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Wavelet-Based Multi-Modality Medical Image Fusion CT/MRI for Medical Diagnosis Purpose Human Visual Perception Compute-Processing Image

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ABSTRACT: Medical image fusion has been used to derive useful information from multimodality medical image data. The idea is to improve the image content by fusing images like computer tomography (CT) and magnetic resonance imaging (MRI) images, so as to provide more information to the doctor and clinical treatment planning system. This paper aims to demonstrate the application of wavelet transformation to multi-modality medical image fusion. This work covers the selection of wavelet function, the use of wavelet based fusion algorithms on medical image fusion of CT and MRI, and the fusion image quality evaluation. We introduce the peak-to-peak signal-to-noise ratio (PSNR) method for measuring fusion effect. The performances of other two methods of image fusion based on pyramid-decomposition and simple image fusion attempts are briefly described for comparison. The experiment results demonstrate the effectiveness of the fusion scheme based on wavelet transform.

Keywords: Image fusion, multimodality medical, peak-to-peak signal-to- noise ratio, wavelet function;

I. INTRODUCTION

IMAGE fusion refers to the techniques that integrate complementary information from multiple image sensor data such that the new images are more suitable for the purpose of human visual perception and the compute-processing tasks. The fused image should have more complete information which is more useful for human or machine perception. The advantages of image fusion are improving reliability and capability [1-3]. As the clinical use of various medical imaging systems extends, the multi-modality imaging plays an increasingly important role in medical imaging field. Different medical imaging techniques may provide scans with complementary and occasionally redundant information. The combination of medical images can often lead to additional clinical information not apparent in the separate images. However, it is difficult to simulate the surgical ability of image fusion when algorithms of image processing are piled up merely. So, many solutions to medical diagnostic image fusion have been proposed today. In this paper medical computer tomography (CT) and magnetic resonance imaging (MRI) images of the same people and same spatial part are presented [4-7]. In recent years, many image fusion techniques and algorithms have been exploited and they have been successfully used in the fusion process. More recently, with the development of wavelet theory, people began to apply wavelet multi-scale decomposition to take the place of pyramid decomposition for image fusion [8-10]. The flowchart of the image fusion

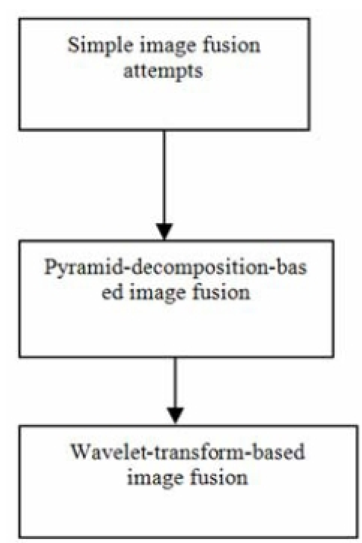


Fig. 1. The flowchart of the image fusion.

the image fusion is performed at the pixel level, other types of image fusion schemes, such as feature or decision fusion, are not considered. We select three methods to experiment and to compare with. They are weighted average method of simple image fusion attempts, laplacian pyramid and Wavelet-transform-based image fusion method.

II. CHARACTERISTICS OF WAVELET TRANSFORMATION

A. Relevant Wavelet Theory Wavelet is a function family $\psi_{a,b}$:

$$\psi_{a,b}(x) = |a|^{-1/2}\psi\left(\frac{x-b}{a}\right), a, b \in R, a \neq$$

$\psi_{a,b}$ is received by locomotion and flexing of function

ψ that satisfies the condition:

$$\int_R \psi(X)dx = 0$$

Usually ψ is named basic wavelet.
Given arbitrary

$f \in L^2(R)$, if $\psi \in L^2(R)$,

we give the following definitions:

The definition of continuous wavelet:

$$W_f(a,b) = \int_R \overline{\psi}_{a,b}(x) f(x)dx = \frac{1}{\sqrt{|a|}}\int_R \overline{\psi}\left(\frac{x-b}{a}\right) f(x)dx$$

The definition of discrete wavelet:

$$C_{(m,n)}(f) = \int_{-\infty}^{\infty} \psi_{m,n}(x) f(x)dx$$

where

$$\psi_{m,n}(x) = a^{-m/2}\psi\left(a_0^{-m}x - nb_0\right), 0 < a_0 < 1, b_0$$

Since image is 2-D signal, we will mainly focus on the2-Dwavelet transforms. With the one-dimensional scaling function, we can give separable two dimensional scaling and wavelet functions:

$$\varphi(x, y) = \varphi(x)\varphi(y),$$

$$\phi^H(x, y) = \phi(x)\varphi(y),$$

$$\phi^V(x, y) = \varphi(x)\phi(y),$$

$$\phi^D(x, y) = \phi(x)\phi(y),$$

where the symbols H, V and D stand for the directional wavelet coefficients. The transformation basis functions are
defined as:

$$\varphi_{j,m,n}(x, y) = 2^{j/2}\varphi(2^j x - m, 2^j y - n)$$

$$\psi^i_{j,m,n}(x, y) = 2^{j/2}\psi^i(2^j x - m, 2^j y - n),$$

$$i = \{H, V, D\}$$

Thus, the resulting two-dimensional wavelet at obtaining as many as information from the different modality images. The fusion criterion is to minimize different error between the fused image and the input images. With respect to the medical diagnosis, the edges and outlines of the interested objects is more important than other information. Therefore, how to preserve the edge-like features is worthy of investigating. for medical image fusion. As we know, the image with higher contrast contain more edge-like features. In term of this view, we proposed a new medical image fusion scheme based on an improved wavelet coefficient contrast. In section 2, the wavelet transform is discussed and then we define a new wavelet coefficient contrast . The Wavelet transform has good spatial and frequency localization characteristics which show itself mainly at three aspects: frequency feature compression (feature compression in the frequency domain), space compression feature and structure similarity of wavelet coefficients among different scales. Frequency compression feature means that the energy of original image concentrates at low frequency sub-band. Space compression feature indicates that the energy of high frequency sub-band mainly distributes at the corresponding positions of the edges of original image. Structure similarity of wavelet coefficients refers to the general consistence of the distributions of wavelet coefficients in high frequency sub-bands of the same orientation. The two-dimensional discrete wavelet transform (The two-dimensional separable wavelet transform can be computed quickly. The transform process can be carried to J stages, where J is the integer J ≤ log (M) for an M-by-M pixel image. At each scale, Aj contains the low-frequency information from the previous stage D ,D and jd D contain the horizontal, vertical and diagonal edge information, respectively. of a different imaging mechanism and high complexity of body tissues and structures, different medical imaging techniques provide non-overlay and complementary information. For instance, CT can clearly express human bone information, but it can not distinguish the soft tissue details; oppositely, MRI can clearly express soft tissue information, but it is not sensitive to bone tissue. Fusing CT and MRI images can get a complete picture which contains both clear CT/MRI images for the wavelet high-frequency coefficients. Compared with the most common wavelet-based fusion algorithm, the presented fusion method can keep more texture. Wavelet transform is kind of multi-resolution decomposition, namely multi-scale decomposition.

Its basic idea is to decompose an image into corresponding multi-scale wavelet coefficient matrixes via separable decomposition filter according to Mallat pyramid decomposition algorithm; each scale contains an approximate coefficient matrix and three details coefficient matrixes indifferent direction. Wavelet multi-resolution expression maps the image to different level of pyramid structure of wavelet coefficient based on scale and direction. To implement wavelet transform image fusion scheme, first, to construct the wavelet coefficient pyramid of the two input images. Second, to combine the coefficient information of corresponding level. Finally, to implement inverse wavelet transform using the fused coefficient. Usually, the contrast of an image is defined as Where, Aj contains the low frequency information from the previous stage of wavelet transform, while h D, D and jd D contain the horizontal, vertical and diagonal edge information, respectively. In this paper, we supposed that the mean value of the local window of the approximate coefficient be the background of the central pixel of the corresponding local window of the detail component. And the maximum coefficients of detail components are respectively taken as the most salient features with the corresponding local window along horizontal, vertical, and diagonal directions. Then the new contrast (we call it 'Ncontr' late) is defined as Actually, wavelet transform can be taken as one special type of pyramid decompositions. After one level of decomposition, there will be four frequency bands, namely Low-Low (LL), Low-High (LH), High-Low (HL) and High-High (HH). The next level decomposition is just apply to the LL band of the current decomposition stage, which forms a recursive decomposition procedure. Thus, an N-level decomposition will finally have 3N+1 different frequency bands, which include 3N high frequency bands and just one LL frequency band. The 2-D DWT will have a pyramid structure shown in the above figure. The frequency bands in higher decomposition levels will have smaller size.

III. QUALITY EVALUATION

We select peak-to-peak signal-to-noise ratio (PSNR) method to evaluate the effect of the fused images. Suppose Ris the source image (standard reference image) and F is the fused image; the root mean square error is defined as follows:

$$RMSE = \sqrt{\frac{\sum_{i-1}^{M}\sum_{j-1}^{N}[R(i,j) - F(i,j)]^2}{M \times N}}$$

The RMSE is used to measure the difference between the source image and the fused image; the smaller the value of RMSE and the smaller the difference, the better the fusion performance.

A. Peak-to-peak signal-to-noise ratio is defined as follows:

Where ln is the natural logarithm operation and *f* max is the maximum gray value of the pixels in the fused image.

TABLE I
THE RESULT OF THE EVALUATION

Method	Peak-to-peak signal-to-noise ratio (PSNR)
Weighted Average method	68.4456
Pyramid	70.1061
wavelet transform(WT)	72.1172

$$PSNR = 10 \times \ln\left(f_{\max} \times f_{\max} / RMSE^2\right)$$

The bigger the value of PSNR, the better the fusion performance [14-16].
The result of the evaluation in table 1.

$$\begin{cases} C_v^j = \max(D_v^j)/M^j, & \textit{vertical contrast} \\ C_h^j = \max(D_h^j)/M^j, & \textit{horizonal contras} \\ C_d^j = \max(D_d^j)/M^j, & \textit{diagonal contrast} \end{cases}$$

Where M j is the matrix of local mean value of theapproximate coefficient at level j. While the max( ), max( ), max(j)v D D D are the respective most maximum coefficients of corresponding detail components at level j. Therefore, we obtain three new contrasts jv C, C C in the wavelet domain, which represent the most significant features relatively to the background of the local window along vertical, horizontal, and diagonal directions respectively.

Based on these new contrasts, a improved image fusion scheme is defined as follows:

$$D^j_{v,F}(i,j)=\begin{cases}D^j_{v,X}(i,j), if\ |C^j_{v,X}(i,j)|>|C^j_{v,Y}(i,j \\ D^{\ j}_{v,Y}(i,j), otherwise\end{cases}$$

$$D^j_{h,F}(i,j)=\begin{cases}D^j_{h,X}(i,j), if\ |C^j_{h,X}(i,j)|>|C^j_{h,Y}(i,j \\ D^{\ j}_{h,Y}(i,j), otherwise\end{cases}$$

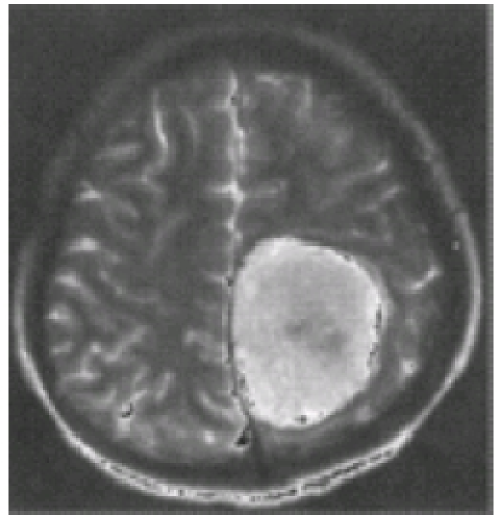
$$D^j_{d,F}(i,j)=\begin{cases}D^j_{d,X}(i,j), if\ |C^j_{d,X}(i,j)|>|C^j_{d,Y}(i, \\ D^{\ j}_{d,Y}(i,j), otherwise\end{cases}$$

(a) CT

The fusion scheme of the approximate component is to average the corresponding low frequency component of the last decomposition level as follows:

$$A^L_F = (A^L_X + A^L_Y)/2$$

Where, L is the max decomposition level of wavelet transform. In spite of the max decomposition level, the approximation coefficient is obtained from the wavelet reconstruction of the next level. That is to say, there construction result of each level is supposed as the approximation coefficient of the smaller level.



(b)MRI

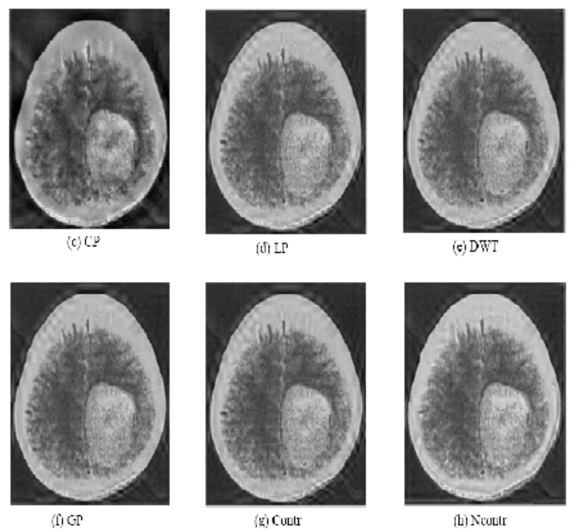


Fig. 2. CT/MRI image fusion.

the two-dimension (2-D) wavelet analysis operation consists in filtering and down-sampling horizontally using the 1-D low-pass filter L and high-pass filter H to each row in the image I. Vertically filtering and down-sampling follows, using the low-pass filter L and high pass filter H to each column, finally produces four sub images LL I, LH I, HL I and HH I for one level of decomposition [6]. LL I, LH I, HL I and HH I respectively represent sub-images of low frequency band, horizontal, vertical and diagonal high frequency bands. The next stage of decomposition is only applied to the low frequency band.

Thus, an N-level decomposition will result in 3N+1 different frequency bands, which include 3N high frequency bands and just one low frequency band. The image can be reconstructed by reversing the decomposition process.

B. Texture feature extraction based on wavelet transforms

The purpose of texture feature extraction is to get characteristic vector of every pixel which can be used to distinguish a different texture pattern. The results of two dimensional wavelet decomposition reflect frequency changes of different direction, also reflects the texture features of images. We select the energy and regional information entropy to express texture features of image.

C. Energy

When the image has more obvious texture features in a certain frequency bands or direction, the corresponding wavelet channel output has larger energy. The bigger energy of corresponding pixel is, the clearer texture feature is. The energy of image is described as below [5]:

IV. PROPOSED RESULTS

Medical image fusion performance can be evaluated in term of doctor's perception and quantitative criterions. In this section, by fusing CT/MRI images we tyro compare the performances of proposed fusion scheme in the previous section to Laplacian pyramid of P.J. Burt [1](calling it 'LP' method), gradient pyramid of P.J. Burt [2](GP), the original contrast pyramid suggested by Toat [3](CP), the conventional DWT using Debauchies 8 filters(DWT), and wavelet coefficient contrast pyramid of [4] (Contr). For medical diagnosis, doctors usually observe the images manually and fuse them in the mind. But it is very tedious and tired job. Here, we try to fuse CT/MRIimages automatically to reduce this workload. Fig. 2 (a), (b) are the source images of CT and MRI of a patient with a brain tumor. Fig. 2 (c), (d), (e), (f), and (g) are the fused results using the methods based on CP, LP, DWT, GP, and Control respectively. Fig. 2 (h) is attained by the proposed method -'Ncontr'. Fig.1 (c) shows that the fused image based on CP method is not so good. And the results of LP, GP, and DWT almost have the same visual effects. The'Contr' method and the proposed fusion method present slightly better visual effect than the others. Especially, the proposed method has less disturbing details and has smooth edges such as the outlines of skulls and brain tumor compared the regular wavelet coefficient contrast ('Contr') method. These edge-like image features is more important than details for doctors to diagnose the tumor status. Therefore, in view of the medical diagnosis, the proposed method provides better results compared with the others. Above, we compare the perception results of 'Ncontr' fusion methods with several classic image fusion schemes. To further evaluate quantitatively the ability of different fusion methods in respect of exacting the large features (or edges), we adopt the QAB/F metric proposed by V. Petrovic [6], which can effectively catch the edges features from the input images. In [8], several popular metrics for image fusion performance assessments are compared in details. Readers interested in this field can refer to this presents the compared results of the above discussed fusion methods using the metric QAB/F. The scores show the proposed method has a little better effect than the others.

V. CONCLUSION

the wavelet transform is a powerful method for fusion of images. The primitive fusion schemes perform the fusion right on the source images, which often have serious side effects such as reducing the contrast. This fusion algorithm, based on wavelet transform, is an effective approach in image fusion area.image fusion scheme based on a new wavelet coefficient contrast is proposed. The visual experiments and the quantitative analysis demonstrate that the 'Ncontr' medical image fusion method can preserve the important structure information such as edges of organs, out lines of tumors compared to other image fusion methods. This characteristic make the proposed methods a promising applications in medical diagnosis. Further practical applications will be investigated in our future work with more medical images.

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