RESEARCH ARTICLE OPEN ACCESS

A Hybrid Medical Image Fusion Based on Undecimated and Complex Wavelet Transforms

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ABSTRACT
Image fusion is the process of merging different information from multiple images to obtain a single composite fused image. The fused image contains the most relevant information from source images. In this paper, a hybrid medical image fusion based on combined Undecimated Wavelet Transform (UDWT) and Dual-Tree Complex Wavelet Transform (DTCWT) is presented. The performance of the proposed method is evaluated with performance metrics like Entropy, Standard Deviation, Peak Signal to Noise Ratio and Edge-based Similarity Measure. Experimental results show that our proposed fusion method outperforms many existing methods.
Keywords – Medical Image Fusion, Undecimated Wavelet Transform, Dual-Tree Complex Wavelet Transform, Average Fusion rule, Maximum Fusion rule.

Date Of Submission:25-08-2018 Date Of Acceptance: 08-09-2018

I. INTRODUCTION

Medical image fusion is a rapidly growing research field in medical imaging [1, 2].Nowadays, various medical imaging sensors are available for clinical assessment and diagnosis of diseases. These multimodal images carry complementary information. For example, Computed Tomography (CT) gives information on the dense structure of the body part like bones, whereas MRI gives information about soft tissues [3]. Therefore, merging multimodal medical images give complete and accurate information in a single composite image.

Generally, image fusion can be done at three levels namely pixel level, feature level and decision level[4,5].In pixel-level fusion, the fused image is obtained by combining the pixel values of different images through algorithms. In feature-level fusion, the features are extracted from input images of the same geographic area. Then they are fused depending on their features. Decision-level fusion uses fuzzy logic, voting and statistics for decision making. Among the three methods, pixel level methods are the simplest and preserve information content of input images more accurately [6].

Pixel-level fusion methods can be used either in the spatial domain [7] or in the wavelet domain [8].In spatial domain based fusion, fusion is performed directly on the pixel values. Some of the spatial domain based fusion methods are averaging, weighted averaging and Principal Component Analysis (PCA).In spatial domain fusion, the fused images obtained are of low contrast and contain less information[9].

To overcome such limitations, pixel level fusion based on wavelet transforms has been developed. In wavelet transforms, the input source images are transformed into frequency parts and then certain fusion rules are applied to merge the image information present in each subband separately. The final fused image is reconstructed by applying the inverse wavelet transform.

Bhavana et al. proposed multimodality medical image fusion using Discrete Wavelet Transform (DWT) [10]. But, DWT based image fusion method suffers from ringing artifacts, lack of shift invariance and directionality [11]. Ellmauthaler et al. suggested an image fusion method based on Undecimated Wavelet Transform (UDWT) [12].UDWT overcomes the limitation of DWT such as lack of shift invariance. Also, it preserves the edges more efficiently. But the problem of lack of directionality remains unsolved [13]. Nandi et al. have proposed the Principal Component Analysis(PCA) which transforms correlated variables into uncorrelated variables called Principal Components[14].PCA reduces redundancy of the image. But PCA based image fusion methods produce edge distortion [15]. Harpreet et al. have explained combined DWT-PCA based image fusion method. This method improves image quality and also reduces redundancy [16]. But the problem of lack of directionality remains unsolved.

To improve the contrast and morphological details, D. Kaur proposed a combination of the UDWT-PCA fusion methods [17]. This would improve the image quality, preserve the edges but it would still suffer from lack of directionality. Singh et al. proposed a complex wavelet transform known as Dual-Tree Complex Wavelet Transform (DTCWT) which overcomes the limitations of DWT, UDWT and PCA [18].DTCWT has some important properties like high directionality and shift invariance. In this paper, a hybrid technique based on the cascade of UDWT and DTCWT has been proposed.

Lack of shift invariance and directionality, ringing artifacts and noise can be overcome by this proposed method. Furthermore, this new method improves the information content, visual quality and edge information. It has been proven hereby experimental results of proposed method performs well in the fusion of multimodal images.

The rest of this paper is organized as follows. In section II, the proposed methodology is described. Section III describes the various performance measures used for evaluation. Section IV describes experimental results. Finally, concluded remarks are given in section V.

II. METHODOLOGY

This section presents the proposed image fusion framework. The block diagram **is** shown in Fig.2.1

Preregistered images from two different medical imaging modalities are taken as input source images. The steps involved in this proposed method are described as follows.

First, the preregistered source images from two different medical imaging modalities are decomposed into approximation and detail coefficients. Approximation coefficients correspond to low-frequency components and detail coefficients correspond to high-frequency components.

(1) The Second step is approximation coefficients from both input images are combined using average fusion rule and detail coefficients are combined using maximum fusion rule.
(2) The fused image is obtained by taking IUDWT.
(3) The fused image obtained from step.3 is again decomposed using DTCWT which gives real and imaginary parts of the image in the complex wavelet domain.
(4) The resulting components are fused using maximum fusion rule.
(5) The final fused image is obtained by taking inverse DTCWT.

2.1 Fusion Rules

Average Fusion Rule:According to this rule, the input images are fused by selecting the average value of pixels from those images.

F(i,j) ={A(i,j) +B(i,j)}/2 (1)

where A(i,j) and B(i,j) are input source images. F(i,j) represents the fused image.

Maximum Fusion Rule: According to this rule, the input images are fused by selecting the maximum value of pixels from those images.

$F(i,j) = \sum_{i=0}^{M} \sum_{j=0}^{N} Max\{A(i,j) + B(i,j)\}$ (2)

where A(i,j) and B(i,j) are input source images.
F(i,j) represents the fused image.

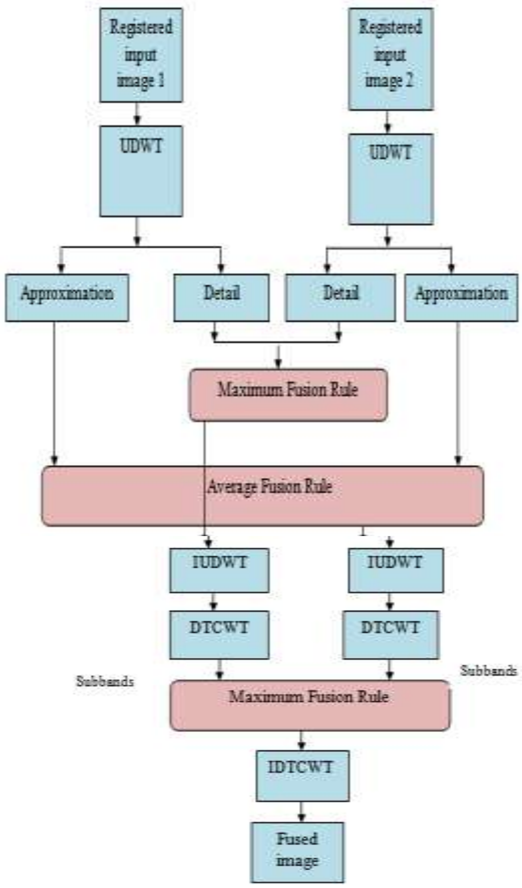


Fig.1 Block Diagram of proposed method

2.2 Performance Measures

In our proposed work, we have considered four performance measures. They are explained as follows

(1) Entropy(E):

Entropy is an important metric used to measure the information content of the fused image. It is given as follows

$$E = -\sum_{i=0}^{L-1} P_i \log P_i \quad (3)$$

where 'L' is the number of grey levels of the fused image. P_i is given by the ratio of the number of pixels with grey level ‘i’ to the total number of pixels.

Higher the values better the information in the fused image.

(2) Standard Deviation(σ):
Standard Deviation represents the contrast of the fused image. It is given by

$$\sigma = \sqrt{\frac{1}{M \times N} \sum_{i=0}^{M} \sum_{y=0}^{N} [F(i,j) - \mu]^2} \qquad (4)$$

where F(i,j) represents the pixel value of the fused image and ‘μ’ represents the mean intensity value of the image.

A large value of ‘σ’ represents better quality of the fused image.

(3) Peak Signal to Noise Ratio(PSNR):

PSNR is given by the ratio between the maximum possible power of a signal to the power of corrupting noise that affects the fidelity of its representation.

Mathematically, it can be expressed as

$$PSNR = 20 \log_{10} \frac{255}{MSE} \qquad (5)$$

Where MSE represents mean square error.

(4) Edge Strength($Q^{AB/F}$):

Edge strength represents the edge information related to the fused image.$Q^{AB/F}$ is given by

$$Q^{AB/F} = \frac{\sum_{i=1}^{M} \sum_{j=1}^{N} Q^{AF}(m,n) W^{A}(m,n) + Q^{BF}(m,n) W^{B}(m,n)}{\sum_{i=1}^{M} \sum_{j=1}^{N} [W^{A}(m,n) + W^{B}(m,n)]} \qquad (6)$$

where $W^A(m,n)$ and $W^B(m,n)$ are weights for edge preservation values $Q^{AF}(m,n)$ and $Q^{BF}(m,n)$ respectively.

$Q^{AB/F}$ value lies between 0 and 1.

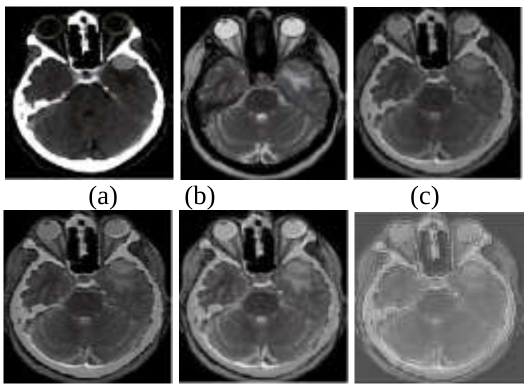
A higher value of $Q^{AB/F}$ represents the fused image with better edge information.

III. RESULTS AND DISCUSSION

In this section, we discuss the experimental results of our proposed method. We have compared our results with various fusion methods such as DWT, PCA, DWT-PCA, UDWT, UDWT-PCA and DTCWT.

The proposed method has been tested on a pair of medical images of different modalities. The human brain images of size 256×256 have been obtained from whole brain atlas data distributed by Harvard University. The first data set contains a CT image and an MRI image. CT and MRI images carry complementary information. CT images give details of hard tissues like bones whereas MRI images give information about soft tissues. The second data set of medical images contains two MRI blurred images. One image is blurred on the lower half and the other image is blurred on the upper half.

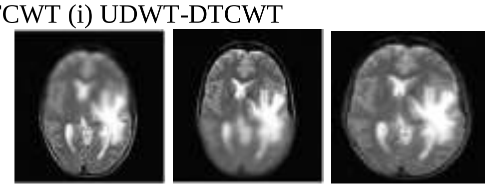
In this proposed work, we have taken preregistered human brain images. The visual results of the proposed fusion method and other existing fusion methods for two data sets are shown in Fig.2 and Fig.3.The proposed method is evaluated using four performance measures namely Entropy, Standard Deviation, Peak Signal to Noise Ratio (PSNR) and Edge Strength (QAB/F). We have shown the comparison of different fusion methods in the form of bar charts and graphs. It is observed that combined UDWT-DTCWT fusion method has high entropy values than other methods used in the comparison. Standard Deviation and PSNR values are also high for our proposed method. This shows that the image quality of the fused image using UDWT-DTCWT method has been improved. Finally, from Fig.2 and Fig.3 it can be understood that the edge representation capability of the proposed method is better compared with other existing fusion methods



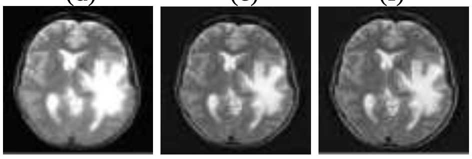
(a) (b) (c)
(d) (e) (f)

(g) (h) (i)

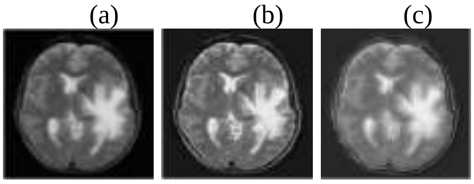
Fig. 2 Fusion results for image set 1 (a), (b) Input source images (c) DWT (d) PCA (e) DWT-PCA (f) UDWT (g) UDWT-PCA (h) DTCWT (i) UDWT-DTCWT



(a) (b) (c)



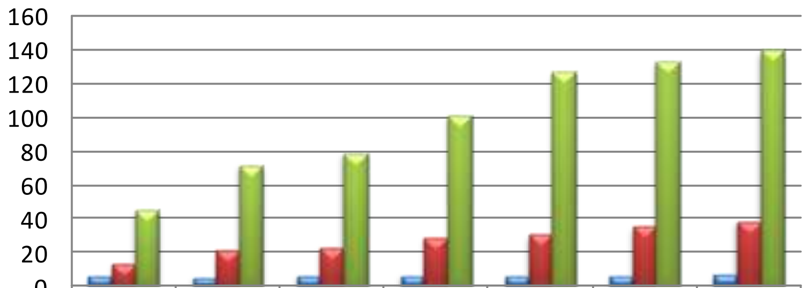
(d) (e) (f)



(g) (h) (i)

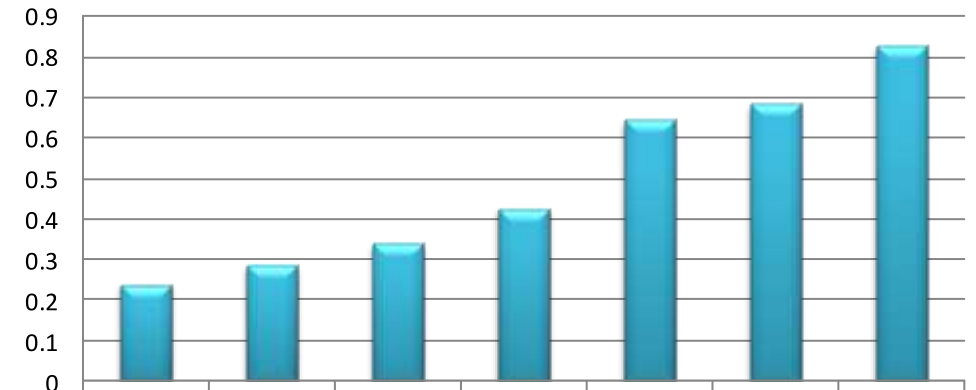
Fig. 3 Fusion results for image set 2 (a), (b) Input source images (c) DWT (d) PCA (e) DWT-PCA (f) UDWT (g) UDWT-PCA (h) DTCWT (i) UDWT-DTCWT.

From Fig.3, we can observe that even though the input images are half blurred we can get in the end a high quality fused image without blurriness. The entropy, PSNR, Standard Deviation and QAB/F of fused images obtained using different image fusion methods like DWT, PCA, DWT-PCA, UDWT, UDWT-PCA, DTCWT and Combined UDWT-DTCWT for two image data sets have been compared and the results are shown in Fig.4-7.Experimental results illustrate the superiority of proposed method over existing fusion methods in terms of entropy, PSNR, Standard Deviation and QAB/F.



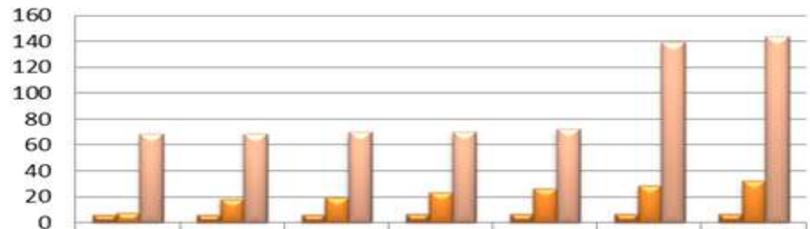
	DWT	PCA	DWT+PCA	UDWT	UDWT+PCA	DTCWT	PROPOSED METHOD
Entropy	6.1428	5.0281	6.2261	6.518	6.5896	6.712	6.8821
PSNR	13.8592	21.1086	23.1126	28.9684	30.8145	35.3972	38.7151
Standard Deviation	44.9147	71.7143	78.8146	101.3569	126.6331	133.6331	140.1367

Fig.4 Comparison of different fusion methods for image set 1 using entropy, PSNR and Standard Deviation.



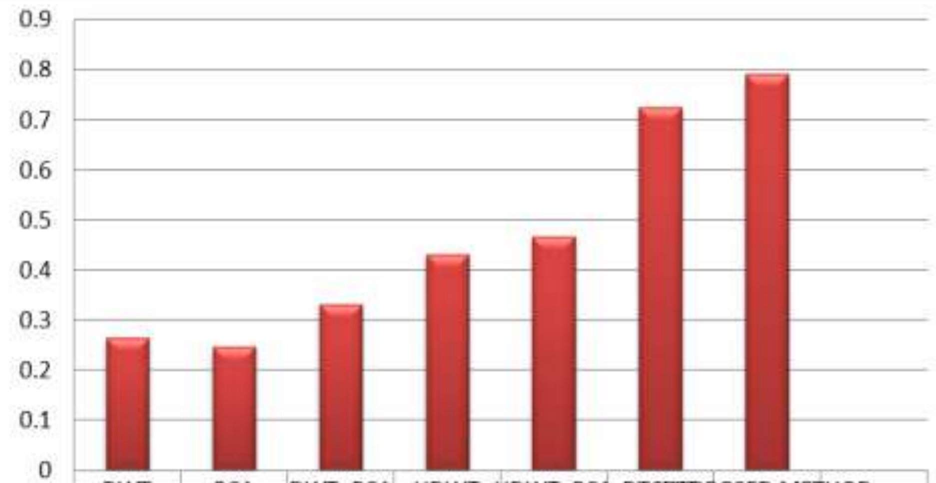
	DWT	PCA	DWT+PCA	UDWT	UDWT+PCA	DTCWT	PROPOSED METHOD
QAB/F	0.2367	0.2843	0.3382	0.4241	0.6437	0.6843	0.8256

Fig. 5 Comparison of different fusion methods for image set 1 using QAB/F.



	DWT	PCA	DWT+PCA	UDWT	UDWT+PCA	DTCWT	PROPOSED METHOD
Entropy	6.1042	6.4657	6.4883	6.6653	6.6828	6.7012	6.7451
PSNR	7.9451	18.2303	19.4735	23.8002	26.5785	28.8002	32.1905
Standard Deviation	69.0048	68.84	69.8238	70.125	72.2385	139.2834	143.5993

Fig.6 Comparison of different fusion methods for image set 2 using entropy, PSNR and Standard Deviation



	DWT	PCA	DWT+PCA	UDWT	UDWT+PCA	DTCWT	PROPOSED METHOD	
QAB/F	0.2654	0.2476	0.3324	0.4321	0.4679	0.7253	0.7912	

Fig.7 Comparison of different fusion methods for image set 2 using QAB/F.

IV. CONCLUSION

In this paper, we have explained a combined UDWT-DTCWT based image fusion approach of human brain images of different modalities. Our fusion framework gives higher contrast and also extracts more information from source images. Additionally, it can preserve better edge information. The performance of the proposed method has been evaluated using four metrics namely entropy, standard deviation, PSNR and edge strength. The results have shown the improved performance over other fusion methods used in the comparison.

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J. Reena Benjamin "A Hybrid Medical Image Fusion Based on Undecimated and Complex Wavelet Transforms ""International Journal of Engineering Research and Applications (IJERA) , vol. 8, no.9, 2018, pp 04-09