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Medical Image Fusion Scheme Using Complex Contourlet Transform based on PCA

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Abstract—**We present an efficient method for the fusion of medical captured images using different modalities that enhances the original images and combines the complementary information of the various modalities. The contourlet transform has mainly been employed as a fusion technique for images obtained from equal or different modalities. The limitation of directional information of dual-tree complex wavelet (DT-CWT) is rectified in dual-tree complex contourlet transform (DT-CCT) by incorporating directional filter banks (DFB) into the DT-CWT. The DT-CCT produces images with improved contours and textures, while the property of shift invariance is retained. To improve the fused image quality, we propose a new method for fusion rules based on principle component analysis (PCA) which depend on frequency component of DT-CCT coefficients (contourlet domain). For low frequency components, PCA method is adopted and for high frequency components, the salient features are picked up based on local energy. The final fusion image is obtained by directly applying inverse dual tree complex contourlet transform (IDT-CCT) to the fused low and high frequency components. The experimental results showed that the proposed method produces fixed image with extensive features on multimodality.**

I. Introduction

With the development of new imaging methods in medical diagnostics, there arises the need for meaningful and correct spatial combination of available image datasets. Image fusion stage supports the combination of multimodal medical images into a single image with more complete and accurate description of the same object. The medical images can include those obtained from anatomical modalities such as magnetic resonance imaging (MRI), Computed Tomography (CT), US (ultrasound), MRA (magnetic resonance angiography) and CTA (computed tomography angiography) or functional modalities such as PET (positron emission tomography) and fMRI (functional MRI). Fusion image from multimodal images can be very useful for clinical applications such as diagnosis, modeling of the human body or treatment planning [18].

Mainly, medical image fusion tries to solve the issue of where there is no single modality that provides both anatomical and functional information. Further more information provided by different modalities may be in agreement or in complementary nature. In general, fusion schemes can be classified into three primary categories: spatial-domain such as PCA, averaging weighted and averaging, transform-domain such as multiresolution decomposition and optimization methods such as Bayesian. It can be found that image fusion in spatial domain based on average reduces the contrast of features of the source images therefore it cannot provide a good outcome. Image fusion in spatial domain based on PCA can produce better results, but the edges of bones and tissues in human brain are very blurred. Several transforms have been proposed for image signals, which have incorporated directionality and multiresolution and hence, could capture edges in natural images more efficiently. Some popular examples are wavelet [3], steerable pyramid [6], curvelet [5] and contourlet [2]. Extensive researches have been conducted on image fusion techniques and various fusion algorithms for medical image [9,10,14,19].

Medical image fusion usually employs the pixel level fusion techniques. The contourlet transform is a geometrical image transform technique, which can efficiently represent images' contours and textures. It also offers a flexible multiresolution and directional decomposition for images, since it allows for different number of directions at each scale. Wavelet is well-known for fusion but it's not suited for the application with improper registration due to the severe problem of shift dependence. As an alternative, Kingsbury [8], proposed dual-tree complex wavelet transform (DT-CWT) that provides shift invariance approximation. DT-CWT has the drawback of limited directional information. Hence, Contourlet transform was proposed to capture the most important salient information in images by incorporating the DT-CWT and DFB [7].

In this paper, pixel-level fusion algorithm for multimodality medical image based on dual tree complex contourlet transform is developed. PCA and local energy are incorporated as the fusion rules. Experimental results show that the proposed DT-CCT-based fusion algorithm provides an effective way to enable more accurate analysis of multimodal images.

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II. Dual Tree Complex Contourlet Transform

A. Decomposition

Dipeneg and Li [7] proposed a complex contourlet transform (CCT) method which incorporates the DT-CWT and DFB to provide a flexible and robust scale-direction representation for source images. CCT consists of two stages, firstly DT-CWT was used [3] in contrast to the critically sampled used in [16], and Laplacian pyramid [4]. The DT-CWT decomposition details space W_j gives six subbands at each scale capturing distinct directions. Traditionally, we obtain the three highpass bands corresponding to the LH, HL, and HH. Each of them has two wavelets as real and complex part. By averaging the outputs of dual tree, we get an approximate of shift invariant [8]. In second stage for each subband applied (l_j) levels' DFB [13] as shown in Fig. 1. The mathematical form is defined as

$$\eta^{i,(l_j)}_{j,k,n} = \sum_{m\in\mathbb{Z}^2} g^{l_j}_k[m - S^{(l_j)}_k n]\,\psi^{i}_{j,m},\ \ i = HL, LH, HH. \qquad (1)$$

The family $\{\eta^{HL,(l_j)}_{j,k,n}, \eta^{LH,(l_j)}_{j,k,n}, \eta^{HH,(l_j)}_{j,k,n}\}_{n\in\mathbb{Z}^2}$ is a basis for the subspace $W^{(l_j)}_{j,k}$, and each consists of a complex dual tree. Here, $g^{(l)}_k$ is the impulse response of the synthesis filter, $S^{(l)}_k$ *is* overall downsampling matrices of DFB and ψ is a wavelet functions. The location shift is denoted as m.

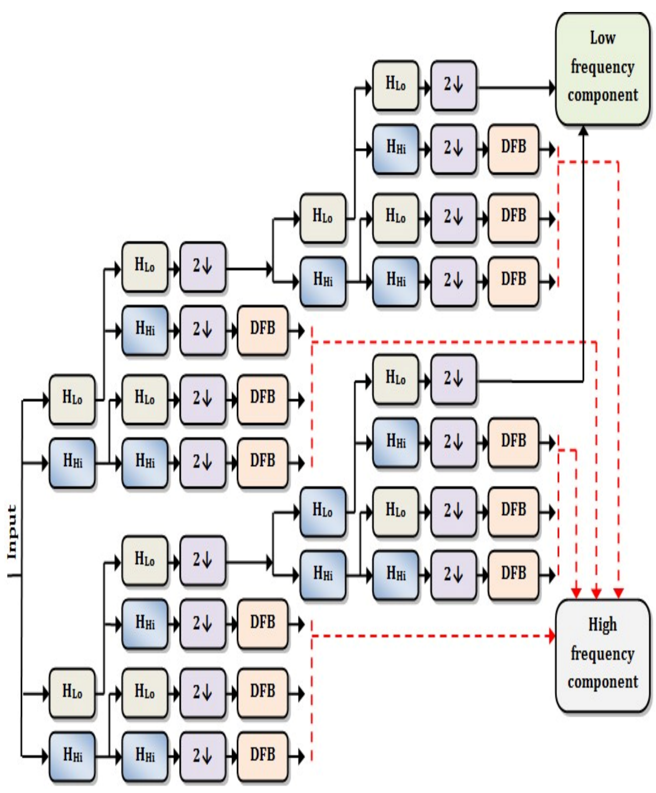

Fig. 1. The proposed of DT-CCT based on PCA.

B. Fusion Scheme

A new algorithm for image fusion has been presented. Fig.2. shows a block diagram of the proposed DT-CCT. In this technique, separate coefficients for the DT-CCT are computed, based on the frequency component of the image. PCA has been employed in previous researches [15] as fusion rules.

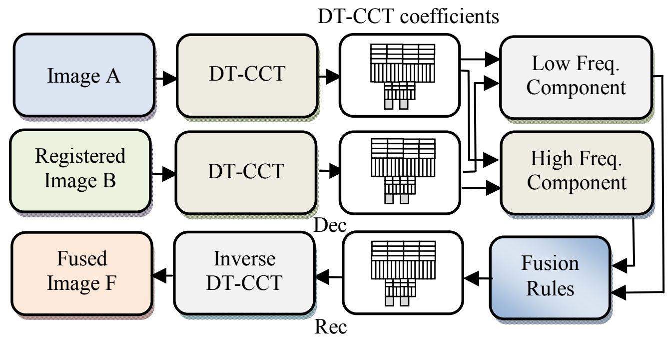

Fig. 2. Block diagram of the proposed DT-CCT.

In our work, PCA is adopted to fuse low frequency components for DT-CCT. PCA is mathematically defined as an orthogonal linear transformation that gives us the eigenvalue and eigenvector. The resultant fused image from the low frequency is not affected strongly by blurring compared to those from the high frequency components.

By supposing i and j are the elements of the principal eigenvector, which are computed by analyzing the original input image A and B for corresponding image coefficients, we obtain,

$$D_{L,A} = i/(i+j) \text{ and } D_{L,B} = j/(i+j) \qquad (2)$$

$D_{L,A}$ and $D_{L,B}$ are the normalized weights. Thus the fused image has the same energy distribution as the original input images. The coefficients of low frequency components for fused image F is,

$$\mathrm{Coff}(L,F) = \mathrm{Coff}(L,A).D_{L,A} + \mathrm{Coff}(L,B).D_{L,B} \qquad (3)$$

Coff(L,A) and Coff(L,B) represent low frequency components of coefficients image A and B respectively. For the coefficients of the high-frequency components, we calculate local energy $E^{(A)}(x,y)$ *and* $E^{(B)}(x,y)$ which is

$$E^{(A)}(x,y) = \sum_m\sum_n \mathrm{Coff}(H,A)(x+m,y+n)^2.W(m,n) \quad (4)$$
$$E^{(B)}(x,y) = \sum_m\sum_n \mathrm{Coff}(H,B)(x+m,y+n)^2.W(m,n) \quad (5)$$

In the equation, W is a template of size 3 × 3 and satisfy the normalization rule.

$$W = \frac{1}{9}\begin{bmatrix}1 & 1 & 1\\ 1 & 1 & 1\\ 1 & 1 & 1\end{bmatrix} \qquad (6)$$

Larger value of local energy $E^{(A \text{ or } B)}(x, y)$ means there is more high frequency information. Weights $D_{H,A}$ and $D_{H,B}$ needs to be calculated as,

$$D_{H,A} = \begin{Bmatrix} 1 & \text{for } E^{(A)}(x,y) \geq E^{(B)}(x,y) \\ 0 & \text{for } E^{(A)}(x,y) < E^{(B)}(x,y) \end{Bmatrix} \tag{7}$$

$$D_{H,B} = 1 - D_{H,A} \tag{8}$$

The coefficients of high frequency components for fused image F is,

$$\mathrm{Coff}(H,F) = \mathrm{Coff}(H,A).D_{H,A} + \mathrm{Coff}(H,B).D_{H,B} \tag{9}$$

C. *Reconstruction of fusion image*

By successively performing inverse dual tree complex contourlet transform to the modified coefficients at all decomposition, the final fused image can be reconstructed.

III. Numerical Experiments

To test our algorithm, two groups of human brain images were selected (see Fig 3). All images have the same size of 512×512 pixel, with 256-level grayscale. The corresponding pixels of two input images have been perfectly co-aligned. The proposed medical fusion algorithm DT-CCT based on PCA, CCT and DT-CWT are applied to these image sets. In our experiment an image is decomposed into 2-levels using biorthogonal Daubechies 9-7 (wavelet) [1,17]. Each subband at each level is fed to the DFB stage with 8-directions at the finest level. In the DFB stage, we use the 23-45 biorthogonal quincunx filters designed and modulate them to obtain the biorthogonal fan filters [11]. DT-CWT is available in Matlab wavelet software [21].

Four indicators were used to measure image quality, that were image quality index (IQI), root mean square error (RMSE), correlation coefficient (CC) and overall cross entropy (OCE) [20,7,10]. The overall cross entropy is used to measure the difference between the two source images and the fused image. Small value corresponds to good fusion result obtained. An experimental result is compared with complex contourlet transform based on maximum amplitudes [7] and dual tree complex wavelet transform. Table I, shows the experimental results. From the indicators we can see that the IQI and CC are the greatest with the proposed method. The OCE and RMSE of the new method are least in the two sets. It is shown that, the proposed method gives the best fusion results in the two fused images.

For the two image sets, the corresponding fused image results are given in Fig. 4. It can be easily seen that image fusion based on DT-CWT produces the details of tissues in human brain to be blurred. The CCT based on maximum amplitudes method performs better than previous method. However, the best image fusion result is obtained by applying the proposed fusion algorithm.

The feature and detailed information presented in proposed method is much richer than other fused images. The image contents like tissues are clearly enhanced. Other useful information like brain boundaries and shape are almost perfectly preserved.

TABLE I: Comparison of image fusion algorithm, IQI is image quality index, RMSE is root mean square error correlation coefficient (CC) and overall cross entropy (OCE).

Data	Algorithm	IQI	RMSE	CC	OCE
Image set 1	Proposed	0.1968	0.1030	0.9861	0.8811
	CCT	0.1511	0.1243	0.9835	0.9082
	DT-CWT	0.1616	0.1290	0.9818	0.4085
Image set 2	Proposed	0.2225	0.0935	0.9763	0.3619
	CCT	0.1389	0.1277	0.9651	0.5040
	DT-CWT	0.1453	0.1299	0.9646	0.5139

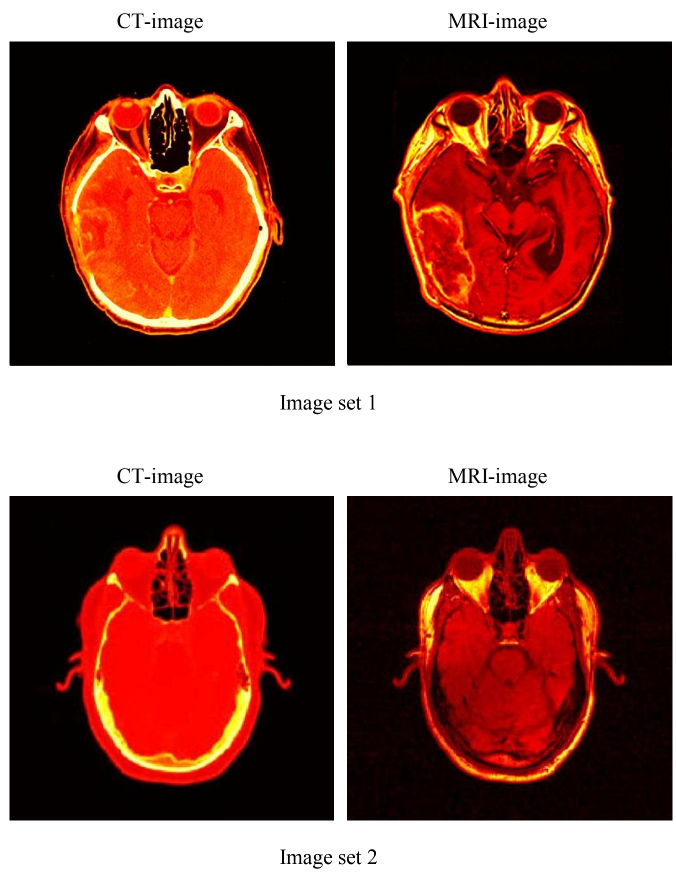

Fig. 3. Original multimodal medical image, dataset 1 and 2.

IV. Conclusion

In this paper a new image fusion method has been proposed that is DT-CCT based on PCA. After comparison of fused image obtain from CCT and DT-CWT, experimental results showed that proposed method is efficient in fusion of multimodal medical image. Visual and statistical comparisons demonstrated that the fusion results of the new method contain more detail information, while information distortion is very small.

DT-CWT CCT based on maximum amplitudes Proposed method

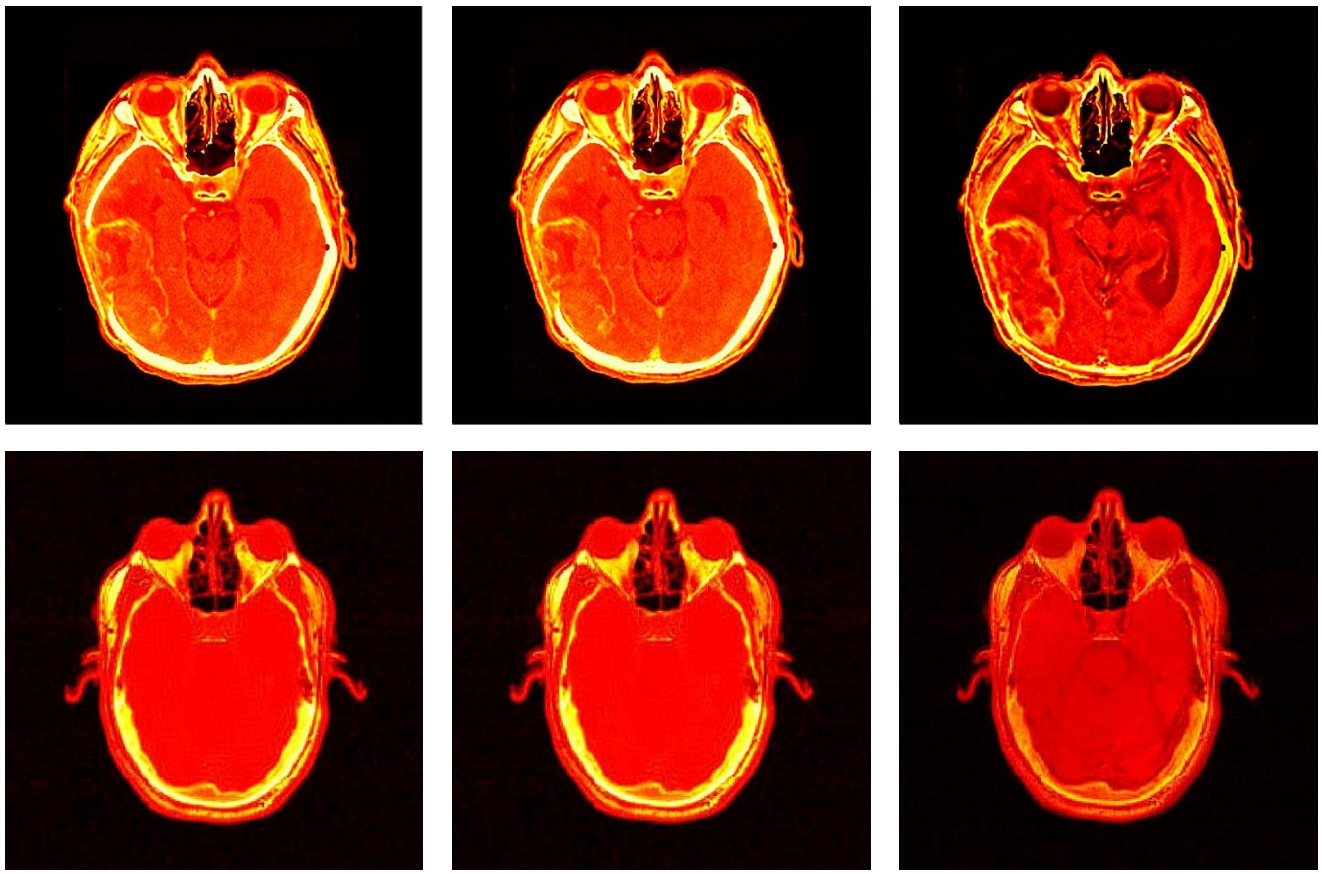

Fig. 4. Fusion results on test Original multimodal image, dataset 1 and 2 using DT-CWT, CCT and proposed method.

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