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Research Paper

Fusion Of Multi Modality Images And Preserving Edge Features In Medical Applications Using Noval Wavelet Coefficient

Engineering

KEYWORDS : wavelet coefficient Contrast, medical image fusion, edge preservation, performance evaluation, Medical diagnosis.

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ABSTRACT

Most of previous 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 novel 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 schemes, especially for medical diagnosis.

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. 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's vision and applications of multi-resolution image processing techniques, the potential benefits of multi-scale,multi-resolution image fusion schemes like Laplacian pyramid based and gradient pyramid based image fusion methods have been explored in order to improve the contrast of the fused image.A wavelet pyramid method is a scheme which can exact the localized characteristics of input images. 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.

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.TWO-DIMENSION DISCRETE WAVELET TRANSFORM

Wavelet transform has good spatial and frequency localization characteristics which shows 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 transforms (forward 2-D DWT) can be expressed as follows:

$$
\begin{aligned}
A^{j+1}(n_1,n_2) &= \sum_{k_1}\sum_{k_2} h_0(2n_1-k_1)\bullet h_0(2n_2-k_2)\bullet A^j(k_1,k_2)\\
D_h^{j+1}(n_1,n_2) &= \sum_{k_1}\sum_{k_2} h_0(2n_1-k_1)\bullet h_1(2n_2-k_2)\bullet A^j(k_1,k_2)\\
D_v^{j+1}(n_1,n_2) &= \sum_{k_1}\sum_{k_2} h_1(2n_1-k_1)\bullet h_0(2n_2-k_2)\bullet A^j(k_1,k_2)\\
D_d^{j+1}(n_1,n_2) &= \sum_{k_1}\sum_{k_2} h_1(2n_1-k_1)\bullet h_1(2n_2-k_2)\bullet A^j(k_1,k_2)
\end{aligned}
\qquad (1)
$$

Its inverse transform (2-D IDWT) becomes:

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

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

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previous stage, while Dhj, Dvj and Ddj contain the horizontal, vertical and diagonal edge information, respectively.

III. FUSION SCHEME BASED ON THE PROPOSED METHOD

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

$$C = (L - L_B) / L_B = L_H / L_B \qquad (3)$$

Where L is the intensity of pixel, LB is the intensity of the background of the pixel (or local low frequency component), LH=L - LB is supposed as the local high frequency component. Then vertical, horizontal and diagonal contrast can be defined as follows

$$\begin{cases} C_v^j = D_v^j / A^j, & vertical \quad contrast \\ C_h^j = D_h^j / A^j, & horizonal \quad contrast \\ C_d^j = D_d^j / A^j, & diagonal \quad contrast \end{cases} \qquad (4)$$

Where, Aj contains the low frequency information from the previous stage of wavelet transform, while Dhj, Dvj and Ddj 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 follows:

$$\begin{cases} C_v^j = \max(D_v^j) / M^j, & vertical\ contrast \\ C_h^j = \max(D_h^j) / M^j, & horizonal\ contrast \\ C_d^j = \max(D_d^j) / M^j, & diagonal\ contrast \end{cases} \qquad (5)$$

Where Mj is the matrix of local mean value of the approximate coefficient at level j. While the max(,Dvj), max(Dhj), max(Ddj) are the respective most maximum coefficients of corresponding detail components at level j. Therefore, we obtain three new contrasts Chj, Cvj , Cdj 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:

$$D_{v,F}^j(i,j) = \begin{cases} D_{v,X}^j(i,j), if \; |C_{v,X}^j(i,j)| > |C_{v,Y}^j(i,j)| \\ D_{v,Y}^j(i,j), otherwise \end{cases}$$
$$D_{h,F}^j(i,j) = \begin{cases} D_{h,X}^j(i,j), if \; |C_{h,X}^j(i,j)| > |C_{h,Y}^j(i,j)| \\ D_{h,Y}^j(i,j), otherwise \end{cases} \qquad (6)$$
$$D_{d,F}^j(i,j) = \begin{cases} D_{d,X}^j(i,j), if \; |C_{d,X}^j(i,j)| > |C_{d,Y}^j(i,j)| \\ D_{d,Y}^j(i,j), otherwise \end{cases}$$

IV.PERFORMANCE EVALUATION

The QAB/F associates important visual information with gradient information and assesses fusion by evaluating the success of gradient information transfer from the inputs to the fused image. Fusion algorithms that transfer more input gradient information into the fused image more accurately are said to perform better. Specifically, assuming two input images A and B and a resulting fused image F, a Sobel edge operator is applied to yield the strength g and orientation α(ε[0,π]) information for each input and fused image pixel. Using these parameters, relative strength and orientation "change" factors G and A, between each input and the fused image, are derived, e.g.:

$$G_{n,m}^{AF} = \begin{cases} \dfrac{g_{n,m}^F}{g_{n,m}^A}, & if \quad g_{n,m}^A > g_{n,m}^F \\ \dfrac{g_{n,m}^A}{g_{n,m}^F}, & otherwise \end{cases} \qquad (1)$$

$$A_{n,m}^{AF} = 2\pi^{-1} \left| \left| \alpha_{n,m}^A - \alpha_{n,m}^F \right| - \pi / 2 \right| \qquad (2)$$

These factors are the basis of the edge information preservation measure QAF obtained by sigmoidal mapping of strength and orientation change factors.This quantity models the perceptual loss of input information in the fused image and constants Γ, Kg, σ g, Kσ, σα determine the exact shape of the sigmoid mappings:

$$Q_{n,m}^{AF} = \Gamma \left(1 + e^{K_g (G_{n,m}^{AF} - \sigma_g)}\right)^{-1} \left(1 + e^{K_\alpha (A_{n,m}^{AF} - \sigma_\alpha)}\right)^{-1} \qquad (3)$$

Total fusion performance QAB/F is evaluated as a weighted sum of edge information preservation values for both input images QAF and QBF where the weights factors wA and wB represent perceptual importance of each input image pixel. The range is 0 = QAB/F = 1, where 0 means complete loss of input information has occurred and QAB/F =1 indicates "ideal fusion" with no loss of input information. In their simplest form, the perceptual weights wA and wB take the values of the corresponding gradient strength parameters gA and gB.

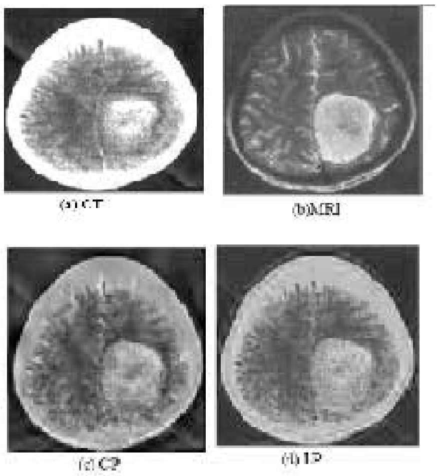
$$Q^{AB/F} = \frac{\sum_{\forall n,m} Q_{n,m}^{AF} w_{n,m}^A + Q_{n,m}^{AF} w_{n,m}^B}{\sum_{\forall n,m} w_{n,m}^A + w_{n,m}^B} \qquad (4)$$

V. EXPERIMENT 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 try to compare the performances of proposed fusion scheme in the previous section to Laplacian pyramid gradient pyramid (GP), the original contrast pyramid (CP), the conventional DWT using Debauchies 8 filters (DWT), and wavelet coefficient contrast pyramid (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 Contr 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 presents lightly 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 which can effectively catch the edges features from the input images. several popular metrics for image fusion performance assessments are compared in details. 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. This conclusion is consistent with visual observations.

TABLE I. COMPARISONS OF IMAGE FUSION PERFORMANCE

	CP	*LP*	*GP*	*DWT*	*Contr*	*Ncontr*
$Q^{AB/F}$	0.556	0.564	0.572	0.561	0.576	0.594



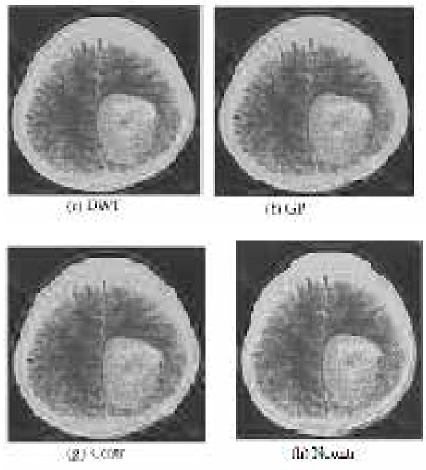


Fig.1 CT/MRI Image fusion

VI. 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,outlines of tumors compared to other image fusion methods. This characteristic make the proposed methods a promising applications in medical diagnosis.

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