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MR brain image segmentation using fuzzy clustering

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Abstract

In anatomical aspects, magnetic resonance (MR) image offers more accurate information for medical examination than other medical images such as X ray, ultrasonic and CT images. In this paper, an automated segmentation and lesion detection algorithm are proposed for axial MR brain images.

The proposed segmentation algorithm consists of two steps in order to reduce computation time for classifying tissues. In the first step, the cerebrum region is extracted by using thresholding, morphological operation, and labeling algorithm. In the second step, white matter, gray matter, and cerebrospinal fluid in the cerebrum are detected using fuzzy c-means (FCM) algorithm.

The new lesion detection algorithm uses anatomical knowledge and local symmetry. A symmetric measure is defined to quantify the normality of MRI slice, which is based on the number of pixels, moment invariants, and Fourier descriptors. The proposed method has been applied forty normal and abnormal slices. And the experimental results show that the proposed segmentation algorithm is appropriate for classifying a large amount of axial brain MR data, and also show that the proposed lesion detection algorithm is successful.

1. Introduction

Magnetic resonance images offer anatomical information for medical examination more accurately than other medical images such as X ray, ultrasonic, and CT images. So MR images are widely used not only for diagnosing brain tumor, heart disease, disk disease, and so on which are difficult to detect by using other images but also for examining anatomical state of tissues. In the aspects of offering good clinical information, the segmentation and recognition algorithm of MR images are becoming important subject of the study on medical image processing. The segmentation of MR images, which is valuable in analysis of MR data itself, becomes the basis of MR data compression, reconstruction of 3D image, and quantifying a specific tissue for medical examinations.

A typical MR analysis of a patient involves multi-modal information in three cross section by itself contains 10-30 2D slices, and generally each slice has three different types of image (T_1-weighted, T_2-weighted, proton density(PD) image) which have different contrast affected by selection of pulse sequence and weighting signal. Thus, even for a single study, there are hundred or more images to be acquired and analyzed. This naturally burdens the computational requirements for computation time and data analysis. For this reason, an automated algorithm for segmentation and recognition is inevitably required. But the study of automated algorithm for MR images is very difficult problem because of characteristics of MR images. In analyzing MR image data, one need to consider complications due to the inherent noise, partial volume effects (where more than one tissue is inside a pixel volume) as well as the wide range of imaging control parameters which affect the tissue intensities. Thus there is a significant inter-patient variance of these signal intensities for the same tissues.

Unsupervised techniques, also called "clustering," automatically find the structure in the data. Unsupervised methods employed for segmentation of MR images include k-means[1], and its fuzzy equivalent, fuzzy c-means(FCM)[2]. The comparison of FCM with a neural network in MR images has been reported by L. O. Hall et al.[3] and showed that for normals the clustering appeared to be superior. C. Li et al.[4] applied oversegmentation techniques to segment brain tissues using FCM, and class merging and splitting process are used in order to classify each tissue.

FCM algorithm is widely used in image processing, because it has robust characteristics for ambiguity and noise-contained image. but it may consume high amount of CPU time and memory for large data set. In this paper, we propose 2 step segmentation algorithm which uses FCM more efficiently to reduce computation time. In the first step of segmentation, cerebrum region is extracted by using thresholding based on histogram, morphological operation, and labeling algorithm. In the second step, we use FCM to segment inner tissues of cerebrum that have ambiguous characteristics at tissue boundaries and low differences in contrast each other. The computation time of FCM is severely affected by the number of class, so we apply FCM to only the region of interest (ROI) in order to reduce computation time. We also propose a new lesion detection algorithm that uses anatomical knowledge and local symmetry. A symmetric measure is defined to quantify the normality of MR image slices, which is based on the number of pixels, Moment invariants, and Fourier descriptors.

The remainder of the paper is divided into five sections. Section II introduces the anatomical knowledge of MR image. Sections III and IV describe the techniques used for the segmentation and lesion detection. The last two sections present the experimental results and a conclusion of them and future directions.

2. Anatomical Knowledge of MR Image

MR image may be classified according to cross section and relaxation time. Fig. 1 shows the classification by the cross section. An axial, and sagittal, coronal image can get through the 3 cross sections, xy plane, yz plane, and zx plane, respectively.

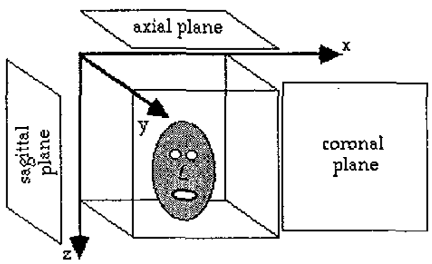

Fig. 1. MR image classification by the 3 cross sections.

The human body is composed of millions of atoms. Under normal conditions, the protons inside these atoms spin randomly. But when such spinning protons find themselves in a powerful magnetic field and radio frequency(RF) pulses are transmitted through the body. The protons inside the body respond to the RF pulses and emit a signal which is received and constructed into an image. The signal intensities emitted by different tissues are depend upon the proton density and values known as the T_1 and T_2 relaxation times. This is the proton density(PD), and T_1-weighted, T_2-weighted image which is classified by the relaxation time(Fig. 2).

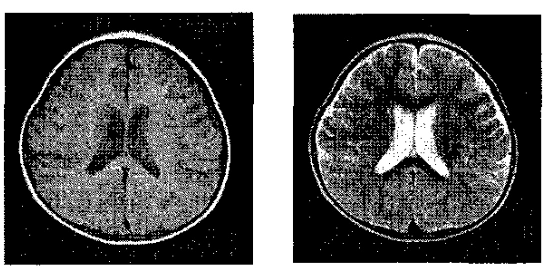

Fig. 2. MR image classification by the signal weight. (a) T_1-weighted image. (b) T_2-weighted image.

In normal brain image, skull tissue surrounds the cerebrum and subarachnoid between skull and cerebrum is filled with cerebrospinal fluid(CSF). And connective and fat tissues are located outside the CSF. Cerebrum is consisted of the brain parenchyma(white and gray matter) and CSF.

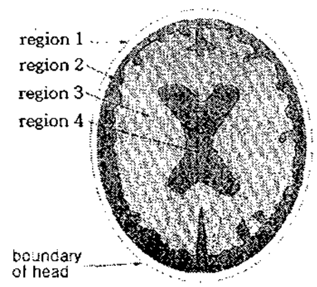

Fig. 3. Anatomical structure of axial MR brain image.

Fig 3 shows the anatomical structure of axial MR brain image. Region 1 is the outside brain and consists of skull, muscle, and fat. Region 2 is subarachnoid space and filled with CSF. Region 3 is brain parenchyma and region 4 is the CSF in lateral ventricle. CSF is shaped butterfly and symmetrical on a vertical axis through its center. Lesions are located in region 3 and 4.

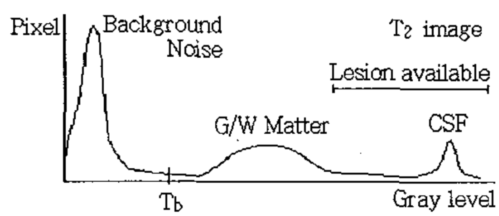

Fig. 4. Histogram of axial MR brain image.

The histogram of the T_2-weighted image is in Fig. 4. Gray and white matter are appeared as a single mode in histogram, so the boundary is not clear in the image. Furthermore, gray value distribution in MR image is not constant because image contrast is decided by the user interaction. And also difficult to detect the boundaries between tissues cause the partial volume effect and noise. In T_2-weighted image, gray matter is brighter than white matter. Lesions are distributed between upper gray matter and all over the CSF.

3. Segmentation

3.1. Extraction of the Cerebrum Region

The first step in the segmentation process is to isolate the cerebrum region from the bone, muscle, and fat tissue. A single threshold is applied to the image, which separates cerebrum region from the background noise. The threshold, T_b in T_2-weighted image, is the gray value of which pixel number does not exceed specific number. In general image, it is difficult to determine threshold value. But there is no matter in extracting cerebrum region from the background

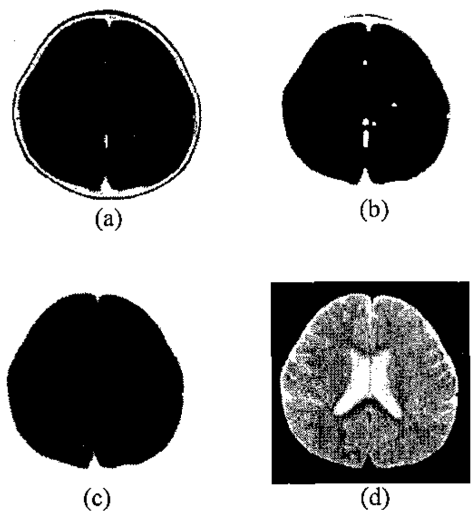

Fig. 5. The process of extracting cerebrum region. (a) binary image. (b) morphologically eroded image. (c) cerebrum mask image. (d) extracted cerebrum image.

noise if T_b shifts a little left or right. So we can determine proper threshold depend on the image size. Fig. 5(a) is the result of thresholding.

The bone and soft tissue are eliminated by using the morphological operation of erosion. A morphological erosion operation with a NxN rectangular shaped structural element is applied to the thresholded image. After erosion, labeling algorithm is applied to the image in Fig. 5(b) and find the biggest region. The biggest region may have a hole due to thresholding. After dilation and filling, we can get the cerebrum mask image like Fig. 5(c). This mask is used to extract the cerebrum region from the original images as shown in Fig. 5(d).

3.2 Segmentation of the Cerebrum Region

The second step in the segmentation process is to split white matter, gray matter, and CSF from the result of the first step using fuzzy clustering. Fuzzy set theory is often used to manage uncertainty cause the lack of the information. In image processing, fuzzy set theory can be used when the boundary or region is not clearly defined. Fuzzy clustering has robust characteristic for noise and ambiguity. But it may consume high amounts of computation time and memory. In this paper, we use FCM algorithm for clustering just cerebrum region to minimize the computation time. The FCM algorithm[5] uses iterative optimization to minimize an objective function. We set 3 initial cluster center to separate white, gray matter, and CSF. It is M- $\sigma/2$, M+$\sigma/2$, M+σ, where M is the mean of the cerebrum image and σ is the standard deviation of that. Fig. 6(a), (b), and (c) is shown the result of segmentation white matter, gray matter, and CSF respectively. White matter is more thick and compact than gray matter. Gray matter is resided between white matter and CSF. Normal CSF is symmetrical on a vertical axis through its center.

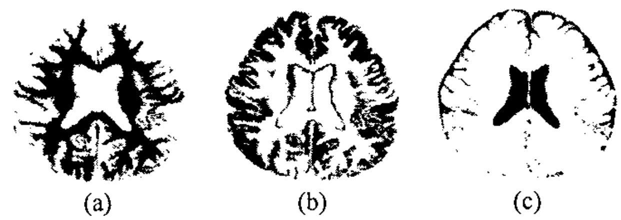

Fig. 6. The segmented classes using FCM algorithm. (a) white matter. (b) gray matter. (c) CSF.

4. Detection of the Lesion Slices

A quadrangle mask is used to get an image for lesion detection. We find 2 subsidence points of the cerebrum mask as a top and bottom point of the quadrangle. And draw a center line to connect the two points. An orthogonal line passing the center point of the center line is drawn. The two points, which cross the orthogonal line and cerebrum mask edge, are left and right point of the quadrangle.

There are no particular characteristics in the shape or location of the lesions. But, most lesions, which have bright intensity, are distributed between upper part of gray matter and all over the CSF as shown in Fig. 4. A new binary image, which is made of upper gray matter and CSF used FCM algorithm, is made for detecting a lesion. And apply erosion to the black pixel of outside the quadrangle mask.

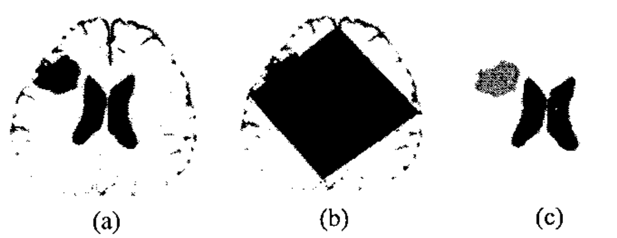

Fig. 7. Acquisition of input image for lesion detection. (a) binary image. (b) quadrangle mask image. (c) input image for disease slice recognition.

Because gray matter and CSF in subarachnoid are narrow, lesions within gray matter are left after erosion. And then, small regions are eliminated. The region laying over the quadrangle boundary can be a lesion, we do not erode and eliminate of that region. Cause lesions shape must be preserved. Fig. 7(c) is the image used to lesion detection.

There are 2 types of lesion. One is isolated lesion apart from CSF, and the other is CSF lesion or gray/white matter lesions break into the CSF. The former case, we call this "abnormal case 1," is easy to detect lesion slice just searching isolated lesion. In the latter case, abnormal case 2, the symmetry of CSF is broken we can detect this lesion slice by measuring the symmetry of CSF. A symmetric measure, S, is defined using the number of pixels, Moment invariant, and Fourier descriptor. Moment invariants and Fourier descriptors are invariant to rotation, translation and symmetry. If both of them are used in pattern recognition, the results are more accurate[6]. The symmetric measure is,

$$S = k_1 \frac{(N_{L,R})_{\min}}{(N_{L,R})_{\max}} + \frac{k_2}{m} \sum_{i=1}^{m} \frac{(M_{L,R})_{\min}}{(M_{L,R})_{\max}} + \frac{k_3}{m} \sum_{i=1}^{m} \frac{(F_{L,R})_{\min}}{(F_{L,R})_{\max}}$$

Where N is the number of pixels in the left and right half of the CSF and M is Moment invariants, F is Fourier descriptors. k_1, and k_2, k_3 are the weight of the pixel numbers, Moment invariants, and Fourier descriptors. We let these values as 0.4, and 0.3, 0.3. It has been found that a threshold of the symmetric value discriminates well between normal and abnormal CSF. The values calculated from normal CSF are bigger than 0.7, and the ones from CSF containing abnormal tissues are smaller than 0.7.

5. Experimental Results and Discussions

Forty slices of MR brain data used in this research are 512x512 8bits/pixel images, which acquired 512x512 16bits/pixel DICOM 3.0 format from Siemens 1.5 Tesla Magnetom. 23 slices are abnormal and the others are normal. Abnormal slices include brain tumor, multiple sclerosis, and CSF lesion. Image acquisition parameters are represented in Table 1.

Table 1. System parameters for image acquisition.

Pulse sequence Type	T_2 weighted image	Slice	
	TR/TE(ms)	Thickness(mm)	Gap(%)
Spin echo	2200/100	7	0.2%

Table 2 compared processing time of proposed 2 step segmentation method and FCM only method at pentium pro 200 MHz using GCC. We assumed FCM only method separate 5 classes. In practically, it took more than 379.8 sec because splitting and merging process between classes must be followed after clustering.

Table 2. Comparison of processing time.

Segmentation Method	Average time for segmenting each slices
FCM	379.8 sec
Proposed Method	95.7 sec

In table 3, relative area ratio of segmented tissue and symmetry of the CSF are compared to the case of normal and abnormal. The symmetry of CSF is extremely broken in abnormal case 2. Fig 8 shows the result of lesion detection. S is bigger than 0.7 in normal case and abnormal case 1. We can see the symmetry fall down below 0.7 in abnormal case 2.

Table 3. Relative area ratio of segmented tissues and average symmetry of CSF.

Compa-Rison / CASE	Relative area ratio of segmented tissue		Average Symmetry of CSF	Number of slice
	CSF	Brain Parenchyma		
Normal	13.23%	86.77%	0.874	17
Abnormal case 1	14.06%	85.94%	0.865	16
Abnormal case 2	15.92%	84.08%	0.597	7

6. Conclusion

In this paper, an automated segmentation and lesion detection algorithm are proposed for MR brain images. The proposed segmentation algorithm consists of two steps in order to reduce computation time for classifying tissues. First step extracts cerebrum region using histogram-based thresholding, morphological operation, and labeling algorithm. In the second step, the FCM algorithm, which has robust characteristic for ambiguity and noise-contained images, is used to separate gray matter, white matter, and CSF in the cerebrum.

Lesions are detected by using an anatomical knowledge and local symmetry. A symmetric measure, which quantifies the normality of MRI slice, is defined based on the number of pixels, moment invariants, and Fourier descriptors. We can offer these lesion information for expert's judgement, and telemedicine, medical image compression. Our study was applied to forty normal and abnormal slices. And the experimental results show that the proposed segmentation

Original T2 image	Image for lesion detection	Symmetry (S)	Abnormality	Original T2 image	Image for lesion detection	Symmetry (S)	Abnormality
		0.918	Normal slice			0.780	Abnormal slice (CASE 1)
		0.881	Normal slice			0.901	Abnormal slice (CASE 1)
		0.894	Normal slice			0.525	Abnormal slice (CASE 2)
		0.876	Normal slice			0.639	Abnormal slice (CASE 2)

Fig. 8. Result of the lesion detection.

algorithm is appropriate for classifying a large amount of axial brain MR data, and also show that the proposed lesion detection algorithm is successful.

In a future study, we are going to analyze the lesion volume quantitatively and reconstruct the 3D volume of MR data based on segmentation.

7. References

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