An Interactive Tool for Segmentation, Visualization, and Navigation of Magnetic Resonance Images

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Abstract

An interactive tool for the segmentation, visualization and navigation of magnetic resonance (MR) images is presented. Previous work has shown the hierarchical self-organizing map (HSOM) to be highly effective in segmenting MR images at multiple scales or levels of abstraction. The resulting abstraction tree represents the multiscale segmentation of the MR image. A segmented MR image at any desired scale or level of detail can be obtained by appropriate traversal of the abstraction tree. The interactive tool permits traversal of the abstraction tree using a user-friendly graphical user interface (GUI) allowing the user to view the segmented MR image or any portion thereof at the desired level of detail. The tool could be used by radiologists to effectively sift through large amounts of MR image data to arrive at accurate diagnoses in an expeditious manner.

1. Introduction

Segmentation of Magnetic Resonance (MR) images has significant ramifications in clinical medicine. This project investigates the potential of an artificial neural network based technique for the segmentation of MR multispectral images. This project further adds an interactive user interface that enables the user to view the segmented image as a whole or at different scales or levels of abstraction depending on the level of detail required. In addition, since the time requirement for the segmentation process is typically longer than desired, this project adds the ability to losslessly reconstruct from disk the multiscale-segmented image that is generated offline, thus allowing the user to keep records of different segmented images for later evaluation.

Segmentation, in general, seeks to present the relevant information in an image in an accessible manner. Multispectral segmentation is the classification of objects within an image space based on the characteristics of the image space in different spectral bands. The (spectral bands) of interest result in three types of images, namely, the T1, T2, and PD weighted images. In the segmentation of MR images, the goal is to make a distinction between normal and pathological tissues. For instance, in cerebral MR images some of the tissue classes of interest are white matter, gray matter, cerebrospinal fluid and abnormal tissues. Furthermore, in MR images of breast tissue, the tissue classes of interest are fatty tissue, glandular tissue, dense glandular tissue and cancerous tissue.

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2. Related Work

Many techniques have been proposed for multispectral MR image segmentation and classification of tissues [6]. Strictly speaking the process of segmentation needs to be followed by a labeling process where each of the segmented regions gets assigned to a particular tissue class [5]. But several studies on the segmentation of MR images have treated the segmentation problem as one of tissue classification, rather than segmentation in the true sense [1, 7]. By definition, segmentation should take into account both spatial and spectral information in the decision criterion for assigning a pixel to a particular region.

Neural network-based tissue classification in MR images has been investigated using both supervised and unsupervised techniques [4]. In a supervised classification method the unknown pattern is compared with all the reference patterns known as the training set and then placed into one of the classes based on some predefined criterion for degree of similarity. In an unsupervised classification method however, no expected output results (i.e., reference patterns) are presented to the neural network. The network learns by itself to infer the inter-input relationships as more inputs are presented to it. The primary advantage of unsupervised classification is that it adapts better to changing input conditions.

Our segmentation method is an extension of the unsupervised clustering technique using a SOM (Self-Organizing Map) artificial neural network [6], which is a spatially interacting neural network. However, the SOM has its limitations in the context of image segmentation. The number of neural units in the SOM must correspond to the number of "segmentable" areas in the image. This initial determination of the number of neural units in the SOM is very subjective. Any mismatch between the number of classes into which the image can be demarcated and the number of neural units that constitute the SOM will result in an under-segmented or over-segmented image [4].

3. The Hierarchical Self-Organizing Map (HSOM)

Our work investigates the application of a unsupervised clustering technique using a Hierarchical Self-Organizing Map (HSOM) for the segmentation of MR multispectral images [4]. The HSOM consists of several layers of the SOM arranged in a pyramidal fashion. The superiority of the HSOM technique over conventional edge-based segmentation techniques for the segmentation of intensity and range images has been shown [3]. The HSOM seeks to remedy some of the shortcomings of the SOM. The HSOM, like a conventional SOM, is a topology-preserving mapping with the advantage of being less sensitive to choice of neighborhood topology [4]. It combines the concepts of self-organization and topographic mapping with the concept of multiscale segmentation [4]. A multiscale image representation is one where different features in the same image are more explicitly represented at different scales. Thus, the segmented result may be viewed at different levels of abstraction. For example, in an MR image of the human brain, gray matter would be represented at one level of abstraction, white matter in another, etc. This could make the identification of potential pathological situations easier since they would be more easily distinguishable if they were more explicitly represented at an appropriate scale or level of abstraction. Our previous work has shown the HSOM to be very effective in the accurate detection and localization of multiple sclerosis (MS) lesions in MR images of the human brain [4].

The HSOM produces a hierarchical or multiscale segmented image that is a domain-independent abstraction of the input image. Each layer of the HSOM after segmentation represents a particular level of abstraction of the input image. Once the segmented process is completed, a hierarchical structure called an abstraction tree can be generated by including the winning neural units (resulting from the competitive learning process in each HSOM layer) from each layer of the HSOM [4]. Traversing the abstraction tree in a breadth-first manner starting from the root node, with a predefined traversal criterion, generates the segmented image (Fig 4). The abstraction tree has a dynamic quality whereby the number of neural units that come into play at different levels of the pyramidal structure can vary according to the scene content in an image if a scene-dependent tree traversal criterion is used. Therefore, it is expected that the HSOM would perform better than a conventional SOM, which has only a fixed number of neural units. In the HSOM, pixels in those regions which correspond to homogenous image attributes, get mapped to higher levels in the HSOM pyramid whereas the more busy regions map to the lower levels. The output of each layer is presented as input to the next layer higher up in the hierarchy. Thus the information propagates through the layers of decreasing dimension. Since a higher layer in the HSOM pyramid contains fewer neural units and hence fewer weight vectors, each weight vector represents a large cluster in input vector space. This gives rise to two assumptions involved in the construction of the HSOM structure:

- Input image matrix is square ($N_f * N_f$)
- Each competitive (hidden) layer is a square array; first layer may be N*N where N= N_f / 2; subsequent layers are (N/2)*(N/2), …, 4*4, 2*2, 1*1.

The SOM layers are initially seeded with random weight vector values. This renders the method almost completely automatic since we do not start off with any specific predetermined seeding of map layers. The competitive and cooperative phases of learning are repeatedly carried out at each layer until the neighborhood size decreases to zero.

The abstraction tree for the HSOM is constructed using the competitive and cooperative phases of learning. Traversing the tree in a breadth-first manner generates the segmented image. A node in the abstraction tree is expanded if the sum of the variances of the T1, T2, and PD intensity values of the pixels in the region exceeds a predefined threshold, otherwise, the node is labeled as *closed*. A closed node represents a candidate region in the final segmented image. The threshold is determined empirically and typically lies within a specific range for a given class of images. It is also conceivable to use a threshold value that is derived via statistical analysis of the pixel values associated with a node.

The HSOM segmentation method provides good results for the multispectral segmentation of MR images [6]. Since the network is randomly seeded, it requires no user intervention. Hence, the inter-user variability is practically nonexistent. In most segmentation algorithms, spatial information is not taken into account. We incorporate spatial information to ensure that two regions with similar T1, T2, and PD intensity values but differing in spatial coordinates, and hence not connected to each other, will get segmented as different regions. It may be more advantageous to take spatial information into account when studying pathology, which would make pathological tissues, with similar MR characteristics as normal tissues but at different locations, more easily distinguishable.

4. Interactive Visualization and Navigation Tool

The HSOM segmentation process is very time consuming and not practical in real time. We have addressed these problems by adding an Interactive Graphical User Interface (GUI) and the capability of storing the abstraction tree that is generated offline on disk for subsequent reconstruction, traversal, and viewing of the segmented images. The storage structure used for the abstraction tree is a B-Tree file. The GUI interacts with an intervening code that reads in the B-Tree file from disk, and recreates the abstraction tree in memory. The GUI allows the navigation of various regions within the image to be more user-friendly (Fig 1). The user is allowed to traverse the individual layers or view the entire image (Figs 2 and 3). Furthermore, the user is able to create and reconstruct the abstraction tree, and also create various segmented images by varying the threshold through the user interface. The GUI also has the ability to create the abstraction tree online by loading the given T1, T2, and PD weighted intensity images, and creating the HSOM structure for image segmentation. If desired, the abstraction tree, thus created, can be stored on disk for offline viewing and traversal. The addition of the Graphical User Interface and the storage routine enhances the HSOM-based segmentation method by making it more efficient, practical, and an attractive interactive tool for presentation, navigation, and analysis of MR images. This tool could be used by radiologists to effectively sift through large amounts of MR image data to arrive at an accurate diagnosis in a time-efficient manner.

5. Conclusions and Future Work

Our study shows the viability of the HSOM technique for the segmentation of MR multispectral images but much work remains in the area of validation. The segmentation results need to be evaluated against manual segmentation by a radiologist. The algorithm can be extended to include a labeling process, so that our existing boundary following program could be used to delineate the boundaries of potential abnormalities such as lesions, tumors, etc. Incorporation of hierarchical indexing schemes for the abstraction tree to support efficient content-based retrieval of the MR image data also needs to be explored. The software in its current form serves as an important and useful interactive tool for the radiologist to examine large amounts of MR image data in a time-efficient manner.

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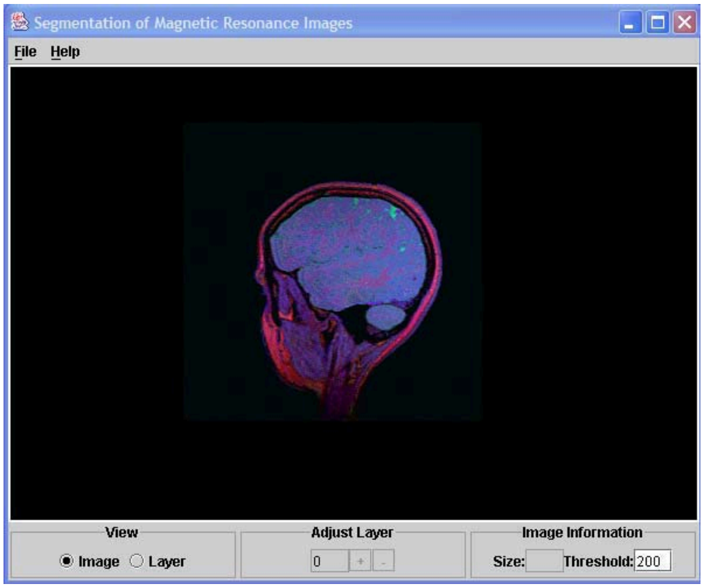

Fig 1. The Graphical User Interface; View of the entire Segmented Image

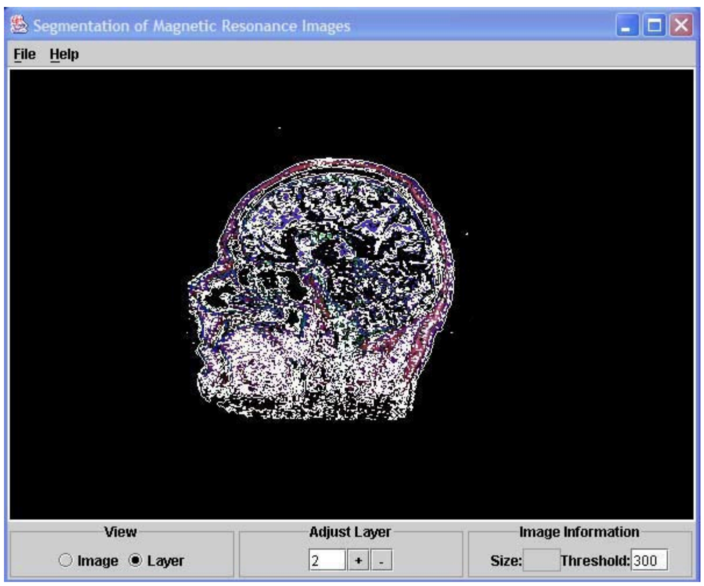

Fig 2. View at Layer 2 with Threshold set to 300

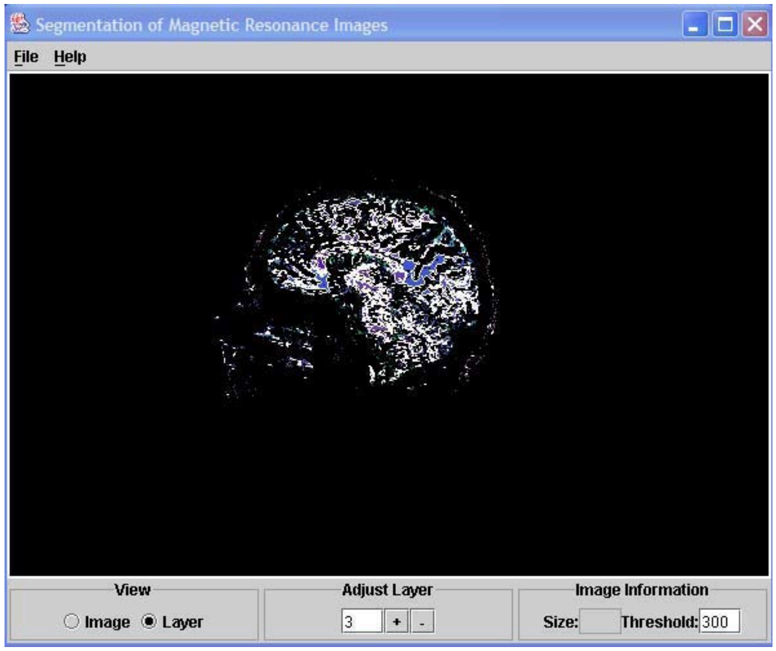

Fig 3. View at Layer 3 with Threshold set to 300

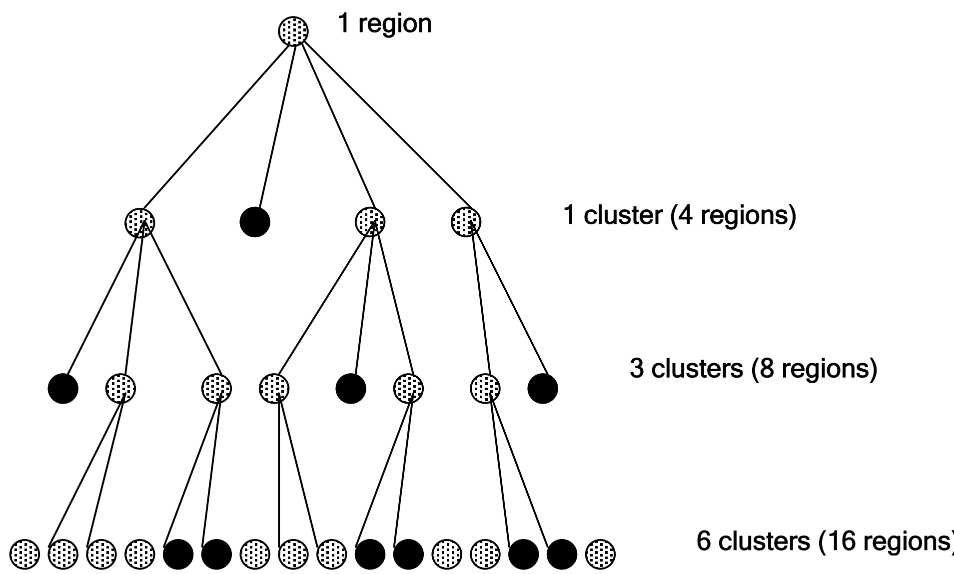

Fig. 4. Abstraction Tree; filled circles represent closed nodes corresponding to segmented regions. Patterned circles are the expandable nodes.