An efficient image fusion method based on dual tree complex wavelet transform

Negar Chabi[1], Mehran Yazdi[1], Mohammad Entezarmahdi [2,3]
[1] Faculty of Electrical and Computer Engineering, Shiraz University, Shiraz, IRAN
[2] Department of medical radiation, Shahid Beheshti University,Tehran,IRAN
[3] Department of nuclear medicine, Shiraz University of Medical Science,Shiraz,IRAN
negarchabi@gmail.com

Abstract—**Image fusion is a process which combines information from two or more images of the same scene into a single image preserving important features from each. The objective of image fusion is to combine complementary information from multiple images into a single resultant image which is more informative, comprehensive, reliable and precise compared to each source images. Fusion is an effective tool within various fields such as remote sensing, robotics and medical applications. In the proposed method the source images were first decomposed using the shift invariant and directionally selective dual tree complex wavelet transform (DT-CWT) and then fusion rules namely, max and local energy were applied to combine low and high frequency coefficients respectively. The final fused image was obtained by applying inverse DT-CWT to the fused low and high frequency components. The obtained fused images were analyzed qualitatively as well as with various quantitative metrics namely mutual information (MI), structural similarity index (SSIM), entropy, standard deviation (STD) and average gradient (AVG) where both analysis show that the proposed scheme can provide more information and better results compared to the other methods.**

Keywords—Image fusion; DT-CWT; WT; Quantitative metrics; fusion rules

The rest of the paper is organized as follows: in the first part (Introduction) there is a brief description about image fusion, in the second part we introduce DT-CWT briefly. 3'rd section is our proposed method then, in the 4'th section experimental results are discussed. Finally, the last part (conclusion) we discuss our method's superior performance.

I. INTRODUCTION

Image fusion is a process which combines information from two or more images of the same scene into a single fused image which provides more comprehensive information compared to each single input image and can provide more reliable and better result for the observers. Today, image fusion has been extended to various fields such as remote sensing, optical microscopy, computer vision, robotics, and medical imaging [1]. There are many techniques for image fusion. These techniques can be classified into two general groups namely spatial domain methods [1] and transform domain methods [2, 3]. For spatial domain methods, we can mention simple averaging methods, PCA [4], linear fusion. These techniques are simple but suffer from spatial distortion and do not present any spectral information. The mentioned disadvantages motivated us to use the transform domain methods. Discrete wavelet transform (DWT) has been widely used for image fusion recently, but it has some problems as it doesn't provide sufficient directional information and resulted in an image with shift variance and additive noise [5, 6]. As an alternative in the present work we propose a new scheme based on DT-CWT which provides approximate shift invariance and more directional information which first is introduced by Kingsbury. This transform overcomes the DWT limitations [7,8]. After image decomposition using DT-CWT, we apply maximum selection and local energy to combine low and high frequency coefficients respectively [18,19]. Then inverse DT-CWT was applied on the fused coefficients to obtain the fused image. Finally the proposed method is compared with DWT and some spatial domain techniques such as simple averaging and PCA using various quantitative metrics such as SSIM, MI, entropy, STD and average gradient (AVG) where both qualitative and quantitative comparisons demonstrated that the proposed scheme has a superior performance.

II. PRINCIPLE OF THE DUAL TREE COMPLEX WAVELET TRANSFORM

Discrete wavelet transform has been widely used in multi sensor image fusion, but it suffers from some major drawbacks such as poor directional selectivity, shift variance and absence of phase information. These mentioned problems were improved by DT-CWT [6,7]. Fortunately, Kingsbury developed DT-CWT to solve these fundamental problems while preserving the properties of nearly shift invariance and directionally selectivity in two and higher dimensions which complex wavelet parts provide [7, 8]. Since a complete discussion on DT-CWT is beyond the scope of this paper, we just bring the basic equations related to 2D DT-CWT, however the reader is referred to the work by Selesnick et al [9] for further studies. A 2D dual-tree complex wavelet can be defined as $\psi(x,y)=\psi(x)\psi(y)$, where $\psi(x)$ and $\psi(y)$ are two complex wavelets, $\psi(x)=\psi_h(x)+j\psi_g(x)$ and $\psi(y)=\psi_h(y)+j\psi_g(y)$, $\psi_h(.)$ and $\psi_g(.)$ are real wavelet transforms of upper filter bank (FB) and lower FB, respectively (Fig.1). Then we get the following equations:

$$\psi(x,y) = [\psi h(x) + j\,\psi g(x)][\psi h(y) + j\,\psi g(y)] = \psi h(x)\psi h(y) - \psi g(x)\psi g(y) + j[\psi g(x)\psi h(y) + \psi h(x)\psi g(y)] \quad (1)$$

The real parts of six oriented complex wavelets of DT-CWT are as follows:

$$\psi i(x,y) = \frac{1}{\sqrt{2}}(\psi 1, i(x,y) - \psi 2, i(x,y)) \quad (2)$$

$$\psi i + 3(x,y) = \frac{1}{\sqrt{2}}(\psi 1, i(x,y) + \psi 2, i(x,y)) \quad (3)$$

For i=1,2,3 , we have:

$$\psi 1,1(x,y) = \phi h(x)\psi h(y), \psi 2,1(x,y) = \phi g(x)\psi g(y), (4)$$

$$\psi 1,2(x,y) = \psi h(x)\phi h(y), \psi 2,2(x,y) = \psi g(x)\phi g(y), (5)$$

$$\psi 1,3(x,y) = \psi h(x)\psi h(y), \psi 2,3(x,y) = \psi g(x)\psi g(y). (6)$$

where The imaginary parts of six oriented complex wavelets of DT-CWT are as follows:

$$\psi i(x,y) = \frac{1}{\sqrt{2}}(\psi 3, i(x,y) + \psi 4, i(x,y)) \quad (7)$$

$$\psi i + 3(x,y) = \frac{1}{\sqrt{2}}(\psi 3, i(x,y) - \psi 4, i(x,y)) \quad (8)$$

For i=1,2,3 , we have:

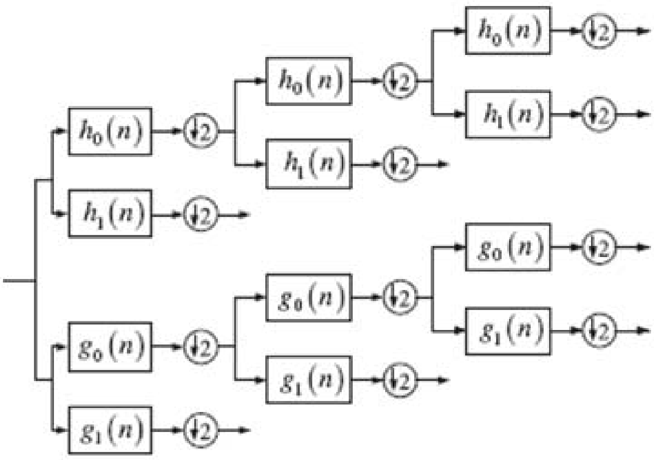
$$\psi 3,1(x,y) = \phi g(x)\psi h(y), \psi 2,1(x,y) = \phi h(x)\psi g(y), \quad (9)$$

$$\psi 1,2(x,y) = \psi g(x)\phi h(y), \psi 2,2(x,y) = \psi h(x)\phi g(y), \quad (10)$$

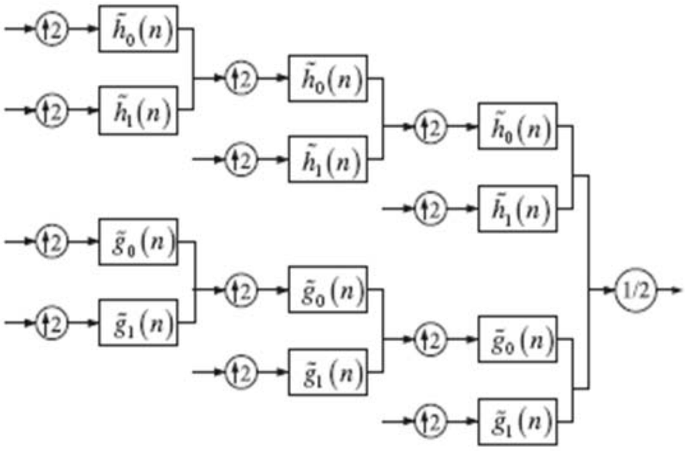
$$\psi 1,3(x,y) = \psi g(x)\psi h(y), \psi 2,3(x,y) = \psi h(x)\psi g(y). \quad (11)$$

In the above equations $\psi_h(.)$ and $\psi_g(.)$ denote the low pass filters of the upper and lower FB while, $\psi_h(.), \psi_g(.)$ represents the high pass filter of the upper and lower FB respectively [7].

DWT only presents limited directions in $0°, 45°, 90°$ while DT-CWT produces six subbands at each scale for both imaginary and real parts in $\pm 15°, \pm 45°, \pm 75°$ which conforms that DT-CWT improves the directional selectivity (Fig.2).



a



b

Fig1. Practical implementation of the DTCWT on a 1D signal. (a) Analysis filter bank for the DTCWT; (b) synthesis filter bank for the DTCWT[10].

75 45 15 -75 -45 -15

Fig.2 . Directional structure of imaginary and real parts of DT-CWT[11].

We proposed a new method to combine various images based on DT-CWT using two different fusion rules for low frequency components and high frequency ones. For the low frequency we apply maximum selection and for the high frequency information local energy is selected [12, 13,18,20]. As the high frequency coefficients carry information about the details and edges it's so important to fuse them in such a way that a little information loses in the process and can transfer information as far as possible in the output fused image. Since, experimental results show that energy of detailed coefficients can represent the most of the structural information such as edges and boundaries therefore we chose energy based fusion methods to combine detail coefficients. The proposed fusion scheme is as follows: first the input source images are decomposed 1 level using DT-CWT to obtain low frequency coefficients (L1, L2) and high frequency coefficients (H1, H2).

$$[L1\ H1] = DT - CWT\left(A(x,y)\right) \quad (12)$$

$$[L2\ H2] = DT - CWT\left(B(x,y)\right) \quad (13)$$

Then we combine source coefficients based on the selected fusion rules to obtain the fused coefficients.

A. *Fusion scheme*

For low frequency coefficients we use maximum selection rule that is as follows:

$$LF = \begin{cases} L1(x,y) & if\ L1(x,y) > L2(x,y) \\ L2(x,y) & if\ L2(x,y) > L1(x,y) \end{cases} \quad (14)$$

Where LF(x,y) denotes the low frequency components of the fused image.

For high frequency coefficients we use local energy fusion rule to combine high frequency components of the input source images. The fusion rule computes the region energy of center pixel and its neighboring pixels. The energy expression is shown below:

$$E = \sum_{(m,n)\in w} f^2(m,n) \qquad (15)$$

Where i-k ≤ m ≤ i+k, j-k ≤ n ≤ j+k and 2k+1 is the window size. w(m,n) is chosen $1/9\begin{bmatrix}1&1&1\\1&1&1\\1&1&1\end{bmatrix}$ and f(m,n) is the pixel value of each source coefficient.

$$HF(i,j) = \begin{cases} H1(i,j) & E_A(i,j) > E_B(i,j) \\ H2(i,j) & E_A(i,j) < E_B(i,j) \\ \frac{H1(i,j)+H2(i,j)}{2} & E_A(i,j) = E_B(i,j) \end{cases} \qquad (16)$$

Every image with the higher region energy indicates having more features so we compare the region energy for each pixel and select the pixel with the maximum energy for the output fused coefficients.

Finally, we apply inverse DT-CWT on the fused coefficients to obtain the output fused image.

IV. EXPERIMENTAL RESULTS AND DISCUSSION

We use 3 image sets to evaluate our proposed method's performance. The source images are from different fields such as medical images (CT/MR), remote sensing images and out of focus images that are available on imagefusion.org. All images are in gray scale format with the same size which perfectly have been registered. The proposed fusion algorithm was applied on these images and the obtained results were compared with the 3 conventional methods.

Applying fusion on these images helps scientists to better recognized features which are not clear on each source images like in medical images (CT/MR), CT provides information about dense tissues while, MRI presents textures and soft tissues. Since, we are not able to receive all kind of information from single image, combining them is more helpful and beneficial. Visual analysis indicates that the proposed method outperforms the other methods. Since, only visual inspection is not sufficient for evaluating the scheme performance, we have used some quantitative metrics namely, standard deviation, entropy, mutual information, structural similarity index, average gradient to measure the method's performance, but first we define each metric.

A. *Metrics Definition*

a) ***Standard Deviation***:

It demonstrates the contrast. Every image with the greater STD has a higher contrast. STD for an image with M*N size is given by:

$$\sigma = \left(\frac{1}{M*N}\sum_{m=1}^{M}\sum_{n=1}^{N}(f(m,n)-\mu)^2\right)^{\frac{1}{2}} \qquad (17)$$

Where f(m,n) denotes pixel value and μ is the mean value of image. Higher value of STD shows the better quality of the fused image [14].

b) ***Average gradient (AVG)***: For an image of size (M*N) is defined as below:

$$AVG = \frac{\sum_{i=1}^{M-1}\sum_{j=1}^{N-1}\sqrt{(\frac{\partial f(i,j)}{\partial i})^2+\frac{\partial f(i,j)}{\partial j}^2}}{(M-1)(N-1)} \qquad (18)$$

f(i,j) denotes the gray value of pixel at position (i,j).

$\frac{\partial f(i,j)}{\partial i}, \frac{\partial f(i,j)}{\partial j}$ represent image derivative at position (i,j).

This metrics shows the image sharpness [15].

c) ***Entropy***:It measures the amount of image information. The higher the entropy illustrates the more information content of the fused image. This is defined by:

$$E = -\sum_{i=0}^{L-1} P_i * log2(P_i) \qquad (19)$$

Where L is the number of intensity level and P_i is the fused image normalized histogram [14].

d) ***Mutual Information (MI)***: MI is a criterion to measure the statistical dependence between the source image and the fused image where the larger the MI means the better the quality of the fused image. That is calculated as below:

$$MI(F,A) = \sum_{u,v} P_{FA}(u,v)\log\left[\frac{P_{FA}(u,v)}{P_F(u)P_A(v)}\right] \qquad (20)$$

Where P_F and P_A denote the normalized histogram of the fused image and source images respectively. P_{FA} is the normalized joint histogram between the fused (F) and the source image (A) [16]. Then we obtain the total mutual information as follow:

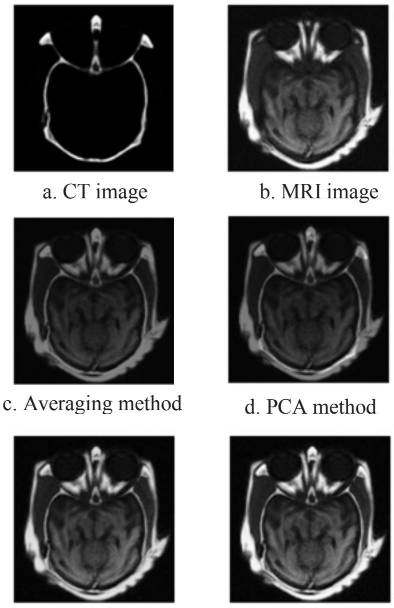
$$MI_F^{AB} = MI_{FA}(I_F,I_A) + MI_{FB}(I_F,I_B) \qquad (21)$$

e) ***Structural Similarity Index***: It compares local patterns of pixel intensities that have been normalized for luminance and contrast and it provides a quality value in the range [0 1].

$$SSIM(R,F) = \frac{\sigma_{RF}}{\sigma_R\sigma_F}\frac{2\mu_R\mu_F}{(\mu_R)^2+(\mu_F)^2}\frac{2\sigma_R\sigma_F}{\sigma_R{}^2\sigma_F{}^2} \qquad (22)$$

Where μ_R is the original image mean and μ_F is the fused image mean; σ is the variance and σ_{RF} is the covariance [17].

We applied the proposed method on 3 different sets of images that the results are shown in Fig.3, Fig.4, Fig.5 and then quantitative comparisons done with the mentioned metrics and the obtained results are shown in Tables1,2,3.

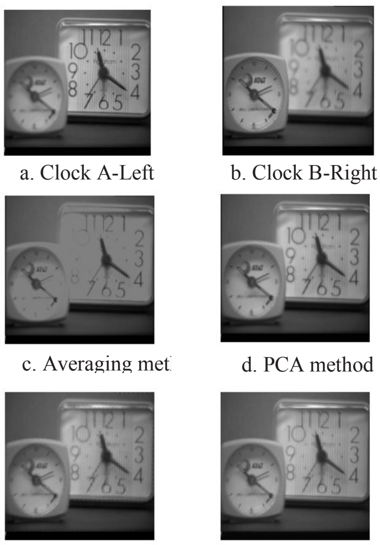


a. CT image b. MRI image

c. Averaging method d. PCA method

e. DWT method f. Proposed method

Fig.3 Fusion of image set 1 medical image (CT/MR)

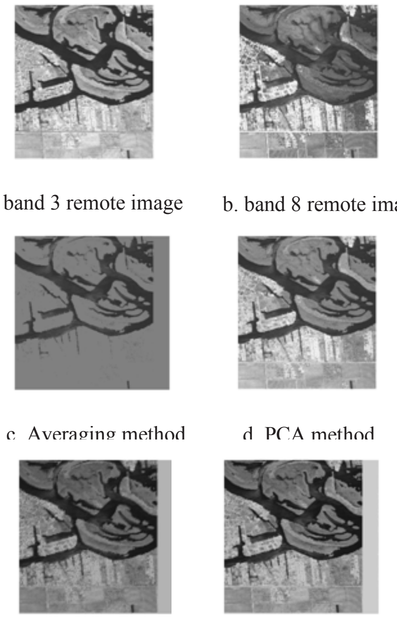


a. Clock A-Left b. Clock B-Right

c. Averaging met d. PCA method

e. DWT method f. Proposed method

Fig.4 Fusion of image set 2 (out of focus image)



a. band 3 remote image b. band 8 remote image

c. Averaging method d. PCA method

e. DWT method f. Proposed method

Fig.5 Fusion of image set 3 (Remote sensing image) Two bands of a mutispectral scanner

TABLE I. QUANTITATIVE COMPARISON RESULTS FOR DATASET 1.

Methods /Metrics	DWT	Proposed Method	PCA	Averaging
Entropy	6.5340	**6.7676**	5.9134	5.7937
SSIM	0.4495	**0.4965**	0.4100	0.4064
MI	2.0015	**3.6115**	0.0813	0.1612
AVG	**6.7045**	6.5834	3.6677	3.4179
STD	61.4553	**61.5746**	34.9280	32.9344

TABLE II. QUANTITATIVE COMPARISON RESULTS FOR DATASET 2.

Methods /Metrics	DWT	Proposed Method	PCA	Averaging
Entropy	7.2351	**7.3193**	7.3000	5.1804
SSIM	0.7873	0.8710	**0.9196**	0.8163
MI	6.0609	**6.8744**	6.7862	5.6183
AVG	4.4652	**4.5190**	4.3467	2.6495
STD	51.0499	**51.1259**	50.3713	40.4090

TABLE III. QUANTITATIVE COMPARISON RESULTS FOR DATASET3.

Methods /Metrics	DWT	Proposed Method	PCA	Averaging
Entropy	6.9754	**7.2263**	7.1413	2.7054
SSIM	0.4911	**0.8219**	0.8219	0.5171
MI	4.6989	**5.5701**	4.2513	2.9700
AVG	**12.4667**	11.9383	10.4684	3.6010
STD	**63.3569**	63.0254	62.2759	27.8908

V. CONCLUSION

Image fusion has been attracted more attention in recent decades especially in multimodal domain. As each source image provides a limited aspect of information it's necessary to combine them in such a way that carry complementary information of each source images into the output fused image.

In this paper we have proposed a new fusion scheme to combine images based on DT-CWT using two different fusion rules for low and high frequency components.

The proposed method applies on three sets of perfectly registered input images.

Our proposed method outperforms the other existing methods since it is shift invariance and it provides multiscale edge information and phase information. Visual analysis implies that the proposed method has a better performance compared to the other methods, in addition the obtained quantitative results that are presented in the tables 1,2,3 show that the proposed method can present more information in the output fused image as well as, it can provide more similarity to the input images and produces fused image with the better edge information.

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