Wavelet-based Texture Fusion of CT/MRI Images

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***Abstract*—Medical image fusion of computer tomography (CT) and magnetic resonance imaging (MRI) is to obtain more information from the CT and MRI respectively. In this paper, we present a wavelet-based texture fusion of CT/MRI images. Wavelet transform is employed to extract energy and regional information entropy of texture features from images. In the process of fusion, we adopt the fusion rule of energy maximum for the wavelet low-frequency coefficients; give the fusion rule according to the comparison of energy and regional information entropy contrast between CT/MRI images for the wavelet high-frequency coefficients. Finally, obtain the fused medical image via inverse wavelet transform. We select two groups of CT/MRI images to simulate, and compare our simulation results with the most common wavelet transform fusion algorithm. The simulation results and fusion performance index show that the presented method is effective.**

Keywords-image fusion; CT/MRI; wavelet transform; texture feature; regional information entropy

I. INTRODUCTION

With the development of medical imaging equipment, the image diagnosis has made tremendous contributions to the raise of medical standard. A single mode of image can not provide comprehensive and accurate information, so medical image fusion has become the focus of image research and processing [1] [2]. Medical image fusion refers to the matching and fusion between two or more images of the same lesion area from different medical imaging equipments. It is to obtain complementary information, increase the amount of information, and make the clinical diagnosis and treatment more accurate and perfect. Wavelet transform [3] is the critical method. Because of its good frequency characteristics, directionality and layered structure coincide with the human vision, wavelet transform has been widely applied in medical image fusion. The key of medical image fusion is to extract the texture feature of lesion. In recent years, the methods of texture feature extraction based on wavelet multi-resolution analysis have attracted more attention [4] [5]. The texture feature extraction, analysis and process via wavelet transform have become a new hotspot in medical field.

Because 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 bone tissue and soft tissue information.

According to the complementarities of CT/MRI images and the characteristics of wavelet transform, this paper presented a wavelet-based texture fusion of CT/MRI images. We used wavelet transform to extract texture features of images; and adopted the fusion rule of energy maximum for the wavelet low-frequency coefficients, the fusion rule according to the comparison of energy and regional information entropy contrast between 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 and details information of source images and obtain a better fusion effect.

II. TWO-DIMENSIONAL WAVELET TRANSFORM AND MULTI-RESOLUTION ANALYSIS

The application of wavelet transform in texture analysis was initiated by Mallat in 1989 [3]. Wavelet transform is a 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 in different direction.

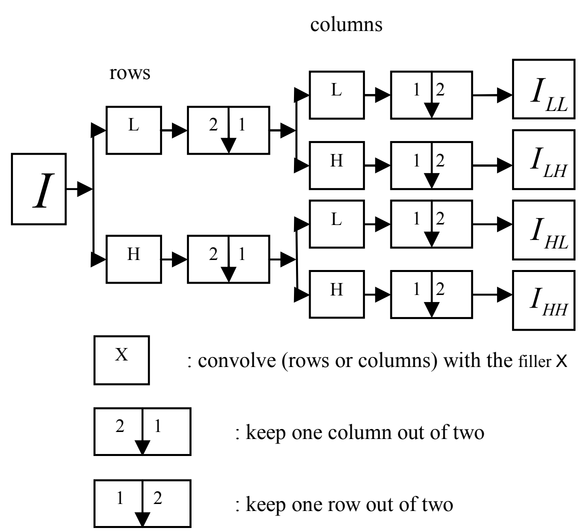

Fig.1 One stage of 2-D wavelet multi-resolution image decomposition

As shown in Fig.1, 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 I_{LL}, I_{LH}, I_{HL} and I_{HH} for one level of decomposition [6]. I_{LL}, I_{LH}, I_{HL} and I_{HH} 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.

III. THE FUSION IMPLEMENT

A. Texture feature extraction based on wavelet transform

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.

1) 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]:

$$E = \frac{\sum_{i=1}^{M}\sum_{j=1}^{N}[f(i,j)]^2}{M \times N} \tag{1}$$

Where, $f(i,j)$ represent pixel gray value of point (i, j). M*N is the size of the image.

2) Regional information entropy

Entropy represents the average information of the image. The bigger entropy is, the richer details contained in image. It can also be measure criterion of image texture complexity. The entropy value is 0 when no texture is in the image. The entropy is maximized when full of texture is in the image.

Because the correlation between pixels of image, the region-based image fusion can reflect image characteristics and trends better than the pixel-based image fusion. Regional information entropy is defined as [7]:

$$H = -\sum_{i=1}^{M}\sum_{j=1}^{N} p_{ij}\log_2 p_{ij} \tag{2}$$

$$p_{ij} = f(i,j) / \sum_{i=1}^{M}\sum_{j=1}^{N} f(i,j) \tag{3}$$

Where H represents the regional information entropy, p_{ij} is the gray value probability of point (i, j) in the regional image, $f(i,j)$ is the gray value of point (i, j) in the regional image. The size of the region is M*N.

The procedure of texture feature extraction is:

- To implement two-dimension discrete wavelet decomposition (DWT) to each source image on the level of N, and obtain 3N+1 sub-image.
- To calculate energy of all sub-images and regional information entropy of high-frequency sub-images on each level.
- To express the image texture feature as $\left\{E_{LL}^{(k)}, E_{LH}^{(k)}, E_{HL}^{(k)}, E_{HH}^{(k)}; H_{LH}^{(k)}, H_{HL}^{(k)}, H_{HH}^{(k)}\right\}$; k represents the wavelet-decomposed progression, k =1,2,3.

B. Wavelet-based Texture Fusion

Image texture feature mainly displays in details, wavelet high-frequency coefficients just reflect the image details. So the feature extracted from the high frequency detail coefficients can give expression to the main feature of image texture.

1) Fusion of High -frequency Coefficients

The fusion of high-frequency coefficients is the key of image fusion. High-frequency coefficients contain image detail information of edge and texture, the processing of high-frequency coefficients directly impact on the clearness and edge distortion of image.

Specific fusion procedure is as follows:

a) Calculate regional information entropy

Select region in size of 3*3 from source image A and B(CT and MRI), respectively calculate regional information entropy H_A, H_B and energy E_A, E_B according to (1) ,(2).

b) Calculate regional information entropy contrast

$$KH_A^l(i,j) = \frac{H_A^l(i,j)}{H_A^H(i,j) + H_A^V(i,j) + H_A^D(i,j)} \tag{4}$$

$$KH_B^l(i,j) = \frac{H_B^l(i,j)}{H_B^H(i,j) + H_B^V(i,j) + H_B^D(i,j)} \tag{5}$$

We define $KH_A^l(i,j)$, $KH_B^l(i,j)$ as regional information entropy contrast of image A and B, and they represent the proportion of high frequency components in one direction l(horizontal, vertical or diagonal) in the high frequency.

c) Select appropriate fusion rule

If the energy and regional information entropy contrast of image A are greater than or equal to image B at the same time, we select wavelet coefficients of image A as high-frequency coefficients. If the energy and regional information entropy contrast of image A are less than image B, we select wavelet coefficients of image B as high-frequency coefficients.

$$f_H(i,j)=\begin{cases} f_A(i,j); E_A^l \geq E_B^l, KH_A^l \geq KH_B^l \\ f_B(i,j); E_A^l < E_B^l, KH_A^l < KH_B^l \end{cases} \tag{6}$$

If the energy and regional information entropy contrast of image A are not greater than or less than image B at the same time, high frequency components are described as follows:

$$f_H(i,j)=\frac{(\alpha f_A(i,j)+\beta f_B(i,j))+(\mu f_A(i,j)+\nu f_B(i,j))}{2} \tag{7}$$

$$\begin{cases} \alpha=\dfrac{E_A^l}{E_A^l+E_B^l} \\ \beta=\dfrac{E_B^l}{E_A^l+E_B^l} \end{cases} \tag{8}$$

$$\begin{cases} \mu=\dfrac{KH_A^l}{KH_A^l+KH_B^l} \\ \nu=\dfrac{KH_B^l}{KH_A^l+KH_B^l} \end{cases} \tag{9}$$

$f_H(i,j)$, $f_A(i,j)$ and $f_B(i,j)$ respectively represent high-frequency coefficients pixel value of fused image, image A and B at point (i, j). E_A^l , E_B^l respectively represent energy of high-frequency coefficients. l represents the horizontal, vertical and diagonal directions of image.

2) Fusion of Low -frequency Coefficients

Medical images are different from common images; they have unique properties and more complex features. Take CT and MRI images for example, the outline of MRI image is more complex, and the range of its wavelet low-frequency coefficients is wide, which means it contains more information. But the outline of CT image is simple, and most of wavelet low-frequency coefficients are zero, the range of other coefficients is narrow. Thus, the traditional fusion method of weighted average [8] [9] may easily causes interested information loss of source image and the contrast reduction of fused image.

The larger transform values of wavelet correspond to sharper brightness changes and to the salient features in the image such as edges and region boundaries. Therefore, a good fusion rule is the maximum-selection scheme, which means just pick the coefficient with the larger feature value.

Low-frequency coefficients contain most energy of image, represent the approximate image information. So we adopt energy maximum fusion rule for the low-frequency coefficients.

Set A and B separately represents the original image (CT and MRI).

Fusion rule is described as below:

$$f_L(i,j)=\begin{cases} f_A'(i,j), E_A{}' > E_B{}' \\ f_B{}'(i,j), else \end{cases} \tag{10}$$

$f_L(i,j)$, $f_A'(i,j)$ and $f_B'(i,j)$ respectively represent low-frequency coefficients pixel value of fused image, image A and B at point (i, j). $E_A{}'$, $E_B{}'$ respectively represent energy of low-frequency coefficients.

IV. Simulation Results

In order to verify the validity of the fusion method presented in our paper, we selected two groups of CT/MRI images to simulate, and compared the simulation results with the most common wavelet transform fusion algorithm.

The most common wavelet transform fusion algorithm: weighted averaging rule for the low-frequency coefficients, and the rule of absolute value maximum for the high-frequency coefficients.

In Fig.2 and Fig.3:

CT1 and MRI1—The first group of images:

- The image type is BMP.
- The pixels value is 256*256.

CT2 and MRI2—The second group of images:

- The image type is JPEG.
- The size is 203*203*3.

FIC1—Fused Image of CT1 and MRI1 with the most common wavelet transform fusion algorithm.

FIP1—Fused Image of CT1 and MRI1 with the presented fusion method.

FIC2—Fused Image of CT2 and MRI2 with the most common wavelet transform fusion algorithm.

FIP2—Fused Image of CT2 and MRI2 with the presented fusion method.

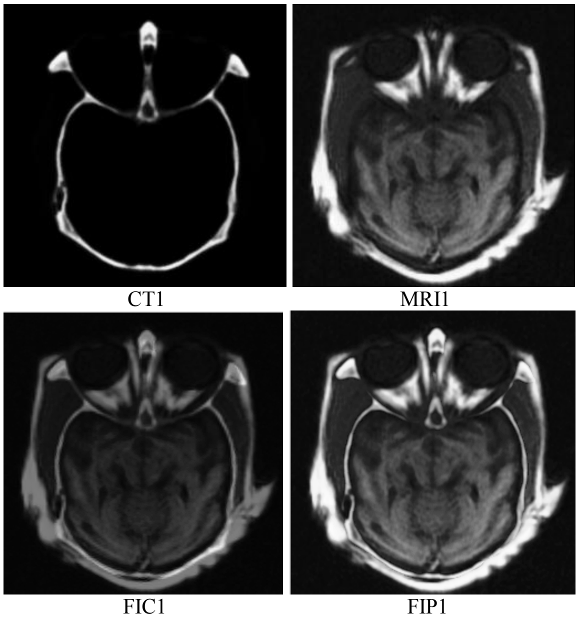

Fig.2 Simulation Results of the first group of images

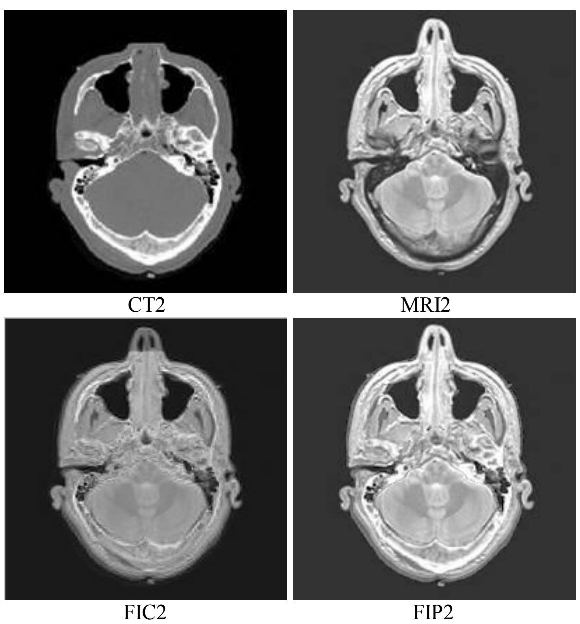

Fig.3 Simulation Results of the second group of images

From the simulation results, it can be seen that fused images using the presented method are clear, both bone tissue and soft tissue can be distinctly reflected; but fused images with the most common wavelet transform algorithm are fuzzy.

V. FUSION PERFORMANCE INDEX

The performance of the fused image is evaluated by entropy and the cross entropy.

Entropy of an image is defined as:

$$EN = -\sum_{i=1}^{m} p_i \ln p_i \tag{11}$$

Where Pi is the probability of gray level (i), and the rang of i is [0,…, m].

LetM1={p1,p2,…,pi,…,pm} and M2={q1,q2,…,qi,…,qm}, then the cross entropy of image M1 and image M2 is defined as:

$$CEN(M1, M2) = \sum_{i=1}^{m} p_i \ln(p_i / q_i) \tag{12}$$

The cross entropy directly reflects the pixel difference between two images, so it can be used to evaluate the effect of fusion. Suppose CEN (M1, M) and CEN (M2, M) are respectively cross entropies of the source image and the fused image. Then the entire cross entropy between the fused image and the two source images is defined as:

$$CEN(M, M1, M2) = \sqrt{(CEN^2(M1, M) + CEN^2(M2, M))/2} \tag{13}$$

Generally, if the entropy is larger and the cross entropy is smaller, the fusion effect is better; otherwise, it is worse. Actually, the cross entropy is also larger while the entropy is larger in some cases. Therefore, using above standards can not evaluate the fusion effect accurately. Integrative entropy [10] is introduced to evaluate performance of fused image.

The cross entropy between image M1 and image M2 is re-defined as [10]:

$$CEN'(M1, M2) = \sum_{i=1}^{m} p_i \left| \ln(p_i / q_i) \right| \tag{14}$$

The average cross entropy between the fused image and the two source images is defined as:

$$CEN'(M, M1, M2) = (CEN'(M1, M) + CEN'(M2, M))/2 \tag{15}$$

Then the integrative entropy, namely IEN , can be calculated as:

$$IEN(M, M1, M2) = EN(M) - CEN'(M, M1, M2) \tag{16}$$

For the fused image, if its entropy is larger and the average cross entropy is smaller, the fusion method is better; otherwise, it is worse. Similarly, the larger the integrative entropy is, the more effective the fusion method is.

TABLE I. FUSION PERFORMANCE INDEX OF THE FIRST GROUP OF IMAGES

Images	Parameters		
	Entropy	*CEN*	*IEN*
CT1	1.7126	—	—
MRI1	5.6561	—	—
FIC1	5.8493	0.8874	5.0844
FIP1	6.7599	0.5632	6.2516

TABLE II. FUSION PERFORMANCE INDEX OF THE SECONDGROUP OF IMAGES

Images	Parameters		
	Entropy	*CEN*	*IEN*
CT2	4.4150	—	—
MRI2	4.7708	—	—
FIC2	4.7088	3.9067	1.2785
FIP2	4.8134	0.4898	4.1696

Seen from TABLE Ⅰ and TABLE Ⅱ, for fused image with the presented fusion method, their integrative entropies are larger than fused image using the most common wavelet transform fusion algorithm, also their entropies are larger and the entire cross entropies are smaller. The results indicate that the presented fusion method is more effective.

VI. CONCLUSIONS

In this paper, we present a wavelet-based texture fusion of CT/MRI images, and show the simulation result and objective evaluation. In the process of fusion, we gave fusion rule based on energy and regional information entropy contrast, which effectively conserved the energy of source images and avoided the loss of useful information. Comparing with the most common algorithm, the wavelet-based texture fusion kept textural features and details of source images better, improved visual effect of fused image. It was indicated that the wavelet-based texture fusion of CT/MRI images is a kind of effective medical image fusion.

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