Brain Magnetic Resonance Images Segmentation via Wavelet-Based Neural Network Approach

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Abstract

A fast, effective and robust wavelet-based neural network approach is realized for the purpose of segmentation of magnetic resonance images in the present research. It should be noted that magnetic resonance image should be considered as reference image in clinical research currently. The segmentation of magnetic resonance images of brain is aimed to specify the structure of its original tissues precisely. The nature of brain can basically be divided into three parts: firstly, the white matter, secondly, the gray matter and, thirdly, the cerebrospinal fluid, as well. The segmentation of magnetic resonance images of brain is here carried out using the following steps: a set of images, collected as the reference data, at first. Each part of the brain in these images as well as the background of the images is then cut and the cut pieces are placed in four separate classes. Subsequently, in the next step, features are extracted from each of these classes by the method of wavelet coefficients and Laws filter, and are given to the neural network for training. Neural network with wavelet transfer function also performs the segmentation process.

Keywords: Feature extraction, Segmentation, Wavelet transform, Magnetic Resonance Image (MRI), Neural network.

Introduction

Segmentation has been the main problem in image analysis, and would probably remain so for long times. Segmentation plays a crucial role in medical imaging by automating and facilitating the description of anatomical structures and other desired regions (Zhang et al., 2005). Segmentation of magnetic resonance images (MR) is extremely important to confirm and improve the treatment, select the route of operation and evaluate the treatment efficacy (Tian & Fan, 2010). MR imaging is the most common used method in radio imaging (Prince & Links, 2006; Macovski, 1983). With the increased use of MR imaging for clinical studies, diagnosis and treatment planning, the use of computer has been almost essential to help radiological skills in clinical diagnosis and treatment planning. Since manual segmentation results depend heavily on the user, automatic and stable algorithms are needed to describe the anatomical structures and other desired areas. Objectives of computer-aided diagnosis (CAD) are as follows: creating a three-dimensional view and reconstructing the brain anatomy of patient, planning surgery, advancing surgery, automating routine so that one can do a lot of tasks with the same accuracy, obtain fast and accurate results, and communicate more quickly in the place where patient care should be done remotely (Sharma & Agganwal, 2009).

Brain is essentially divided into three parts: the white matter (WM), gray matter (GM) and the cerebrospinal fluid (CSF). Precise segmentation of the components is necessary for applications in research, diagnosis and treatment. MR imaging can produce a large number of different images from the same section of internal anatomical structures of the brain, the differences of which are due to local changes of spin-lattice relaxation time (T1), spin-spin relaxation time (T2) and proton density (PD) (Javeed Hussain et al., 2011). Thus, MR images can be divided into the three images sets T1, T2 and PD-weighted, in which the brightness of tissues appears to be different. Compared to other imaging techniques such as computed tomography, MR imaging is less harmful to human health, and has better effect of imaging on the brain parenchyma (Tian & Fan, 2010). For the segmentation of brain MR image, there are many advanced algorithms proposed, such as threshold methods (Suzuki & Toriwaki, 1991), edge-based methods (Lin et al., 2002), region growing methods (Fan et al., 2001), statistical methods (Pieczynski et al., 2002), methods of artificial neural
network (Shen et al., 2005; Middleton & Damper, 2004), etc. Because of their robustness and easy availability in the image processing, great attention has been paid to the approaches of neural networks, however, a very long training time and the influence of noise on its results are the disadvantages that limit the use of this technique (Tian & Fan, 2010). Various artificial neural networks have been used for image segmentation. Segmentation method using artificial neural network was introduced in (Alirezaie et al., 1997). Moghaddam and Soltanian-Zadeh (2009) improved the method of neural network segmentation by the aid of MLP neural network and geometric moment invariants (GMI). One of the most popular methods is the segmentation by SOM neural networks (Reddick et al., 1998; Ahmed and Farag, 1997). Another popular approach to neural network is probabilistic neural network (PNN) (Christensen, 2003; Wang et al., 1998), which makes use of PNN to create a probability density function to approximate the desired region. to overcome the limitations of automatic or semi-automatic segmentation methods by a neural network, new combined methods have been proposed. Reddick et al (1997) have suggested a combination of SOM and multilayer back propagation neural network for the segmentation of brain. Middleton et al (2004) proposed a different approach by combining neural networks and active contour models. An approach combining the wavelet transform and neural networks was proposed for the segmentation of a certain part of the brain called put amem (Liu et al., 2006).

In this study wavelet coefficients and Laws filter are used to extract the features of images. A MLP neural network with wavelet transfer function was used for segmentation, which is much faster and more accurate than previous methods. To train the wavelet neural network, a set of MR images was considered and each of the three parts of the brain (white matter, gray matter and cerebrospinal fluid) in these images and also their background were cut and placed in four separate classes: their feature vectors were then extracted. This feature vectors have been given to wavelet neural network for training. In Section 2, a new solution titled the proposed method for the segmentation of brain MR images has been presented, since in Section 3, the results obtained from the simulation on two brain MR images are shown and the percentage of correct segmentation of the proposed algorithm is calculated. The concluding remark is finally given in Section 4.

**The proposed method for the segmentation of brain MR images**

In this paper, a new algorithm is presented, which has not been so far used in the segmentation of brain MR images. In this method, a set of images was first considered as reference data for training the neural network. For training the neural network by the images, their features need to be extracted. Thus, four classes have been considered: the first class includes cut pieces of the brain white matter associated with reference images, the second class is related to the gray matter of these images, the third class is related to the Cerebrospinal fluid; and the fourth class is related to the background. The feature vector of each class, which is representative of that class, has then been given to wavelet neural network for training. To segment the images of input test, their features must first be extracted and therefore the MR images of the brain are divided into windows with size of D×D. In other words, an image with a size of M×N is converted to M/D×M/D images with a size of D×D using this technique. The features are then extracted from all these windows. The main idea of this paper is its new feature extracting method. After feature extraction, feature vector is given to the wavelet neural network; and depending on the input feature vector, the neural network recognizes the class to which the window belongs; and thus, the operation of segmentation is performed by wavelet neural network.

**Feature extraction**

One of the most sensitive parts of the pattern classification tasks is the selection of features proportional to the system application. The algorithm that is used in this study to extract feature is as follows: image input is converted to windows with the size of D×D, the Haar wavelet coefficients at level 5 are then calculated for each window.

Frequency content of a signal can be obtained by frequency analysis. The most common method for frequency analysis of the signals is Fourier transform which determines which frequencies with which amount are in the signal. Stationary signals have time-invariant frequency content; and all frequency components exist at all times. Therefore, the Fourier transform is suitable for the analysis of stationary signals; but this transform is not suitable for frequency analysis of non- stationary signals in which the frequency content changes with time. In other words, the Fourier transform cannot detect the time during which a particular frequency appears in the signal, and shows only the frequencies that exist in the signal. Therefore, the need to display the time and signal frequencies at the same time is felt. The solution to this problem is the wavelet transform. This transform, which was introduced in the early 80s by Morlet et al was used as a new tool for the analysis of seismic signals. Since then, many different types of wavelet transforms have been developed, and have found many other uses. Continuous wavelet transform (CWT) has found its greatest application in the data analysis.

The most famous type of these transforms is discrete wavelet transform (DWT). This transform has the most excellent properties of signal compression for many real-world signals along with highly efficient computational aspects. Thus, it is used in almost all technical fields, including image compression, numerical integration and pattern recognition. If an image is illustrated carefully, the closed areas will be found that have the same backgrounds or similar gray levels, and form an object. If an object has a small size or low contrast, it will be investigated at high resolution; and if it has a large size or high contrast it can be evaluated at lower resolutions. All these objects together lead us towards processing at different scales. This is the main reason for multi-resolution processing. Discrete wavelet transform is performed in two dimensions, using separable filters, in a way that the filter is first applied along the rows, and the corresponding filter is then applied to the image along the columns. By doing so, the image is divided into four images, wherein the number of pixels would be the quadrant of the actual image after the samples were removed. After each stage, there are four sub-bands of images. Four images obtained are referred to as LL and LH and HL and HH. Image LL, which has the original body of the image, is called approximation. Images HL, HH and LH, are called vertical details, horizontal
details and two-dimensional details, respectively. Unlike the other three images which include details such as edges, image LL includes basic information of an image with a lower resolution. In fact, processing of multi-resolution algorithms is performed on this image that includes the original data. To extract the shorter feature vector, it is reasonable to apply discrete wavelet to the image LL so that a deeper decomposition of the image are acquired, and so forth.

In this paper, feature vectors are obtained by calculating the mean, standard deviation and variance of the vertical details, horizontal details, and two-dimensional details calculated from the image decomposition by wavelet at level 5. A schematic image of the decomposition at level 5 is shown in figure 1.

![Figure 1. Applying 2D-DWT a Original image b Decomposition at level 5.](image)

The next feature used is Laws filter. In this study, the Laws filter of E3L3 type was used, which was normalized by the following coefficient:

\[
Laws = \frac{1}{12} \begin{bmatrix} 1 & 0 & -1 \\ 2 & 0 & -2 \\ 1 & 0 & -1 \end{bmatrix}
\]

After applying the above filter on the cut image, the mean and the standard deviation were calculated from the resulting matrix. Finally, the feature vectors are put together, and the final feature vector is obtained. Since the optimal set of features is unknown, there are usually two common methods for feature selection: forward selection and backward elimination. The forward selection method, which starts with a set of features, adds the features one by one to the set until the final set is formed. The backward elimination method provides a full set of features and removes inefficient features one by one until the optimal set of features is finally formed. In this study, the method of forward selection is used to select a set of features.

**Wavelet-based neural network**

In wavelet neural network, the theories of wavelet and neural network are combined together. In general, a wavelet neural network is composed of a feed forward neural network with one hidden layer, wherein the activation function belongs to the family of orthonormal wavelet. In this method, a neural network is used for segmentation, wherein the transfer function is Mexican Hat wavelet, and the hidden layer consists of 10 neurons. The relation of Mexican Hat wavelet used is as follows:

\[
\psi(t) = \frac{2}{\sqrt{3}\sigma\pi^4} \left(1 - \frac{t^2}{\sigma^2}\right) e^{-\frac{t^2}{2\sigma^2}} (1)
\]

In the above equation, \(\sigma\) is called the scale parameter or dilation, which specifies the width of Mexican Hat wavelet function and is equivalent to the standard deviation of the Gaussian function. Given the input feature vector, the trained neural network recognizes the class to which the input window. The block diagram of the research done is given in Figure 2.
Results

Performance of the proposed algorithm on the arbitrary input MR image of T1 type is shown in this section. Firstly, the bior 5.5 and Daubechies 4 wavelets along with the Laws filter were used to extract features, and the results are given in Figure 3. As can be seen in Figure 3, the results have no acceptable precision, and some areas were not correctly classified. This is why Haar wavelet was used here, and the results are shown in Figure 4. It should be noted that the D was considered to be equal to 5.

Figure 3. Segmentation results of the proposed algorithm a Input MR image b Output image by extracting features through bior5.5 wavelet coefficients and Laws filter c Output image by extracting features through Daubechies 4 wavelet coefficients and Laws filter.

Figure 4. The images on the left are the input MR images, and the images on the right are the segmented images obtained by the proposed algorithm by extracting features through Haar wavelet and Laws filter.
As can be seen in Figure 4, all parts of the input MR image are fully specified; and white matter, gray matter and the cerebrospinal fluid are well recognizable. They are shown in the output with certain colors. The advantage of the proposed algorithm is that it identifies the white areas resulting from noise as noise, and not as new region. Low quality of input image does not affect the quality of the segmentation. In the proposed method, 50 MR images were tested; output images were compared with the images segmented by an expert; and it was found that the results had very good accuracy in 96 percent of the images.

Conclusion

In this paper, a neural network, in which its transfer function is Mexican Hat wavelet, was used for the segmentation of brain MR images. The wavelet transform and Laws filter were used for feature extraction, which gave better results compared to other feature extraction methods tested on MR images. The method proposed in this study has a good accuracy and is much faster than the other algorithms presented in this regard. In the previous methods proposed, the neural network training time is very long; but a new idea is presented in the proposed method that significantly reduces the time to train the neural network and is robust against noise. The algorithm can be expanded in the future to detect tumors.

References


