AUTOMATIC SEGMENTATION OF BRAIN MRI THROUGH LEARNING BY EXAMPLE

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ABSTRACT

We propose a method for automatic segmentation of brain magnetic resonance images (MRI) using a new approach based on learning. The learning process uses only two images, the original one and its ideal segmented version to generate the decision matrix for each pixel. Re-using the knowledge acquired in the decision matrix carries the segmentation of another similar images. New images are segmented by means of a strategy based on the nearest neighbors, that seeks the best solution in the decision matrix. Performed tests on magnetic resonance non-enhancing images showed promising results in segmenting non-enhancing brain tumors. The main advantages of this method are the facility to faithfully reproduce the objectives of the user, the use of only two images, and it does not require the use of heuristic parameters neither the interaction of a specialist user after the learning process.

1. INTRODUCTION

Magnetic Resonance Imaging is an advanced medical imaging technique providing rich information about the anatomy of human soft tissue. Segmentation of MR brain images into different classes of tissues is an important task for improving the understanding of many neurological disorders.

Most MRI segmentation techniques can be categorized into automatic and semi-automatic like clustering (k-means and fuzzy c-means clustering [1]), region growing-based [2] morphological [3] and two-dimensional histogram [4] approaches. Most of these techniques require a medical expert to actively control the segmentation process and interactively correct the results. Therefore, the accuracy of the process depends upon the accuracy and repeatability of the necessary operator intervention. Neural networks [5] are also used to learn in order to segment. In this case, it is necessary to train a great group of pairs of images (sample in/ideal out) to ensure a good accuracy

This paper presents a new brain MR image segmentation approach through learning by example strategy. The main idea is to use and take advantage of the user's knowledge and his expertise to segment a gray level image into several classes. The present approach consists in teaching the computer how to segment, employing for this purpose images that possess known solutions. Differently from the neural networks or genetic training algorithms, this approach learns from a single pair of sample/ideal images.

The process consists of two stages, learning and segmentation. In the first stage, a sample image and its ideal segmented image are submitted in order to extract the relevant features around each pixel neighborhood along with its ideal segmented pixel. The term "ideal image" means the expected image generated by an expert. The second stage consists in segmenting new images re-using the knowledge acquired in the decision matrix

2. THE LEARNING APPROACH

Our learning segmentation consists in analyzing two images, the first one in gray scale levels, also called the sample, and the second one being its ideal segmented version. Each pair of pixels proceeding from both images is analyzed in the respective neighborhoods and a set of features is defined. From this step, one feature vector is generated for each pixel and each gray level. The association of this feature vector set with its respective ideal output is named the decision matrix. The generation of this decision matrix needs to:

- Select the appropriate features;
- Compute the feature vector for each pixel in its neighborhood (centered window) in the sample image;
- Adaptively compute the adequate window size of the learning neighborhood. To avoid the existence of two input pixels with the same feature vector and different

ideal outputs, the window must be adaptively resized to eliminate these confusions.

2.1. Feature selection

Among the wide variety of possibilities of features available in literature, efforts were taken to select those that:

- Better define the relationship between the sample image and the ideal segmented image;
- Reproduce the learning results in images of different universes;
- Reduce the computational cost and learning confusions.

The features used in the proposed learning approach are the pixel gray level, neighborhood mean, neighborhood variance and neighborhood gradient mean.

2.2. Adaptive window sizing

Any learning process is efficient only if it is able to recognize and solve any ambiguity. In our approach based on feature extraction between two images, it is not rare to find input pixels with the same gray level corresponding to different ideal outputs (with different gray levels). How to solve this kind of learning ambiguities? For instance, by increasing the feature set, which will expressively increase the computational complexity and cost. Otherwise, by choosing a small feature set and by verifying if it efficiently discriminates the situation into the chosen neighborhood. We decided to perform the second solution and to adaptively adjust the learning window.

The feature computation stage begins with a 3x3 window. In case of two input pixels with the same feature vector but with different ideal outputs, the system detects a conflicting situation, and automatically increases the window size. This process is automatically repeated until no conflicting situation remains. This step concluded, the window size is stored.

2.3. The decision matrix construction

In the decision matrix, the feature vectors computed for all pixels are stored in accordance to the gray levels. The number of feature vectors in the decision matrix is equal to the number of the pair of pixels learned from sample input and its correspondent ideal output images. The decision matrix is built with all its feature vectors ordered sequentially by pixel gray level.

2.4. Application of segmentation for new images

The learning stage solved, the system is ready to segment other similar images. To carry out the segmentation, the system:

- Sets the window size with the value which has permitted to solve the ambiguities;
- Computes the feature vector for each pixel in the new image;
- Find the most similar feature vector in the decision matrix;
- Assign to this pixel the output value stored in the decision matrix.

The Nearest Neighbor strategy was used to find the most similar feature vector in the decision matrix and to select its output value.

4. EXPERIMENTAL RESULTS AND DISCUSSIONS

Tests were carried out onto a MRI database composed of abnormality brain MR images available at the Unified Image Science Lab at PUCPR. The 700 images were obtained using a Shimadzu 50X 0.5T MRI equipment in DICOM format.

The challenge was to extract the abnormality and the gray matter GM classes, which represent the sickest tissues. The learning stage was performed using a partial sample image and its ideal segmented image for each class (Figures 1-(a) to (b) and Figures 2 (a) to (b)). The abnormality and GM class segmentation are shown in Figures 1 and 2 for two brain MR non-enhancing images each. In both cases, it is possible to observe that the proposed method has recovered the two classes as expected. Ideal segmented images were We should emphasize that images used during the learning stage are different from those used in the segmentation stage.

To statistically evaluate the efficiency of our approach, other experimental tests were carried out onto the Montréal Neurological Institute's Simulated Brain Database (SBD) [6]. This public database is available for the neuroimaging community to evaluate the performance of image analysis approaches. It contains a set of realistic MRI data volumes produced by an MRI Simulator, developed at the McConnell Brain Imaging Centre. The advantage of using this database is the availability of groundtruth gray matter (GM), white matter (WM) and cerebrospinal fluid (CSF) classes for each image.

From this simulator, a set of 44 Brain MR images from the Anatomical Model of Normal Brain was generated, composed of 11 simulated normal crisp Brain T1 MRI, and the corresponding GM, WM and CSF groundtruth images. The simulation parameters used were grayscale format with a separation of 5 mm between each slice and 1 mm slice thickness.

To achieve the learning stage for the 3 classes separately, one of 11 simulated Brain images (and its GM, WM and CSF groundtruth images) was randomly chosen. The learning stage solved, the segmentation was performed for the remaining 10 images. The accuracy of the proposed method was measured by computing the pixel similarity between the segmented images and the corresponding ground truth ones. Recall again that images used during the learning stage are not used in the segmentation stage. Figure 3 illustrates the learning-based segmentation results. Figures 3-(a) to (d) respectively represent a sample image and the corresponding CSF, GM and WM groundtruth ones used during the learning stage. Figures 3-(f) to (h) respectively represent the CSF, GM and WM segmented classes relatively to Figure 3-(e). These results can be visually compared with Figures 3-(i) to (k), which represent the CSF, GM and WM groundtruth classes. Independently of the considered class, it can be seen that the learning-based segmentation results are significant and promising. From Table 1, that shows the average segmentation rates for the three classes onto the 10 simulated images, one can verify the accuracy of the proposed method.

Software was developed using VisualC++. Average processing time for the segmentation of a 350 x 350 pixel image is about 10 s running in an AMD 2200xp+ processor.

5. CONCLUSIONS

An automatic segmentation approach of brain magnetic resonance images (MRI) through "learning by example" was presented. The learning procedure is based on computing a feature vector for each pixel in an adaptive window. In our approach, choosing the appropriate window size was fundamental for the overall performance of the process, and it is computed automatically instead of using a fixed-sized one.

The segmentation task is performed on the Nearest Neighbor strategy. Experimental tests on healthy and abnormality non-enhancing images show that the proposed segmentation approach recovers the classes as expected. Main advantages of the proposed method are:

- Learning can be achieved from a single pair of sample/ideal images which can be partial;
- The method does not require the use of heuristic parameters nor the interaction with an expert after the learning process;
- The subjective human operator knowledge can be learned and inserted into an automatic process that can faithfully reproduce it;
- This approach permits a segmentation into several classes;

Pre and post-processing should increase segmentation accuracy results, but they were not used in this work since they are application-dependent.

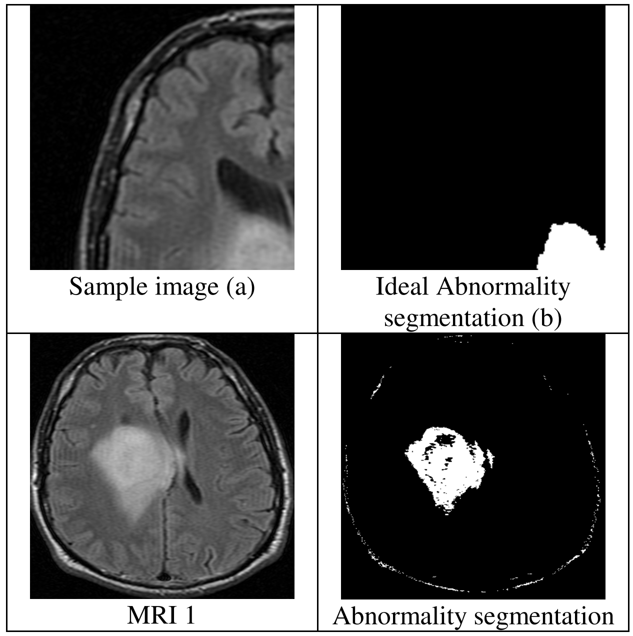

Figure 1. Abnormality segmentation of abnormality brain MR non-enhancing images through learning by example.

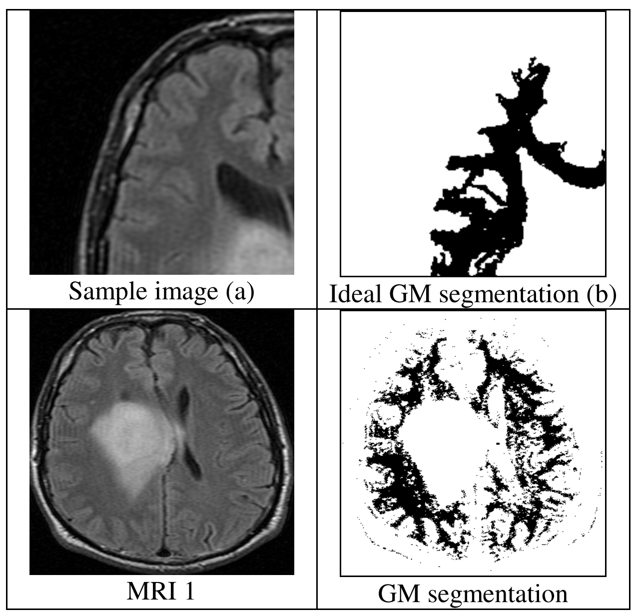

Figure 2. GM segmentation of abnormality brain MR non-enhancing images through learning by example.

6. REFERENCES

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Table 1. Average segmentation rates

Class	Accuracy by pixel ($\mu \pm \sigma$)
WM	97.11% ± 0.52%
GM	97.08% ± 0.65%
CSF	97.38% ± 2.49%

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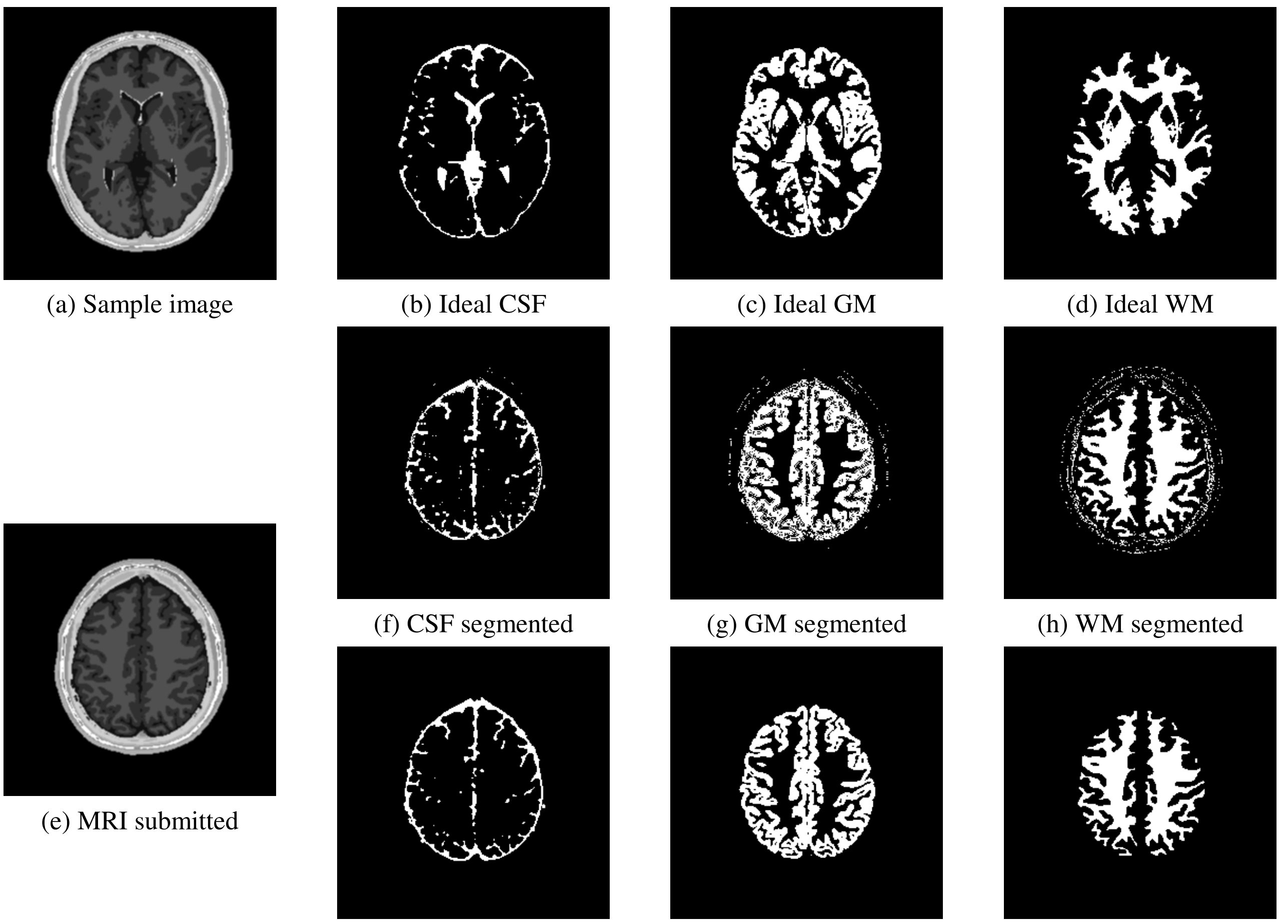

(a) Sample image (b) Ideal CSF (c) Ideal GM (d) Ideal WM

(f) CSF segmented (g) GM segmented (h) WM segmented

(e) MRI submitted

(i) CSF groundthruth (j) GM groundthruth (k) WM groundthruth

Figure 3. Learning-based segmentation results