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An Improved Fuzzy C-means Method for Brain MR Images Segmentation

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Abstract Due to the effect of noise in brain MR images, it is difficult for the traditional fuzzy c-means (FCM) clustering algorithm to obtain desirable segmentation results. Combining the information of patch to reduce the effect of noise has been a focus of current research. However, the traditional patch method is isotropic, so that it would lose the structure information easily. In this paper, a novel fuzzy C-means method based on the spatial similarity information is proposed. To be anisotropy and preserve more structure information, this method takes both the non-local information and spatial structural similarity (SSIM) between the image patches into consideration, and then a new distance function is established between every pixels and category centers for image segmentation. The efficiency of the proposed algorithm is demonstrated by experiments of synthetic brain MR images.

Keywords Brain MRI; Fuzzy c-means clustering; Image segmentation; Structural similarity measurement

1 Introduction

Brain disease is one of the principal diseases menacing human health nowadays. Utilizing the brain imaging techniques to analyze its function quantitatively is an important help for the diagnosis of brain disease. Magnetic resonance (MR) image acquisition is a medical imaging technique used in radiology to display internal structures of the body in detail. Reliable quantitative analysis of MR images can be performed by using image segmentation.

Image segmentation is defined as the partitioning of an image into non-overlapped, consistent regions, each with distinct characteristics, such as intensity, texture or color. Fuzzy segmentation methods are of considerable benefits, owing to the uncertainty of MR image. In particular, the transitional regions between tissues are unclear and their memberships are intrinsically vague [1]. Fuzzy c-means (FCM) clustering algorithm [2] is the best known and powerful method in fuzzy segmentations methods and its success chiefly attributes to the introduction of fuzziness for the belongingness of each image pixels. Unfortunately, MR images always contain uncertainly and unknown noise evoked by imaging mechanism. There is no consideration of spatial

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information in standard FCM clustering algorithm, so it is very sensitive to noise.

In this paper, we propose a novel fuzzy c-means method for brain MRI segmentation. This method incorporates two influential factors. One is the non-local information determined by pixels whose neighborhood configurations look like the neighborhood of the pixel of interest; the other is the spatial structural similarity (SSIM) [3, 4] to extract structure information from image patches sufficiently. Consideration of the two constraints can effectively restrain the noise in the image and preserve more structure information as shown in our experiments.

2 Proposed method

In this section, a novel fuzzy C-means method based on the spatial similarity information is proposed to overcome the drawback of the standard FCM. We replace each pixel used in constructing the objective function of FCM with the corresponding image patch. Our proposed method views each image patch, instead of each pixel, so that spatial information is incorporated intrinsically into the segmentation process. It incorporates the non-local information and SSIM to be anisotropy and preserve more structure information.

It is common knowledge that the FCM-based image segmentation result is decided by the membership value. The membership value is decided by the distance measurement. So we can infer that the distance measurement is the key to segmentation success. In our method, a new distance function is established by non-local information and SSIM.

2.1 Structural similarity (SSIM) measurement

The structural similarity (SSIM) index [3] is proposed by Zhou Wang et. al. to measure image similarity. It has shown superior performance over signal to noise ratio (SNR) and peak signal to noise ratio (PSNR). In SSIM theory, natural image are of highly structured, adjacent pixels have strong inter-dependencies, and these dependencies carry important information about the structure of the image.

The SSIM metric is calculated between two patches x and y of common size $N \times N$ is

where $\boldsymbol{\mu}$ is the average, $\boldsymbol{\sigma}^2$ is the variance, and $\boldsymbol{\sigma}_{xy}$ is the covariance of x and y. c_1 and c_2 are two variables to stabilize the division with weak denominator, which are defined as

, (2)

(1)

where L is the dynamic range of the pixel-values. k_1=0.01 and k_2=0.03 are selected in our study.

The larger the value of SSIM is, the higher the similarity of two patches.

2.2 Algorithm

The proposed method takes the SSIM into the weight measurement between the adjacent patches to establish a new distance function. The new distance function between x_k and v_i is given as follows

(3)

where N_k denote a search window of fixed size with respect to a center pixel x_k. The weight function is defined as

(4)

Here we set P_k denote a patch of fixed size with respect to a center pixel x_{k}, as same for P_j to x_j. Then the weight influenced by SSIM is presented as

$Z(x)$ (5

where represents the SSIM-weight between P_k and P_j. $R(x_k)$ is sum of SSIM-weight in N_k. In fact, the resultant SSIM value is a decimal value between -1 and 1, so we set the SSIM-weight as

and (7)

In addition, the weight function influenced by non-local information is given as follows

(4)

1

(8)

(( ))

where is the exponential form of the similarity, and is the normalizing constant

(9)

(10)

The similarity between two pixels x_k and x_j depends on the similarity of the intensity gray level vector $v(N_k)$ and $v(N_j)$. The similarity is measured as a decreasing function of the weighted Euclidean distance ,

where α is the standard deviation of the Gaussian kernel. The parameter h is a degree of filtering to control the decay of the exponential function.

Finally, the tradeoff parameter of two weights is defined as

(11)

Then new distance function has been defined, the update equations of the membership function and the cluster center are given as follows

(12)

$$v \quad \square \quad \frac{1}{\square} \tag{13}$$

We can describe our proposed method as below

Step 1: Set the number of clusters c. Initialize the fuzzy cluster centroid vector $V= [v_1, v_2 \ldots v_c]$ by k-means clustering algorithm and set $c>0$ to a very small value.

Step 2: Set the patch size and search window size.

Step 3: Calculate $w(x_j,x_k)$ using Eq. (4).

Step 4: Update $D^2(x_j,x_k)^{(t+1)}$ using Eq. (3).

Step 5: Update using Eq. (12).

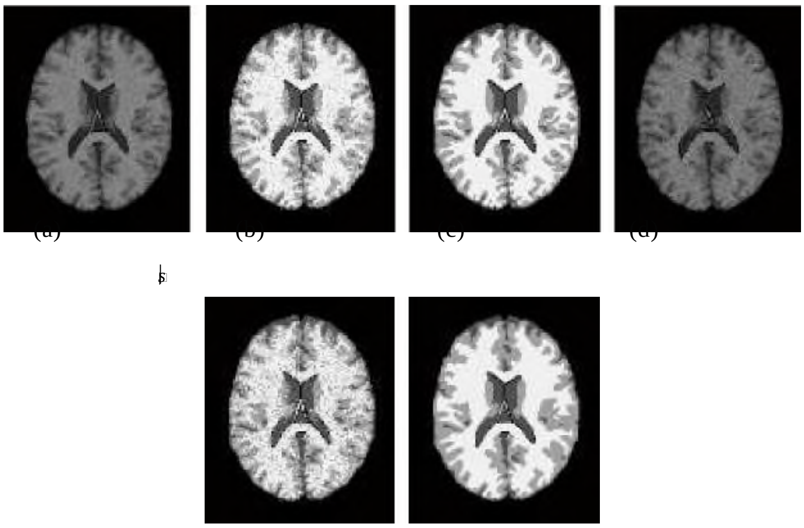
Step 6: Update using Eq. (13).

Step 7: Repeat Steps 4-6 until satisfy the termination criterion $||\boldsymbol{V(t+1)}-\boldsymbol{V(t)}||<\varepsilon$.

3 Experimental results and analysis

In order to test the reliability and validity of the algorithm, we execute the segmentation on synthetic brain MR images from the McConnell Brain Imaging Center at the Montreal Neurological Institute, McGill University. We set c=4, h=16, $\varepsilon=10^{-5}$, the radius of search window is 5, and the radius of patch is 3.

Fig.1. (a) and (d) shows original images with noise level 5% and 7%, respectively. Fig.1. (b) and (e) shows segmentation result by FCM, we can find that due to the effect of the noise, many wrong results appear especially on white matter. Fig.1. (c) and (f) shows result by our proposed method, this method can not only be robust to noise, but also preserve the slender structure effectively.



(e) (f)

Fig.1. Segmentation of the synthetic brain MR images. (a) Original image with noise level 5%; (b) Result of FCM; (c) Result of our method; (d) Original image with noise level 7%; (e) Result of FCM; (f) Result of our method

In order to quantitatively evaluate the benefits, we segmentation 20 sets of synthetic brain MR images with different levels of noise. We use the Jaccard similarity (JS) index to estimate the accuracy of segmentation.

(14)

where S_1 is the ground truth, and S_2 is the segmentation result. A good algorithm would give high JS values. The average quantitative results of white matter

(WM) and gray matter (GM) are listed in Table.1. It can be seen that our method is more accurate than FCM.

Table.1. Evaluation of tissue segmentation in terms of Jaccard Similarity Coefficients (%)

noise level	tissue	FCM	our method
5%	WM	82.56	92.03
	GM	71.79	85.42
7%	WM	69.17	89.49
	GM	55.73	80.68

4 Conclusion

In this paper, we have presented a novel fuzzy C-means method based on the spatial similarity information. The method was formulated by modifying the distance function to compensate for noise by using both the non-local information and SSIM. Experimental results have shown that our method can outperform original FCM for the images with noise.

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