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Wavelet-Based High-Frequency Texture Fusion Low Energy CT/MRI Images

Yadvendra Singh and Amit Rajput
Department of Electronic and Communication Engineering,
RITS, Bhopal, (MP), India

(Corresponding author Yadvendra Singh)
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ABSTRACT: Most of wavelet-based texture fusion of CT/MRI images image fusion methods aim 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 schemes, especially for medical diagnosis. Magnetic resonance imaging (MRI) is to obtain more information from the CT and 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 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, which is defined as the ratio of the maximum of detail components to the local mean of the corresponding approximate component. The visual experiments and quantitative assessments demonstrate the effectiveness of this method compared to present image fusion

Key Words: Medical image fusion, wavelet coefficient contrast, edge preservation, performance evaluation, Medical diagnosis**,** CT/MRI;

I. INTRODUCTION

In recent years, multimodality medical image fusion has drawn lots of attention with the increasing rate at which multimodality medical images are available in many clinic application fields. Radiotherapy plan, for instance, often benefits from the complementary information in images of different modalities. Dose calculation is based on the computed tomography (CT) data, while tumor outline is often better performed in the corresponding magnetic resonance (MR) image. For medical diagnosis, CT provides the better information on denser tissue with less distortion, while MRI offers better information on soft tissue with more distortion. With more available multimodality medical images in clinic application, the idea of encompassing different image information comes up very important, and medical image fusion has been emerging as a new and promising research area. The goal of image fusion is to obtain useful complementary information from multimodality images as much as possible. A number of solutions for image fusion have been introduced in previous literatures. The simplest way to obtain a fused image from two or more medical images is to average them. Although mostly preserving the original meaning of the images, it is prone to reduce the contrast of the fused image. With developments of Marr'svision and applications of multi-resolution image processing techniques, the potential benefits of multi-scale, multi-resolution image fusion schemes have been explore din order to improve the contrast of the fused image. P.J. Burt [1] [2] proposed the Laplacian pyramid based and gradient pyramid based image fusion methods. H.Li [5]employed wavelet pyramid to develop a scheme which can exact the localized characteristics of input images. Y.Chibani [7] used the multi-scale pyramid, which is over-complete representation of the original images, to merge different images into a single one to adapt the invariance with respect to elementary geometric operations such as translation, scaling, and rotations. More multi-resolution image fusion schemes refer to [9].Most of present image fusion methods aim 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 image fusion Scheme is described in detail in the section 3.Finally, different image fusion scheme on the medical image are compared according to some effective image fusion evaluation

II. DIMENSION DISCRETE WAVELET TRANSFORM

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 (forward 2-D DWT) can be expressed as follows:

$$A^{j+1}(n_1,n_2)=\sum_{k_1}\sum_{k_2}h_0(2n_1-k_1)\bullet h_0(2n_2-k_2)\bullet A^j(k_1,k_2)$$

$$D_h^{j+1}(n_1,n_2)=\sum_{k_1}\sum_{k_2}h_0(2n_1-k_1)\bullet h_1(2n_2-k_2)\bullet A^j(k_1,k_2)$$

$$D_v^{j+1}(n_1,n_2)=\sum_{k_1}\sum_{k_2}h_1(2n_1-k_1)\bullet h_0(2n_2-k_2)\bullet A^j(k_1,k_2)$$

$$D_d^{j+1}(n_1,n_2)=\sum_{k_1}\sum_{k_2}h_1(2n_1-k_1)\bullet h_1(2n_2-k_2)\bullet A^j(k_1,k_2)$$

Its inverse transform (2-D IDWT) becomes:

$$\begin{aligned}A^j(k_1,k_2)=&\sum_{n_1}\sum_{n_2}\overline{h}_0(k_1-2n_1)\bullet\overline{h}_0(k_2-2n_2)\bullet A^{j+1}(n_1,n_2)+\\&\sum_{n_1}\sum_{n_2}\overline{h}_0(k_1-2n_1)\bullet\overline{h}_1(k_2-2n_2)\bullet D_h^{j+1}(n_1,n_2)+\\&\sum_{n_1}\sum_{n_2}\overline{h}_1(k_1-2n_1)\bullet\overline{h}_0(k_2-2n_2)\bullet D_v^{j+1}(n_1,n_2)+\\&\sum_{n_1}\sum_{n_2}\overline{h}_1(k_1-2n_1)\bullet\overline{h}_1(k_2-2n_2)\bullet D_d^{j+1}(n_1,n_2)\end{aligned}$$

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

$$C = (L - L_B)/ L_B = L_H/ L_B$$

Where L is the intensity of pixel, B L is the intensity of the background of the pixel (or local low frequency component), *H B Lh* ̣*L* ̣*L* is supposed as the local high frequency component. Then vertical, horizontal and diagonal contrast can be defined as follows [5]:

$$\begin{cases} C_v^j = D_v^j / A^j, & vertical \quad contrast \\ C_h^j = D_h^j / A^j, & horizonal \quad contrast \\ C_d^j = D_d^j / A^j, & diagonal \quad contrast \end{cases}$$

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 centralpixel 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 follows:

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

Where M j is the matrix of local mean value of the approximate 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:

$$D_{v,F}^{j}(i,j)=\begin{cases} D_{v,X}^{j}(i,j), if \mid C_{v,X}^{i}(i,j)\mid > \mid C_{v,Y}^{j}(i,j)\mid \\ D_{v,Y}^{j}(i,j), otherwise \end{cases}$$

$$D_{h,F}^{j}(i,j)=\begin{cases} D_{h,X}^{j}(i,j), if \mid C_{h,X}^{i}(i,j)\mid > \mid C_{h,Y}^{j}(i,j)\mid \\ D_{h,Y}^{j}(i,j), otherwise \end{cases}$$

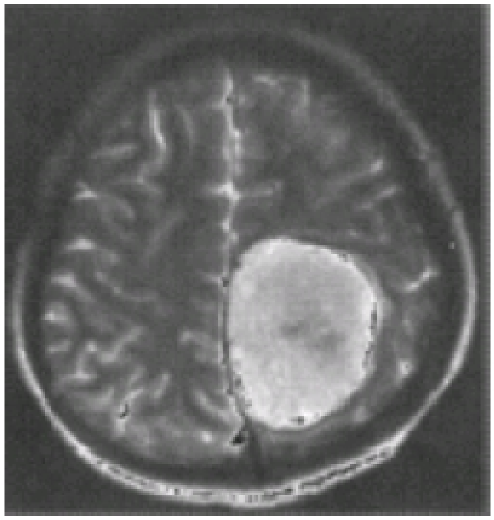
$$D_{d,F}^{j}(i,j)=\begin{cases} D_{d,X}^{j}(i,j), if \mid C_{d,X}^{i}(i,j)\mid > \mid C_{d,Y}^{j}(i,j)\mid \\ D_{d,Y}^{j}(i,j), otherwise \end{cases}$$


(a) CT

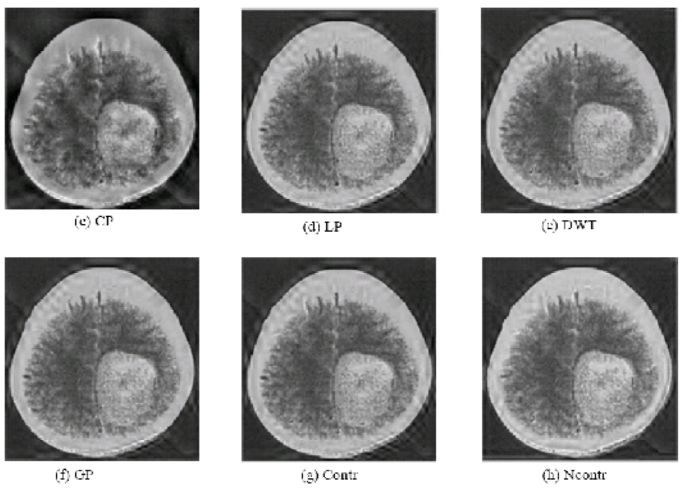
The fusion scheme of the approximate component is to average the corresponding low frequency omponent of the last decomposition level as follows:

$$A_F^L = (A_X^L + A_Y^L)/2$$

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. 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 in3N+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)MRI



CT/MRI image fusion

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.

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.

III. 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/MRI images automatically to reduce this workload. Fig. 1 (a),(b) are the source images of CT and MRI of a patient with a brain tumor. Fig.1 (c), (d), (e), (f), and (g) are the fused results using the methods based on CP, LP, DWT, GP, and Control respectively. Fig.1 (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 byV. 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 paper. Table I 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.

IV. CONCLUSION

In this article, an 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.

REFERENCES

[1]. P.J. Burt and E.H. Adelson,The Laplacian pyramid as a compact image code, *IEEE Transactions on Communications*, **31** (4), pp.532--540 (1983).

[2]. P.J. Burt and R.J. Kolczynski, Enhanced Image Capture through Fusion, *Proceedings Fourth International Conference on Computer Vision, Berlin*, pp. 173--182, *IEEE* (1993).

[3]. A. Toet, Image Fusion by a Ratio of Low-Pass pyramid, Pattern Recognition letters, 1989, 9(4): 245-253.

[4]. PU Tian, FANG Qing zhe, NI Guo qiang,,Contrast-Based Multiresolution Image Fusion Acta Electronica Sinica,2000 V.**12**,p. 116-118 (in Chinese).

[5]. H. Li, S. Munjanath, and S. Mitra, Multisensor Image Fusion Using the Wavelet Transform, Graphical Models Image Proc, 1995, 57(3):235-245.

[6]. V. Petrovic and C. S.Xydeas, Objective Image Fusion Performance Measure, Electronics Letters, 2000, 36(4): 308-309.

[7]. Y. Chibani, A. Houacine, Redundant versus orthogonal wavelet decomposition for multisensor image fusion, *Journal of Pattern Recognition* **36** (2003) 879–887.

[8]. V. Petrovic′, Subjective tests for image fusion evaluation and objective metric validation, Information Fusion (2005).

[9]. G. Piella, A general framework for multiresolution image fusion: from pixels to regions, International Journal of Information Fusion **4**(2003)258–280.4

[10]. M. Celebi, Y. Aslandogan, and P. Bergstresser, “Unsupervised borderdetection of skin lesion images,” in *Proc. Int. Conf. Inf. Technol.:Coding Comput.* (ITCC05), 2005, vol. **2**, pp. 123–128.

[11]. O. Chapelle, V. Vapnik, O. Bousquet, and S. Mukherjee, “Choosing kernel parameters for support vector machines,” Machine Learning, pp.