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Adaptive Template Filtering Method for MRI

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Abstract—**Denoising is an important step for image processing. One of the most important characteristics of MRI (MRI) is the complicated changes of gray level. For MRI, preservation of useful information is more important than simple improvement of Signal-Noise Ratio (SNR). Traditional filtering algorithms are not fit for MRI. Adaptive Template Filtering Method (ATFM) can dynamically match the best template from the predetermined multi templates based on local texture characteristics for each pixel. In this paper, detail algorithm and analysis are given. Compared with other filtering methods, the performance of ATFM is better than that of other filtering methods as our experiment demonstrates. It can both effectively suppresses noise and best preserve useful information at the same time for MRI. Thus, ATFM can meet the need of clinical diagnosis and image processing.**

I. INTRODUCTION

WITH the development of medical imaging technology, clinical diagnosis and image processing have been more and more dependent on the high quality medical image. However, in the process of imaging, many factors directly affect the acquisition of high quality medical image. For example, noise is introduced into Magnetic Resonance Imaging (MRI) image due to inhomogeneity of magnetic field, excursion of temperature and motion of tissue, etc. [1]. In order to obtain high quality medical image, denoising process is obligatory. Although image processing can not provide new information for diagnosis, it can improve the visual effect to help diagnose accurately for clinic. In addition, it builds solid foundation for image segmentation and image 3-D reconstruction.

Many denoising methods were proposed to markedly improve Signal-Noise Ratio (SNR), but these denoising methods lose much high frequency edge information at the same time. The high frequency part of an image includes the edge information and noise. In an image, high frequency part decides the sharpness of image edge. Visual effect becomes blurring when high frequency information is attenuated [2]. Some filtering algorithms convolute the image and pre-determined template to accomplish denoising. But these templates restricted by orientation can not be fit for complicated changes of edges. Butterworth filtering algorithm is one kind of low-pass filter. It can make the image smooth, but high frequency information is eliminated [3]. Median filtering algorithm can preserve the edge information to some degree while attenuating noise [4] [5]. But it is not effective for MRI since the edge information of MRI is much complicated. In general, although these traditional methods can effectively suppress noise, a lot of useful information is lost. The visual effect becomes blurring. In order to obtain high quality medical image, preservation of useful information is more important than simple improvement of SNR [6]. One of the most important characteristics of MRI is the complicated changes of gray level, i.e., MRI is abundant in much high frequency information [7]. Traditional filtering algorithms are not fit for MRI.

Adaptive Template Filtering Method (ATFM) can dynamically match the best template from the predetermined multi templates based on local texture characteristics for each pixel. This method not only effectively suppresses random noise, but best preserves the useful information as well for MRI. So it is a filtering method appropriate for medical image processing.

II. ADAPTIVE TEMPLATE FILTERING ALGORITHM

A MRI image is made up of a series of finite regions in which the gray level is continuous or slow changed, and these regions are segmented by discontinuous edges [8]. The main idea of ATFM is, from the predetermined templates, to find a template which is the best match for the finite continuous region including input pixel. Then the best denoising effect of input pixel can be obtained using this best matching template. So a set of templates should be pre-determined as follows (see figure 1).

From figure 1, black point and gray point represent input pixel and non-background neighboring pixel respectively. The total number of templates is $\sum_{n=2}^{9} C_8^{n-1} = 255$. For each pixel, we should find out the best matching template based on Standard Deviation (STD) of pixel values in template:

$$\delta_j = \sqrt{\tfrac{1}{N_j - 1}\sum_{k=1}^{N_j}\left(I_k(x,y) - m_j\right)^2} \qquad (1)$$

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$$m_j = \frac{1}{N_j}\sum_{k=1}^{N_j} I_k(x,y) \qquad (2)$$

In a template, $I(x,y)$ is the pixel value, N_j is the number of non-background neighboring pixels, m_j is the mean value of pixels and δ_j is STD of pixel values.

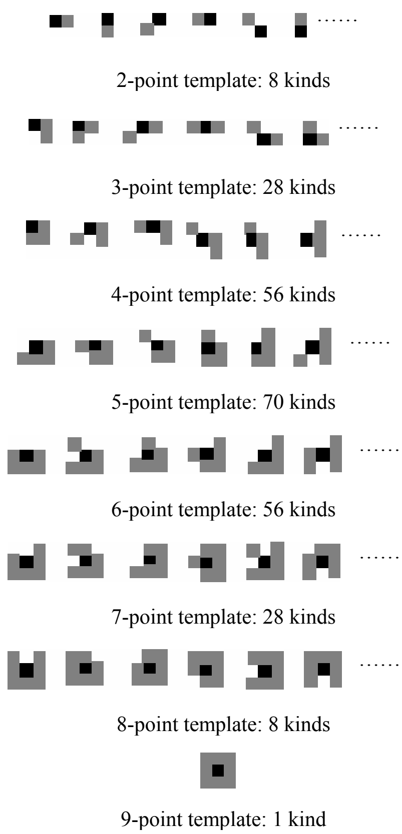

Fig. 1. A set of predetermined templates

For finite continuous region of template, the change of gray level results from random noise. In the template which the change of gray level is smooth, its STD is relatively small. This kind of template is named smooth template. So the best matching template T is the template which has the most non-background neighboring pixels in the finite continuous region:

$$T = \arg\max_{T_j} N_j \{T_j \mid \delta_j < t\} \qquad j = 1,...,255 \qquad (3)$$

In the circumstances of edge existing in the template, its STD is relatively big since gray level changes markedly. This kind of template is named edge template. So the best matching template T is the template in which STD is minimal:

$$T = \arg\min_{T_j} \delta_j \{T_j \mid \delta_j \geq t\} \qquad j = 1,...,255 \qquad (4)$$

Using which kind of template depends on the threshold t.

In order to expedite selecting template, we can start to compute the STD from the template which has the most non-background neighboring pixels. Thus, the first template in which STD is less than t is the best matching template. If STDs of every templates is not less than t, the template in which STD is minimal is the best matching template. By this way, the process of algorithm is expedited since exhaustive searching is avoided.

After the best matching template is obtained, the output of adaptive template filtering is formulized as follows:

$$O(x,y) = \frac{\delta_k^2 I(x,y) + \delta_n^2 m_j}{\delta_k^2 + \delta_n^2} \qquad (5)$$

$$\delta_k^2 = \max\{0, \delta_j^2 - \delta_n^2\} \qquad (6)$$

$$\delta_n = 1.526\delta_B \qquad (7)$$

$$t = \alpha\delta_n \qquad (8)$$

δ_B is STD of image background region. δ_n is STD of image non-background region representing the change of noise. δ_j is STD of pixel values in template representing the change of gray level. $O(x,y)$ is the filtering output. α is a proportion factor, different α can produce different threshold t, and directly affects the filtering result.

From equation (5), the filtering result is simply viewed as the mean value of the best matching template if the change of gray level is close to the change of noise. On the contrary, if the change of gray level is far from the change of noise, the filtering result approximates to original value of input pixel.

The performance of adaptive template filtering is evaluated by Peak Signal to Noise Ratio (PSNR):

$$PSNR = 20\log_{10} \frac{I_{peak}}{\sqrt{\frac{\sum_{k,l}(O(x,y) - I(x,y))^2}{K \times L}}} \qquad (9)$$

Here I_{peak} is the maximum of gray level, and $K \times L$ is the size of image.

III. Experimental Result and Analysis

MRI data were provided by Brigham & Women's Hospital, Harvard Medical School. It is T2 weighted image. 256*256 pixels for one slice, the thickness of each slice is 1mm, no gap between the slices, the gray level is 2^{16}, the total number of slices is 150 from left ear to right ear. The original images of 105^{th} slice and 120^{th} slice are shown in figure 2.

Analyzing the normalized histograms of original images, we find that almost all pixels concentrate within [0 0.4] interval. That is the reason why the original images are too black. Through adjusting histograms from [0 0.4] to [0 0.8], we get the enhanced images of 105th slice and 120th slice shown in figure 3.

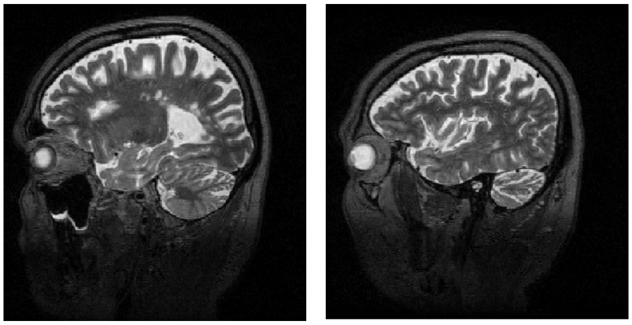

Fig. 2. Original 105th slice and 120th slice

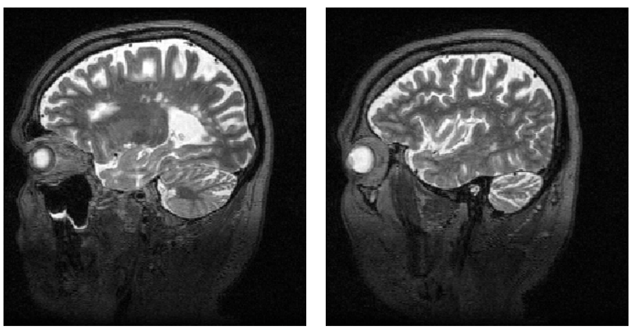

Fig. 3. Enhanced 105th slice and 120th slice

Then third-order Butterworth filtering algorithm is used for 2 enhanced images. It is a kind of low-pass filter. The filtering results are shown in figure 4.

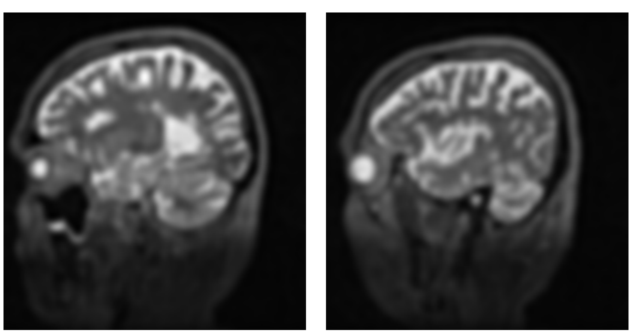

Fig. 4. Butterworth filtered 105th slice and 120th slice

Median filtering algorithm is used for 2 enhanced images. The size of template is 3×3. The filtering results are shown in figure 5.

Adaptive Wiener filtering algorithm is used for 2 enhanced images. It is based on statistics estimated from a local neighborhood of each pixel. The size of template is 3×3. The filtering results are shown in figure 6.

ATFM is used for 2 enhanced images. For 105th slice, threshold t = 0.002; for 120th slice, threshold t = 0.001. The filtering results are shown in figure 7.

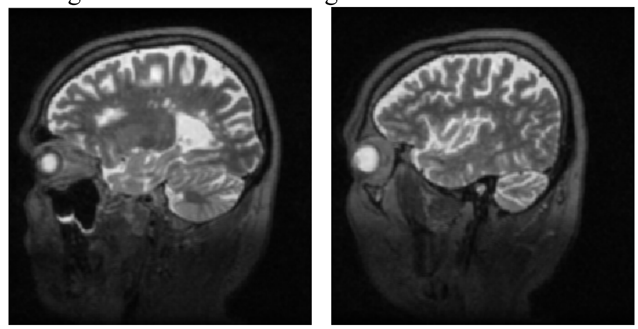

Fig. 5. Median filtered 105th slice and 120th slice

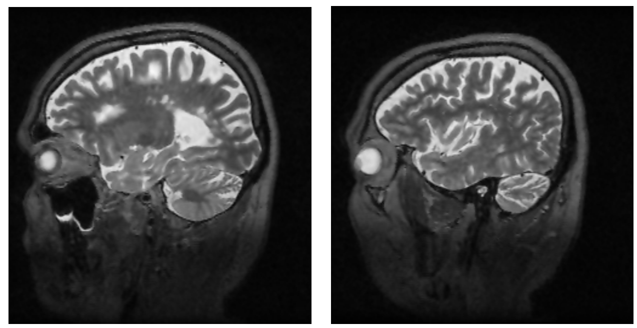

Fig. 6. Adaptive Wiener filtered 105th slice and 120th slice

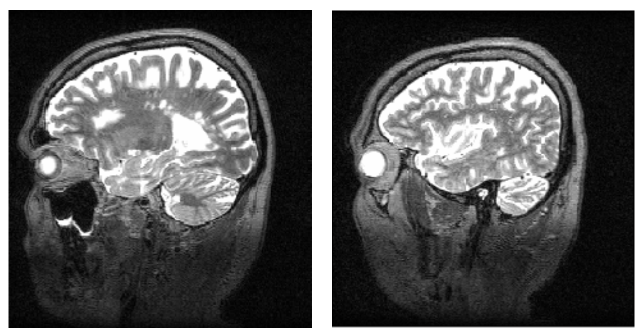

Fig. 7. Adaptive template filtered 105th slice and 120th slice

In our experiment, we have used the third-order Butterworth filtering algorithm, median filtering algorithm, adaptive Wiener filtering algorithm and ATFM respectively to denoise the enhanced images of 105th slice and 120th slice. PSNRs are calculated for four denoising methods according to equation (9). The performances of four filtering methods are shown as Table I.

TABLE I
THE PERFORMANCES OF THREE DENOISING METHODS

	Butterworth Filtering	Median Filtering	Adaptive Wiener filtering	Adaptive Template Filtering
PSNR of 105th slice	24.02	30.01	32.75	50.13
PSNR of 120th slice	24.43	30.49	33.37	50.54

From Table I, it manifests that the ATFM outperforms other filtering methods. Butterworth filter is low-pass filtering, its denoising effect excessively depends on the selection of the order and cutoff frequency. In spite of transition band existing between the pass band and cutoff band, it can not deal with complicated change of gray level for MRI well. Median filter is a kind of non-linear filter, the denoising effect is close to the size of template. Although it does not blur the image markedly, it can ruin sharp thin curve in the image [9]. So the problems, such as losing information and blurring image, still exist. Based on statistics, adaptive Wiener filter can preserve useful information in some degree. Our experiment demonstrates that the result of median filter is better than that of Butterworth filter. Adaptive Wiener filter surpasses Butterworth filter and median filter. ATFM can dynamically match the best template from the predetermined multi templates based on local texture characteristics for each pixel. Compared with three methods mentioned above, ATFM can produce satisfactory visual effect as shown in figure 7.

IV. Conclusion

Denoising image has great significance for both clinical diagnosis and image processing, such as two dimensional segmentation and three dimensional reconstruction of image [10]. It is impossible to suppress all the noise and not to damage any original signal [11]. Our target is how to best preserve original signal while noise is attenuated as much as possible. The typical characteristic of a medical image is the complicated change of gray level, especially for MRI. ATFM can dynamically match the best template from the pre-determined multi templates based on local texture characteristics for each pixel. In this paper, detail algorithm and analysis are given. This method not only effectively suppresses random noise, but best preserves the useful information for MRI. As our experiment demonstrates, this method can produce satisfactory result and its performance surpasses other well-known filtering methods. Our further study is to generalize this method for 3-D medical image. In general, ATFM is appropriate for medical image and it can meet the need of clinical diagnosis and image processing.

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