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Multi modality Image fusion by using improved Wavelet Coefficient Contrast

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Abstract: *Image fusion play an important role in medical diagnosis .In medical diagnosis, the edges and outlines are very important than other information. Therefore to preserve edge like features we are using image fusion technique. Image fusion is the process of combining relevant information from two or more images in to single image .The fused image should give more complete information. As we know that the image with higher contrast contains more edge like features. In this view, we proposed a new medical image fusion scheme based on 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 analysis explains the effectiveness of this contrast image fusion method compared to present image fusion methods especially for medical diagnosis.*

Keywords: *Medical image fusion, wavelet coefficient contrast, edge preservation, performance evaluation, medical diagnosis.*

1. INTRODUCTION

In several situations in Image Processing high spatial and spectral resolution in a single technique allow the integration to different multimodality images. Now – a – day's multimodality medical image fusion has got lots of attention with the increasing rate at which multimodality images are available in medical diagnosis. In Radiotherapy plan, complementary information in images of different modalities used for the diagnosis of diseases. Dose diagnosis is based on the computed tomography (CT) data and based on magnetic resonance (MR) image data.

For medical diagnosis CT provides better information on denser tissue with less distortion, while in RI offers better information on soft tissue with more distortion. With more available multimodality medical images in Clinic application, the idea of combining different information sources by using 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. More number of solutions for image fusion was developed, but the simplest way to obtain a fund image from two or more medical images is to average them. Although mostly preserving the original meaning of the images. But there is possibility the contrast of fused image may reduced with developments of Marr's vision and applications of multi resolution image from schemes have been explored in order to improve the contract of the fused image.

P.J. Butt [1] [2] proposed the Laplacian pyramid based and gradient pyramid to develop a scheme which can exact the localized characteristics of input image.Y. Chibani [3] 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 scheme refer to [4].

Most of image fusion methods are used for obtaining complete information from the different modality images. The fusion process is to minimize different error between the fused images and input images. In medical diagnosis, the edges and out lines of the objects to preserve edge like factures is more important for medical image fusion.

But we know that the image with higher contrast contain more edge like features. From 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 detain in sections. Finally, different image fusion scheme on the medical image are compared according to some effective image fusion evaluation

2. TWO-DIMENSION DISCRETE WAVELET TRANSFORM

Wavelet transform has a good spatial and frequency localization characteristic 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 the wavelet coefficients in high frequency sub-bands of the same orientation.

The two-dimensional discrete wavelet transform can be expressed as follows.

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

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Its inverse transform (2D – IDWT) becomes:

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

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, A^j contains the low-frequency information from the previous stage, while D_h^j, D_v^j and D_d^j contain the horizontal, vertical and diagonal edge information, respectively.

3. FUSION SCHEME BASED ON THE NEW WAVELET COEFFICIENT CONTRAST

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, 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

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

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

$C_v^j = D_v^j / A^j$, vertical contrast

$C_h^j = D_h^j / A^j$, horizontal contrast

$C_d^j = D_d^j / A^j$, diagonal contrast (4)

Where A^j contains the low-frequency information from the previous stage of wavelet transform. While $D_h^j, D_v^j and D_d^j$ 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.

$C_v^j = \max(D_v^j) / M^j$, vertical contrast

$C_h^j = \max(D_h^j) / M^j$, horizontal contrast

$C_d^j = \max(D_d^j) / M^j$, diagonal contrast (5)

Where M^j is the matrix of the local mean value of the approximate coefficient at level j. While the max (D_v^j), max (D_h^j), max (D_d^j) are the respective most maximum coefficients of corresponding detail components at level j. therefore we obtain three new contrasts C_v^j, C_h^j, C_d^j 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 contrasts, a improved image fusion scheme is defined as follows.

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

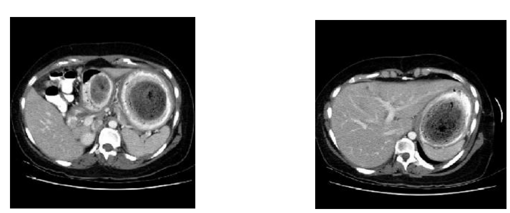
$$D_{h,F}^j(i,j)=\begin{cases}D_{h,X}^j(i,j), if\ |C_{h,X}^j(i,j)|>|C_{h,Y}^j(i,j)|\\ D_{h,Y}^{\ j}(i,j), otherwise\end{cases}\quad (6)$$

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

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

$$A_F^L = (A_X^L + A_Y^L) / 2 \quad (7)$$

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, the reconstruction result of each level is supposed as the approximation coefficient of the smaller level. Where L is the intensity of the pixel L_B is the intensity of the background the pixel (or local low frequency component), L_H = L - L_B is supposed as the local high frequency component. Then vertical, horizontal and diagonal contrast can be defined as follows. 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



(a) **(b)**

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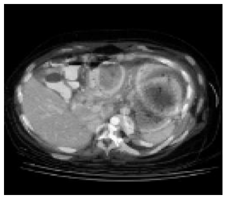

(c)

Figure 1: (a) CT, (b) MRI, (c) Fused Image

4. EXPERIMENTAL RESULTS

Medical image fusion based on improved wavelet coefficient contrast can be evaluated which give abundance information for the doctors to diagnosis diseases. In this method by fusing CT and MRI images of same object we try to compare the performances of proposed fusion scheme with other fusion schemes. For medical diagnosis, doctors usually observe the images manually and fuse them in the mind. But it is very difficult and tired job. For this purpose we try to fuse CT and MRI images to minimize the work load. Fig. 1 (a) and 1 (b) are the source images of CT and MRI images of a patient. Fig. 1 (c) is the fused image by using contrast method, this proposed methods has less disturbing details and more edge like features. We calculate the Entropy, mean Standard Deviation of proposed method; they will be compared with DWT method, contrast method. The proposed method has a little better effect than the other methods.

Table 1: Comparisons of image fusion performance

	Proposed	**Contrast**	**DWT**
Entropy	5.54228	6.0992	5.53394
Avg. Grad.	4.05149	5.53023	4.0266
STD	14.3341	21.3428	14.3178
Mean	21.6703	60836	21.6655

5. CONCLUSION

In this paper an image fusion scheme based on improved wavelet coefficient contrast is proposed. The visual experiments and the validations of proposed method can preserve the important structure can preserve the important structure information such as edges and outlines of object compared to other fusion methods. This proposed scheme gives abundance information to the doctors for medical diagnosis.

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