(t+1) = w_{ij}(t) + \alpha_{ij}(t)(x_i - w_{ij}(t)) \quad (2)$$

The algorithm works as shown in [2], [3] and [6]. However, SOFM algorithms are, firstly, highly dependent on the training data representatives and the initialisation of the connection weights. Secondly, they are very computationally expensive since as the dimensions of the data increases, dimension reduction visualization techniques become more important, but unfortunately the time to compute them also increases. For calculating that black and white similarity map, the more neighbours we use to calculate the distance the better similarity map we will get, but the number of distances the algorithm needs to compute increases exponentially.

B. The Markov Random Field Model

For better segmentation results, we add the extra spatial constraints into the SOFM training algorithm to update the connection weights by introducing the Markov Random Field model. In a normal brain images, the tissues are classified as WM, GM, CSF, Skull, Scalp and the background, The intensity of pixel *i* in the image is denoted by s_i and its label denoted by f_i. $f_i = c_i$ means that the pixel *i* belongs to region c_i. Let $F-\{f_i\}$ indicate the segmentation of the image except the *ith* pixel $i(f_i)$.

The spatial connectivity (region process) is modelled by a Markov random field as:

$$P(f_i \mid F-\{f_i\}) = P(f_i \mid f_j, j \in N_i). \tag{3}$$

Here N_i indicates the neighbourhood of the pixel *i*. According to the Hammerley-Clifford theorem [11], the density of *f* is given by the Gibbs density which has the following form:

$$P(f_i \mid f_j, j \in N_i) = \frac{1}{Z}\exp\{-\sum_{C_i} V_c(f_i)\} \tag{4}$$

Here C_i is the set of all possible cliques that include *ith* pixel. $V_C(f_i)$ is clique potentials. The value of $V_C(f_i)$ depends on the local configuration on the clique *c*. $Z = \sum_{f \in F} e^{-\sum_{c \in C} V_c(f)}$ is a normalizing constant called the partition function.

$$U(f_i) = \sum_{C_i} V_c(f_i) \tag{5}$$

$U(f_i)$ is a sum of clique potentials $V_C(f_i)$ over all possible cliques *C*. It is the energy function, which is called MRF term in the paper.

The four-neighborhood is used, so that there are only one-point and two-point cliques. The two point clique potentials are defined as:

$$V_c(f) = \begin{cases} -\xi(s_i - \mu_{f_i}) & \text{if } f_i = f_j \text{ and } i, j \in C \\ 0 & \text{if } f_i \neq f_j \text{ and } i, j \in C \end{cases} \tag{6}$$

Here $0 < \xi < 1$ and μ_{f_i} is the mean intensity of region f_i.

C. The Modified SOFM Algorithm

By taking Equation (5) into consideration, the final modified SOFM weight connection update rule is:

$$w_{ij}(t+1) = w_{ij}(t) + \alpha_{ij}(t)(x_i - w_{ij}(t)) + U(f_i) \tag{7}$$

The MRF term, $U(f_i)$, is added to characterize the spatial clustering of pixels into regions. It provides prior spatial information regarding the size, shape and orientation of the regions to be segmented. The spatial smoothness constraint accounts for the natural contiguity of pixels belonging to the same tissue type. If a pixel is a certain tissue type, the neighbour pixels should

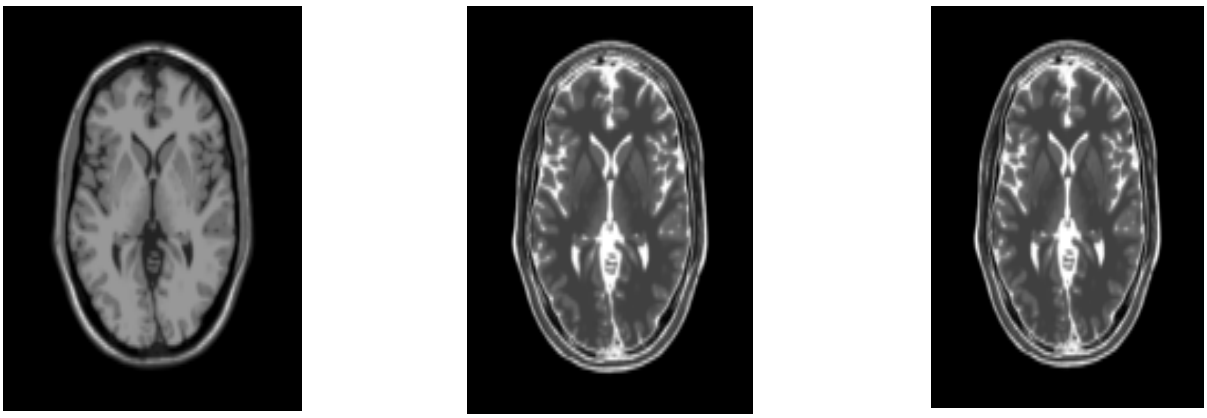
have a high probability of being the same tissue type. The MRF term improves the segmentation results without adding more data samples into the training set.

III. The Experimental Results

The above modified SOFM neural network is employed to segment MR images in this section. The inputs to the network are the corresponding T1-weighted, T2-weighted, and PD image intensity values for each training pixel. The resulting six outputs of the network are the segmented tissue classes, namely the scalp, skull, CSF, cortex (greymatter), white matter, and background.

The MR images used in this paper are obtained from the *http://www.bic.mni.mcgill.ca/brainweb* web site in Montreal Neurological Institute, McGill University, McConnell Brain Imaging Centre (McBIC)[12]. The database is the result of a research work developed at McBIC and contains quantitative 3D investigation of brain structure and function. The brain phantom and simulated MR images have been made publicly available and can be used to test algorithms such as classification procedures which seek to identify the tissue 'type" of each image pixel [13]. The three modalities, T1-weighted, T2-weighted and PD are downloaded from the website as our experimental data. The training sets are selected from the representative regions of interests. To guarantee the correct sampling on all the modalities and anatomical models, the training set are selected arbitrarily according to the coordinates on one of the images and are automatically echoed on the two others. The pixel's coordinates, intensity values, and class memberships are then stored in one file as the training set. For testing set, another set of data are arbitrarily selected in the same way.

Figure 2 shows the three planar multi-spectra brain images: T1-weighted, T2 weighted and PD images used in the experiments.



T1-weighted T2-weighted PD Modality

Figure 2 The planar simulated T1, T2 and PD brain images

The segmented Gray matter, CSF and Scalp using the proposed method are shown in Figure 3. It is noted that there is still noise, some "pepper and salt", in the images in the figure. Similar results are also happened in White matter, Skull and Background. The training iterations are 2000 for the results shown in Figure 3. More training iterations can improve the problem though much longer training time is needed. Due to the simplicity of the network used, it is noted that the number of the training cycles should be more than 3000 for a better segmentation.

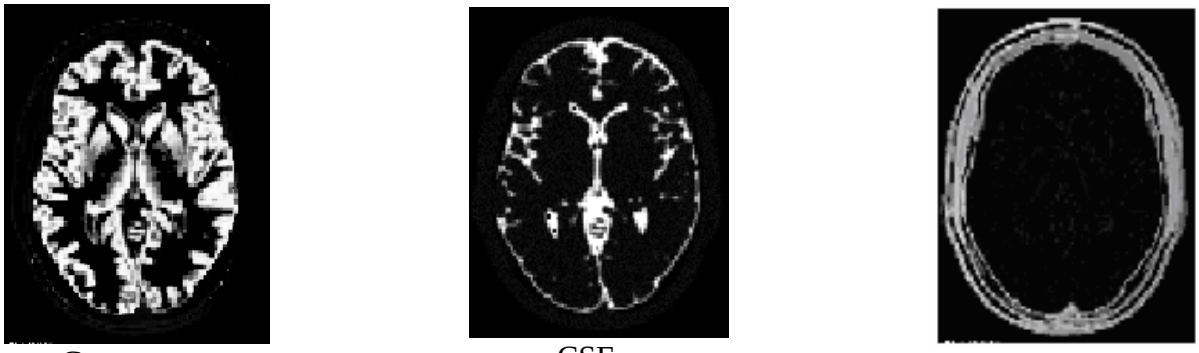


Figure 3 The segmented tissues: Grey matter, CSF and Scalp with 2000 training iterations

Figure 4 shows the segmented White matter, CSF, Grey Matter, Scalp, Skull and Background results with 3200 training iterations. The results are much better, however, still with a little noise.

It is observed that the spatial constraint, the Markov Random Field (MRF) term, should not be considered as the main factor for the image segmentation. The MRF constraint is used to help eliminate the effect of noise and smooth the boundaries. ξ=0.37 for the results shown in Figure 3 and 4.

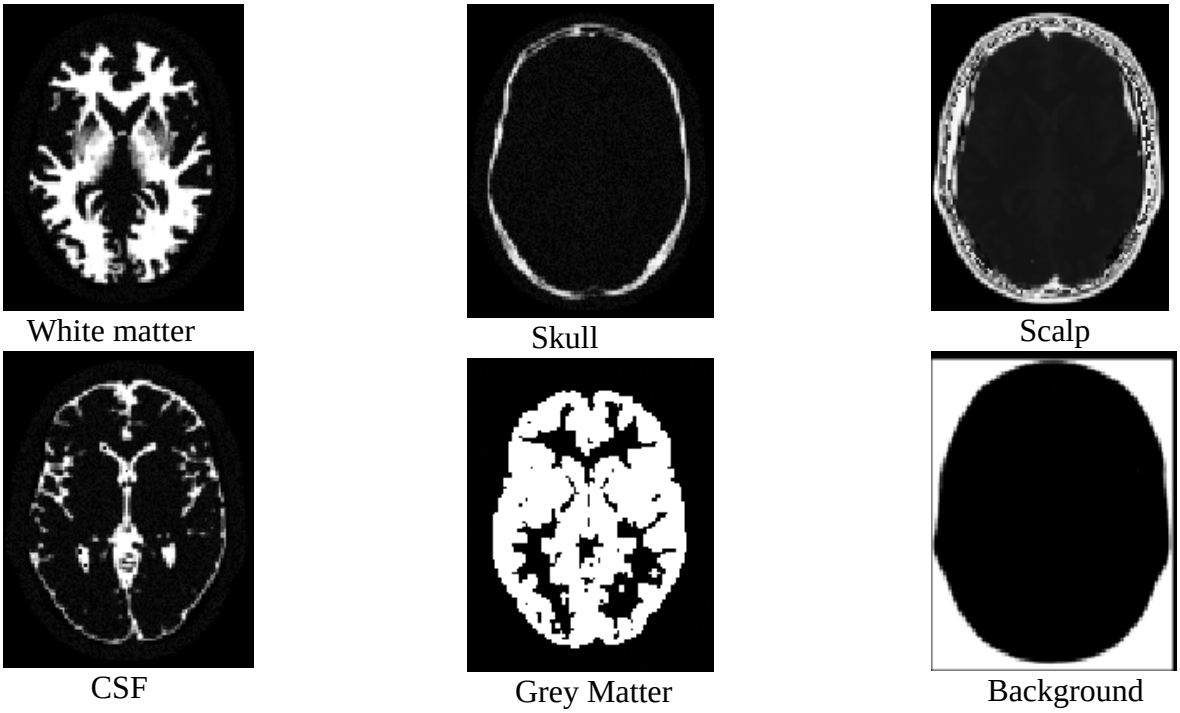


Figure 4 The segmented tissues using 3200 training iterations

Figure 5 shows the brain MR image Phantoms. They are considered as the true segmented tissues used in this paper.

Table 1 shows the comparison errors of the segmented images in Figure 4 and the brain MR image Phantoms in Figure 5. Because the number of pixels in different segments (such as White matter,

Scalp and Grey matter etc.) is different, the segmentation error is compared individually for each segmented image. The performance measurement is the sum of mean squared errors pixel by pixel.

$$\sum_{i=1}^{n}(o_i - s_i)^2 \tag{8}$$

Where o_i is the intensity value in a Phantom image at pixel i. s_i is the intensity value in the corresponding segmented image at pixel i. n is the total pixel number for the concerned tissue type in an image.

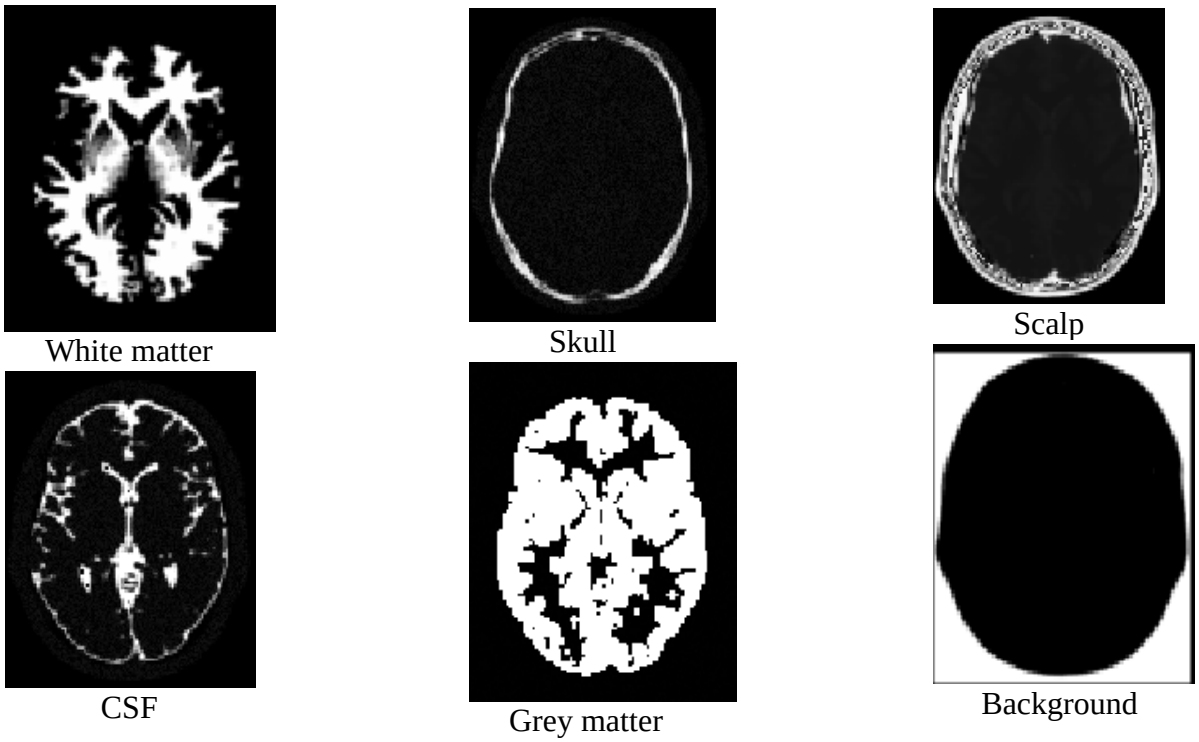


Figure 5 The brain MR image Phantoms

Table 1 The comparison errors between the segmented images and Phantoms

Tissue Type	White matter	CSF	Skull	Grey matter	Scalp	Background
MSE	2.638	1.825	0.649	3.742	1.384	4.219

Additional experiments were performed with the pixel's coordinates as extra inputs to the neural network. The results were unsatisfactory considering the additional complexity and training time as no reasonable segmentation was available. It is, probably, because the coordinates on their own do not carry on the classification information of the tissues.

IV. Conclusion

MR image segmentation is an important but inherently difficult problem in medical image processing. In general, it can not be solved using straightforward, conventional image processing techniques. Due to the characteristics of MR images, development of automated algorithms is challenging. There is a significant inter-patient variation of signal intensities for one same tissue type because of partial volume effect, inherent noise and wide range of imaging parameters, which affect the tissue intensities.

In this paper, we present a new unsupervised MRI segmentation method based on self-organising feature map. The proposed algorithm includes extra spatial information about a pixel region by using a Markov Random Field (MRF) model. The MRF term improves the segmentation results without extra data samples in the training set. The cooperation of MRF into SOFM has shown its great potentials as MRF term models the smoothness of the segmented regions. It verifies that the neighboring pixels should have similar segmentation assignment unless they are on the boundary of two distinct regions.

The simulation results demonstrate that the proposed algorithm works well. The further work is to compare the method with other existing approaches.

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