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Medical Image Contrast Enhancement via Wavelet Homomorphic Filtering Transform

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Abstract

A novel enhancement algorithm for magnetic resonance (MR) images based on spatial homomorphic filtering transform is proposed in this paper. By this method, the source image is decomposed into different sub-images by dyadic wavelet transform. Homomorphic filtering functions are applied in performing filtering of corresponding sub-band images to attenuate the low frequencies as well as amplify the high frequencies, and a linear adjustment is carried out on the low frequency of the highest level. Later, inverse dyadic wavelet transform is applied to reconstruct the object image. Experiment results on MR images illustrate that the proposed method can eliminate non-uniformity luminance distribution effectively, some subtle tissues can be improved effectually, and some weak sections have not been smoothed by the novel method.

Keywords*: medical image, wavelet transform, homomorphic filtering, image enhancement*

1. Introduction

With the rapid development of medicine phantom technology, more and more medical images have become the important means, which used in the medicine clinical diagnosis and treatment. But all kinds of digital medical images, especially magnetic resonance (MR) images, have the characteristics of edge blurry, noise and low contrast between objects and background, as well as being disturbed by pseudo image. Accordingly, great difficulties are left for further analysis and doctor's diagnosis accuracy on a certain degree.

Under many circumstances, the low contrast can be considered because of bad distribution of pixel intensities over the dynamic range of display devices. It suggests the application of contrast improving methods for an attempt to modify the intensity distribution. Contrast enhancement for medical images is an important technique that can be applied in highlighting interesting range in the image [1]. Nowadays, it has become one of the research focuses, and it is widely used in the processing of medical images. Until now, more and more techniques have been proposed for classifying into spatial uniform operators and spatially non-uniform operators.

Linear contrast stretching and histogram equalization, are two spatially uniform techniques, which are most widely used for image processing. However, the method of linear contrast-extension can hardly enhance all parts of the image at the same time. Images containing large homogeneous regions, so applying histogram equalization are not effective. In fact, it serves to magnify noise. The great disadvantage of spatially uniform methods is their limiting ability in incorporating local context into transformation [2].

In order to vary adaptively with the local characteristic of the image, usually spatially non-uniform methods finish an input-output transformation and have better performance. However, contrast-limited adaptive histogram equalization (CLAHE) and adaptive histogram-equalization (AHE) belong to the other class. In each small region of the image, AHE method applies locally varying of gray-scale transformation, which requires the determination of the block size, but it cannot adapt to characteristics of different size. As an improvement on this method, other methods are presented, such as CLAHE method, just-noticeable-difference (JND), and guided adaptive contrast-enhancement method (GACE). However, these methods tend to increase noise in smooth regions proportionally, and image-dependent is regarded as

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the selection of the contrast-gain limits. The other drawback with these methods is following the AHE method as above, which is that as brightness is changed, enhanced images look far from natural images, at the same time, the extend of enhancement is non-controllable. These methods can only improve the contrast of a narrow range of sizes. Nowadays, some progress have obtained, but there is still no better method to solve the problem.

With the further research of the wavelet theory, spatial filtering has become a major algorithm for image enhancement. Distinguished from traditional signal scale techniques, multi-resolution or multi-scale algorithms enhance image components adaptively based on their spatial frequency properties [3]. The main idea of these methods is to use a redundant wavelet transform and linear or non-linear mapping functions on Laplacian [4]. Significant contrast enhancement of medical images has been demonstrated in above methods. Lu and Healy's algorithm of multi-scale edge representation improves the image contrast by choosing the scale variable stretching factor to enhance the image edges by reducing low contrast [5]. Wang and Chen et al. proposed a mixture scope model for wavelet multi-scale transform based on enhancing algorithm of medical computed tomography (CT) [6], and several adaptive algorithms of wavelet-based spatially have been proposed for mammographic contrast enhancement [7].

However, magnetic resonance (MR) images cannot be analyzed, processed by traditional image enhancement methods [8]. Nowadays, many studies are carried out on homomorphic filtering, which are applied for face recognition [9][10]. Benefit from these thoughts, a novel homomorphic algorithm for image enhancement is proposed in this paper. Firstly, a source image is decomposed into different sub-images by dyadic wavelet transform, and then, homomorphic-filtering algorithm is performed on wavelet coefficients of this image. In this method, different sub-band images are processed by high-pass filter or linear adjust algorithm for attenuating low spatial frequencies and amplifying high spatial frequencies. Finally, inverse dyadic wavelet transform is applied to reconstruct the object image.

This paper is organized as below. In Section 2, the traditional homomorphic filtering method is analyzed. In addition, the dyadic wavelet transform is given a description in Section 3. Furthermore, in Section 4, a novel algorithm, which applies homomorphic filtering, is proposed. Finally, experiment results of the proposed algorithm on MR image are given, and some existing representative methods for contrast enhancement on real MR images are presented for comparison in Section 5.

2. Traditional Homorphic Filtering Method

As an important contrast enhancement technique, Homomorphic filtering method has been applied in correcting the slowly varying illumination of image successfully. During the image processing, there is a powerful alternative to histogram equalization because of the possibility of optical implementation for the homomorphic filter. One can retrieve lost details in dark regions of the image by equalizing the illumination variation. The homomorphic method is useful for image enhancement, and it contributes to brightness range compression and contrast enhancement too.

2.1 Reflectance Model for Illumination

Generally, an original image can be transformed as a binary function of the formula $f(x,y)$. Its value (x,y) is a positive scalar quantity, which physical meaning is dependent on the source image. A source image can be expressed according to the intensity spatial distribution as follows:

$$f(x,y) = i(x,y)r(i,y) \tag{1}$$

$i(x,y)$: illumination intensity;

$r(i,y)$: object or scene reflectance;

These illumination results from the lighting conditions may be changed when lighting conditions change. While reflectance results in the image reflect light, which is dependent on the intrinsic properties of object images, may be changed too.

This is a common illumination-reflectance model, which can be applied to improve the quality of a source image under the condition of poor illumination.

2.2 Basic Homomorophic Filtering

As a domain filtering method, Homomorophic filtering decomposes the image into two components for enhancing the reflectance, reducing the contributions of illumination [11]. Homomorophic filtering method separates the image separated into two components, which attenuating the low spatial frequencies, amplifying the high spatial frequencies, so the undesired contributions of the source image can be reduced, and the object characteristics can be enhanced [12].

The log function of image enhancement is as follows:

$$Z(x,y)=\ln(f(x,y))=\ln(i(x,y))+\ln(r(i,y)) \tag{2}$$

By calculating the linear expression which involving two additive variables, and then the Fourier Transform ξ can be obtained as follows:

$$\xi(Z(x,y))=\xi(\ln[i(x,y])+\xi(\ln[r(i,y)]) \tag{3}$$

Function declaration: $Z(u,v)=F_L(u,v)+F_R(u,v)$,
$F_L(u,v)$: Fourier transform of $\ln[i(x,y]$;
$F_R(u,v)$: Fourier transform of $\ln[r(i,y)]$;

According to a filter function $H(u,v)$ and $Z(u,v)$, a filtered function can be obtained as follow:

$$S(u,v)=H(u,v)\cdot Z(u,v)=H(u,v)\cdot F_L(u,v)+H(u,v)\cdot F_R(u,v) \tag{4}$$

The corresponding inverse function of Fourier Transform:

$$s(x,y)=\xi^{-1}(S(x,y))=\xi^{-1}(H(u,v)\cdot F_L(u,v))+\xi^{-1}(H(u,v)\cdot F_R(u,v)) \tag{5}$$

Finally, the function $g(x,y)$ of improved image can be obtained:

$$g(x,y)=\exp(s(x,y)) \tag{6}$$

A dynamic range component and a contrast enhancement of the gray level scale can be obtained through the above calculating process. The course of homomorphic filtering can be seen from the following flow chart [13]:

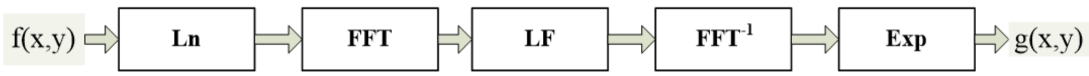


Figure 1. Homomorphic filtering procedure

Symbols specification: Ln: logarithm, FFT: Fourier transform, LF: linear Filtering, LFT: inverse Fourier transform function, Exp: exponential function, $f(x,y)$: the source image function, $g(x,y)$: the improved image function.

Generally, three filtering functions for second–order homomorphic high-pass are applied in the function of the linear filtering. The expression of Gaussian filtering function can be described as follows:

$$H(u,v)=(r_H-r_L)(1-\exp[-c\left(\frac{\rho(u,v)}{\rho_C}\right)^2])+r_L \tag{7}$$

In the above expression, r_H and r_L denote high and low frequencies respectively, under normal conditions, r_H >1 and r_L <1. The numeric constant c is used to sharpen the filtering function slope.

The distance ρ between (u,v) can be expressed: $\rho = \sqrt{(u-u_0)^2 + (v-v_0)^2}$, (u_0, v_0): the center coordinates, ρ_C: the cutoff spatial frequency of the filter, it takes value of ρ under the condition of (u,v)=(0,0).

The function of Butterworth filtering is defined as follows:

$$H(u,v) = (r_H - r_L)/(1 + \left(\frac{\rho(u,v)}{\rho_C}\right)^2 / c) + r_L \quad (8)$$

The function of exponentiation filtering is defined as follows:

$$H(u,v) = (r_H - r_L)(1 - \exp[(-c\frac{\rho(u,v)}{\rho_C})^2]) + r_L \quad (9)$$

There are some kinds of high pass filters mentioned above, in which the Butterworth type is far superior to the other two filter functions for frequency-domain. Better results in contrast Butterworth filtering, so it is suitable for the homomorphic filtering method, can obtain enhancement and dynamic range compression. In this method, because using all pixels in the source image, global property can keep overall appearance very well. However, as not considering local spatial characteristics, it cannot satisfy the result of local contrast enhancement in image.

3. Dyadic Wavelet Transform

Recently, more and more multi-scale and multi-resolution analyses have been widely applied to the research of contrast enhancement. A multi-resolution representation for images of continuous or discrete signals is provided by Wavelet analysis. The great advantage of this method is that structures of different sizes appear at different scales, which can be processed independently [14].

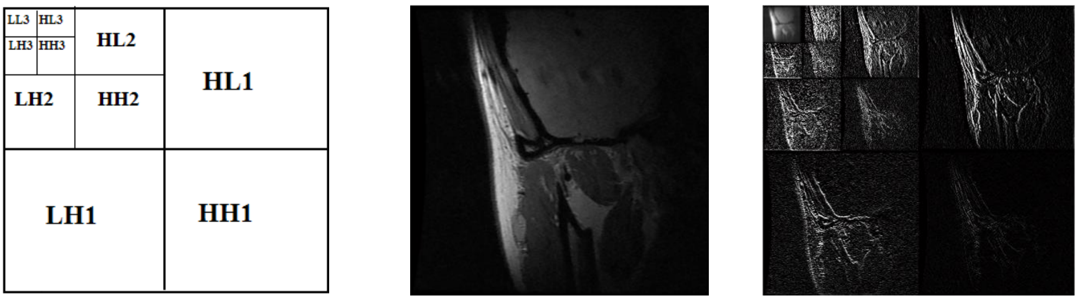
The researching results indicate that biorthogonal wavelet transform is better than orthogonal wavelet transform. In the method of biorthogonal wavelet transform, sub-images are invariant and not aliasing under the translation of images. At the same time, usually smooth symmetrical or anti-symmetrical wavelet transform is applied to allow alleviation of boundary effects. Because of these advantages, biorthogonal wavelet transform has been extensively applied on image enhancement. Owing to the above factors, a redundant discrete, and biorthogonal wavelet transform function $\psi(x)$ is utilized for image enhancement in this paper.

$\varsigma_s(x,y) = (1/s^2)\varsigma(x/s, y/s)$ denotes the dilation of the 2D function $\varsigma_s(x,y)$ at scale s. 2D function $f(x,y)$ can be approximated at the scale $s = 2^j$ by an approximated operator S_{2^j} ,which is defined by a convolution with a dilated scaling function: $S_{2^j} f(x,y) = f * \phi_{2^j}(x,y)$.The scaling function $\phi(x,y)$ is a low pass function, its Fourier transform is an aggregation of wavelet functions dilated by scales than 1. A discrete image $I_{n,m}$ can be considered at the uniform sampling of a function approximation $f(x,y)$ at the measured scale 1: $S_1 f(m,n) = I_{n,m}$. The discrete wavelet transform is a uniform sampling of the corresponding continuous wavelet transform, discretized over the scale parameter s at the dyadic scale 2^j. The wavelet transform of $f(x,y)$ has two components [15], for a particular class of spline wavelet functions, it is defined as follows:

$$\begin{Bmatrix} W^1_{2^j}(x,y) \\ W^2_{2^j}(x,y) \end{Bmatrix} = 2^j \begin{Bmatrix} f*\psi^1_{2^j}(x,y) \\ f*\psi^2_{2^j}(x,y) \end{Bmatrix} = 2^j \begin{Bmatrix} \frac{\partial}{\partial x}(f*\theta^1_{2^j}(x,y)) \\ \frac{\partial}{\partial y}(f*\theta^2_{2^j}(x,y)) \end{Bmatrix} = 2^j \cdot \vec{\nabla}(f*\theta_{2^j})(x,y) \qquad (10)$$

In the above expression, $\psi^1(x,y)$ and $\psi^2(x,y)$ denote partial derivate of a symmetrical and smoothing function $\theta(x,y)$, j denotes the dyadic scale. The source image is decomposed into sub-band images for multi-resolution hierarchy. $S_{2^j}f(m,n)$: a coarse approximation image, $\left\{W^1_{2^j}(x,y), W^2_{2^j}(x,y)\right\}$: a set of wavelet images (j=1…J), which provide details available in $S_1 f$ but not in $S_{2^j}f$. At the condition of dyadic scale j, discrete filters are LH_j, HL_j, HH_j, which can be obtained by setting 2^j-1 zeros between each coefficients of the corresponding filters.

By the method of dyadic wavelet transform, images can be decomposed into multi-scale wavelet coefficients, and each level can be composed by LH_j, HL_j. HH_j denotes high frequencies in the horizontal, vertical and diagonal direction, LL_J denotes low frequencies in the highest level [16]. The basic information and illumination distribution can be reflected by the parameter LL_J. The result of dyadic wavelet transform of images is shown by the following figure.



Three level wavelet decomposition **Image wavelet decomposition**

Figure 2. Charts of dyadic wavelet decomposition

Generally, wavelet coefficients can be high-pass processed for amplifying the high frequencies and attenuating the low frequencies, which reflect the spatial characteristic of wavelet transform to some extent. Accordingly, different wavelet transform algorithms can be used to handle different sub-band images for enhancement.

4. A novel homomorphic-filtering algorithm

Differ from the other methods of homomorphic filtering, a novel homomorphic-filtering algorithm presented in this paper, which performs homomorphic filtering on spatial domain, but not on frequency domain. Particularly, the proposed method accomplishes filtering by applying the improved Butterworth filtering on sub-band images. With the result is that different wavelet sub-band coefficients can be improved to some extent. The fundamental thought of this algorithm is introduced by the following flow chart:

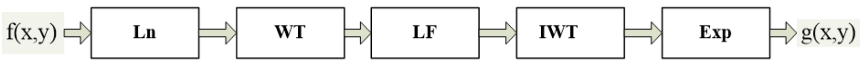


Figure 3. Fundamental thought of Wavelet homomorphic filtering transform

Symbols specification: WT: wavelet transform, IWT: inverse wavelet transform, LF: the novel high-pass filtering. It is important to point out that the above filtering algorithm is based on wavelet transform.

For the purpose of the local contrast enhancement of source images, many scholars develop further research and obtain a great deal of progress. Liviu *et al.* proposed the modified function on Butterworth filtering [17], which is defined as follows:

$$H(\rho) = r_1 - r_2 \frac{1}{1 + 2.145(\frac{\rho}{\rho_C})^4} \quad (11)$$

In the above expression, parameters r_1 and r_2 are added in it for flexibility. Here r_H and r_L denote high and low frequencies, respectively. When r_1 and r_2 are varied, the value between r_1 and r_2 can be obtained for arbitrary circumstances. In the particular case of $\frac{\rho}{\rho_C}$ >>1, the relationship between r_H and r_L can be derived: $r_H \approx r_1$; When the condition of $\frac{\rho}{\rho_C}$ <<1 is true, the result of $r_L \approx r_1 - r_2$ can be drawn. Based on the above research, a modified homomorphic-filtering algorithm proposed in this paper can control the transition between r_H and r_L by varying the value of the cutoff frequency ρ_C. In this method, $\frac{\rho}{\rho_C}$ can be calculated as follows:

$$\frac{\rho}{\rho_C} = \sigma^2 / \sum_{u=1}^{M} \sum_{v=1}^{N} \left[(u-u_0)^2 + (v-v_0)^2 \right] \quad (12)$$

In the above expression, parameters M and N denote the different size of the j level sub-band, (u_0, v_0) denotes the center of the sub-band, and the parameter σ denotes the standard deviation, which can be got as follows:

$$H(\rho) = r_1 - r_2 \frac{1}{1 + 2.145 \left(\sigma^2 / \sum_{u=1}^{M} \sum_{v=1}^{N} \left[(u-u_0)^2 + (v-v_0)^2 \right] \right)^4} \quad (13)$$

During the calculating of HH_j, the condition of $\frac{\rho}{\rho_C} = 1/(2^j \cdot k_b)$ is set, the parameter j denotes the decomposition level, and k_b denotes the cutoff coefficient. For calculating convenience, k_b is set to be the value of 1/8. Owing to the above factors, the improved function of Butterworth filtering is defined as follows:

$$H(\rho) = r_1 - r_2 \frac{1}{1 + 2.145 \left(\frac{1}{2^j k_b} \right)^4} \quad (14)$$

In order to calculate LL_N under the condition of $\frac{\rho}{\rho_C}=1/(2^j \cdot k_b)$, the mentioned above equation can be changed as follows. For revising its illumination non-uniformity, it can be processed by linear or nonlinear adjust. The following equation is used to aim at this purpose:

$$H_{LL_N}=(r_1-r_2)(k(x-m)+m) \tag{15}$$

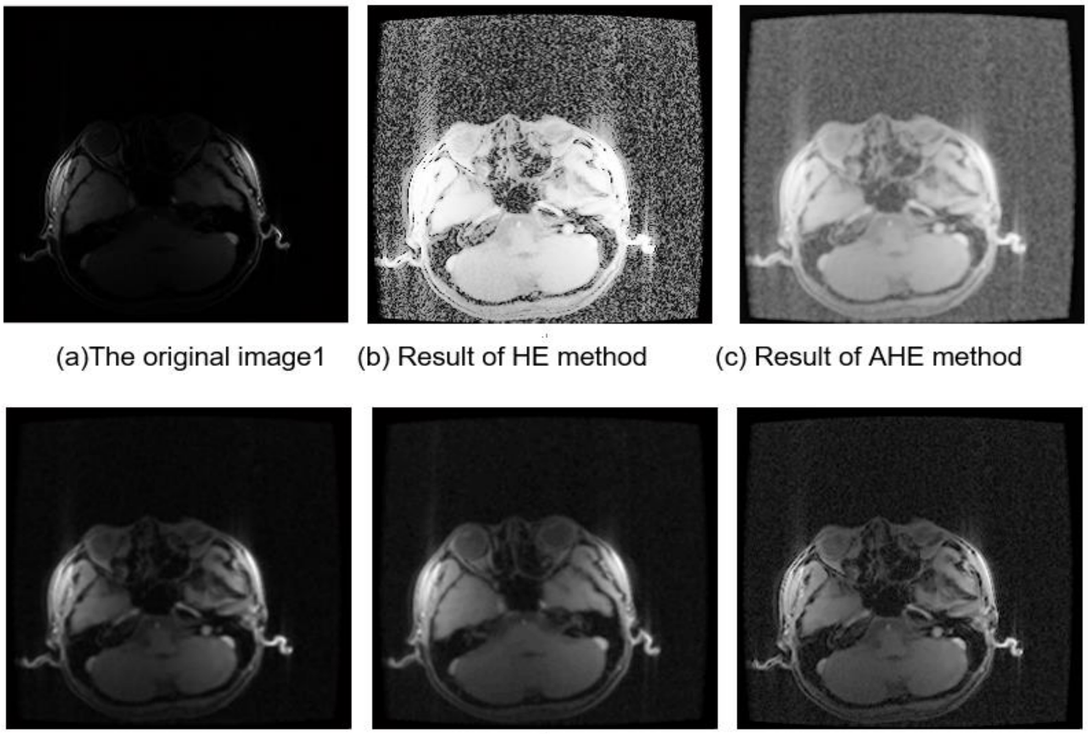
Symbols specification: m : the mean of the coefficient on LL_N, x : the coefficient on LL_N, k : the regulatory factor. When the condition of k=1 is true, the results that high frequencies amplifying but the illumination non-uniformity remaining obviously can be presented. Additionally, When the condition of k=0 is true, because of the completely removing of low frequencies of LL_N, which can eliminates the illumination non-uniformity, the transformation of the original image is very obviously. Accordingly, the condition of k=1 or k=0 is not logical. For this reason, the condition of $k=1-1/m$ is set for adjusting the local contrast of the original image, at the same time, keeping its original appearance.

Simultaneously, as a filtering method of high-pass, the improved Butterworth filtering has the following features: low frequencies participating in next iterations, numbers of decomposition increasing, and high frequencies between two neighboring levels decreasing. Therefore, the bigger values of filtering function can be used for contrasting higher level. Furthermore, conditions of $r_1 = j/(j+1)$ and $r_2 = 2j/5(j+1)$ are set, the parameter j means the decomposition level. $j=1\cdots J$, and the results of $r_{11}<r_{12}<\cdots r_{1J}$ and $r_{21}<r_{22}<\cdots r_{2J}$. r_1 can be obtained. During the calculating of H_{LL_J}, the parameter r_2 of the highest level is very important.

5. Experiment Results

In order to demonstrate the validity and better performance of the proposed algorithm, we have implemented the proposed algorithm in MATLAB R2010 and carried out several contrast experiments on three low contrast MR images. Contrast experiments are mainly carried out on some representative algorithms for image enhancement, which are HE method, AHE method, IBF method and DWT method. In the proposed homomorphic-filtering algorithm, three level dyadic wavelet transform is applied in the IBF method. For the ease of experimental rationality, we set the cutoff frequency ρ_C to be the constant of 80. Three groups of contrast experiment results are presented as follows.

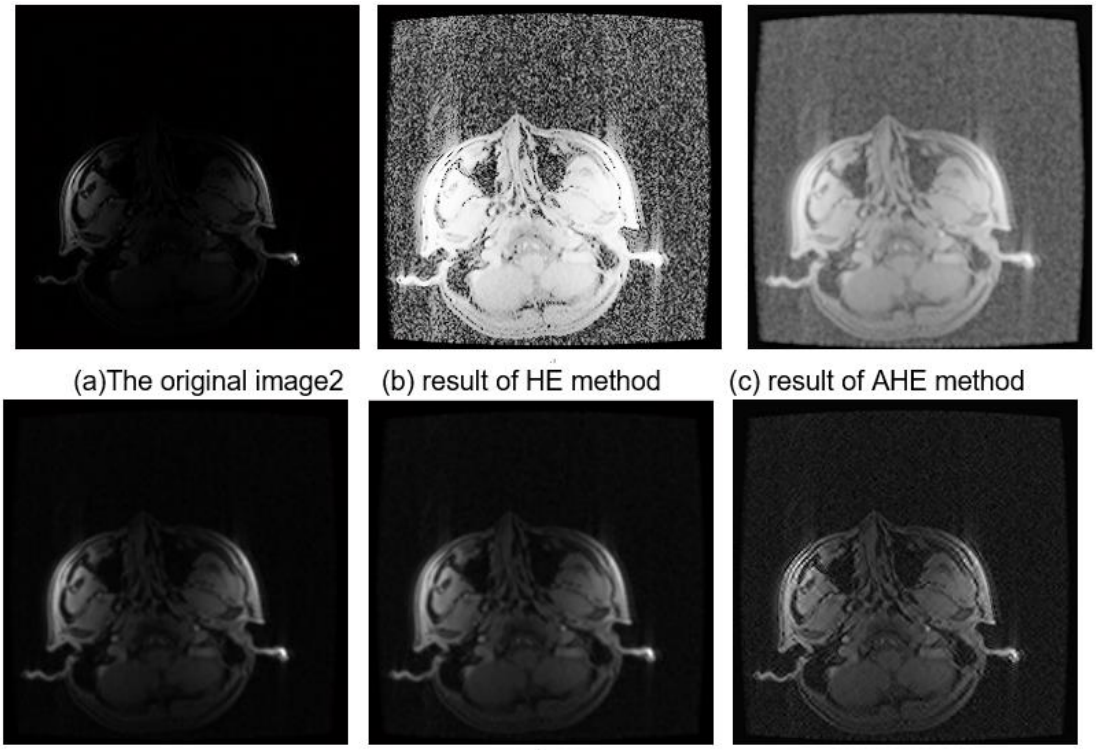
From the following experiment results, firstly it can be found that there are large homogeneous regions in MR images. As greatly magnifying noise in smooth regions by the HE method and AHE method, the brightness of images have been changed greatly too. Obviously, the effect that the improved images look rather unnatural is not the kind of result we want. Simultaneously, the result of IBF method superiors to the basic Butterworth method largely. However, images processed by IBF method are a bit blurry, and there are also some brightness in images. Among these representative methods, the result obtained by the DWT method is preferable. As a whole, it is very clear that the results obtained by our method on MR image enhancement are very satisfactory.



(a)The original image1 (b) Result of HE method (c) Result of AHE method

(d) Result of IBF method (e) Result of DWT method (f) Result of our method

Figure 4. Experiment results on image1



(a)The original image2 (b) result of HE method (c) result of AHE method

(d) Result of IBF method (e) Result of DWT method (f) Result of our method

Figure 5. Experiment results on image2

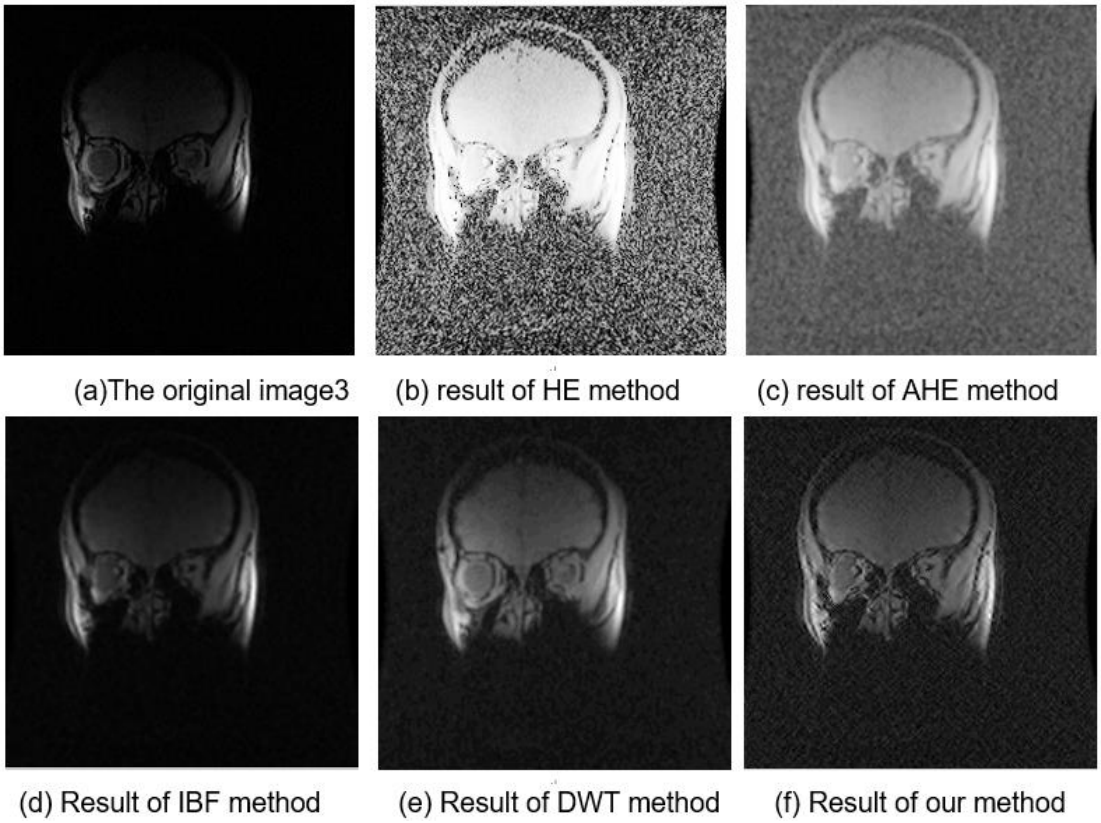


Figure 6. Experiment results on image3

It can be seen that the results of our method and DWT method are very similar. Accordingly, it is very necessary that drawing the comparison between them. Firstly, in Figure 4, the image processed by our method is much clearer, but there is some subtle tissues in DWT method. Secondly, in Figure 5, the comparison of the two methods explains that the former can obtain more exact and concrete tissues. Finally, in Figure 6, some subtle tissues have not been improved effectually, and some weak sections have been enhanced by DWT method. Conversely, these facets can be solved by our method well.

6. Conclusion

In this paper, as magnetic resonance (MR) images cannot be analyzed and processed by traditional image enhancement methods, a novel spatial homomorphic filtering algorithm for MR image enhancement is proposed. Distinguished from the traditional methods, the proposed algorithm can enhance MR image components adaptively based on their spatial frequency properties. The main idea of this method is inverse dyadic wavelet transform is applied to reconstruct the object image. Experiment results on MR images illustrate that the spatial homomorphic filtering algorithm performs well in enhancement of MR image, and maintains its global appearance very well too. This method is better to the other methods, particularly, compared to DWT method, some subtle tissues can been improved effectually, and some weak sections have not been smoothed by the proposed method.

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