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Medical Image Fusion Based On Redundant Wavelet Transform and Morphological Processing

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***Abstract*—**The process in which the complementary information from multiple images is integrated to provide composite image that contains more information than the original input images is called image fusion. Medical image fusion provides useful information from multimodality medical images that provides additional information to the doctor for diagnosis of diseases in a better way. This paper represents the wavelet based medical image fusion algorithm on different multimodality medical images. In order to fuse the medical images, images are decomposed using Redundant Wavelet Transform (RWT). The high frequency coefficients are convolved with morphological operator followed by the maximum-selection (MS) rule. The low frequency coefficients are processed by MS rule. The reconstructed image is obtained by inverse RWT. The quantitative measures which includes Mean, Standard Deviation, Average Gradient, Spatial frequency, Edge based Similarity Measures are considered for evaluating the fused images. The performance of this proposed method is compared with Pixel averaging, PCA, and DWT fusion methods. When compared with conventional methods, the proposed framework provides better performance for analysis of multimodality medical images.

***Keywords*—**Discrete Wavelet Transform (DWT), Image Fusion, Morphological Processing, Redundant Wavelet Transform (RWT).

I. Introduction

THE image fusion is widely used in various fields which includes medical imaging, machine vision, remote sensing, microscopic imaging and military applications. The goal of the image fusion is to form one composite image from multiple source images. The fused image provides more useful information for machine or human perception [1]. In the recent years, medical imaging plays important role to analyse the diseases. The different types of multimodality medical images such as Computed Tomography (CT), Magnetic Resonance Angiography (MRA), Magnetic Resonance Imaging (MRI), Positron Emission Tomography (PET), Single-Photon Emission Computed Tomography (SPECT) images, X-rays, etc provides limited information. These multimodality medical images usually provide complementary information. For example, the Computed tomography image provides the information about bones, but it cannot provide the information about physiological changes, while the Magnetic Resonance image provides the information about pathological soft tissues, but it cannot provide the information about bones [2]. As a result, these images can be combined to produce one composite image which gives more information. It helps in diagnosing diseases and also reduces storage cost by storing single fused image instead of multiple-input images. The image fusion techniques are categorised into pixel, feature and decision levels [3]. Pixel level image fusion techniques involve operation on each and every image pixel which are easy to implement and computationally efficient. The simplest image fusion method consists in taking the average of the source images, pixel by pixel, to create the fused image. However, this method creates the blurred images where the details are rather reduced [4].For this reason, the various methods have been developed such as Principal Component Analysis (PCA), Intensity-Hue-Saturation (IHS), Brovey transform, Gradient pyramid [5], Laplacian pyramid [6], Ratio of low pass pyramid [7], Contrast pyramid [8], Morphological pyramid [9], Discrete Wavelet Transform (DWT) based methods [10]-[12]. The disadvantage of pyramid based method is that it produces blurred images. The wavelet based method which is commonly used performs multi resolution decomposition on preferred input images. The composite image is obtained by performing an inverse multi resolution transform. Although DWT provides good localization both in time and spatial frequency domain, one of the major drawbacks of DWT is shift variance. It arises from the use of down-sampling while decomposing the images. This leads to major change in the wavelet coefficients of the image even for small shifts in the input image. In medical image fusion, preservation of edge information is needed, but DWT based fusion may produce peculiarities along the edges.

In order to overcome the drawbacks in DWT, Image fusion technique using Redundant Wavelet Transform (RWT) [13] which is shift invariant is proposed for medical images. Similar to DWT, RWT and Inverse RWT (IRWT) of 2D image is obtained by computing each dimension separately where detailed and approximation bands are same size as the source images. For fusion of medical images, different fusion rules are performed on the approximation bands and detailed bands. Experimental results on medical images show that the proposed algorithm improves the quality of fused medical images compared with other conventional approaches.

The rest of the paper is organized as follows. The wavelet-based image fusion technique is described in Section II. Experimental results and analysis are presented in Section III and the conclusion is given in Section IV.

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II. Multimodal Medical Image Fusion Using RWT And Morphological Processing

The important step in image fusion based on wavelet transform is the coefficient combination as shown in Fig. 1, because it will decide how to merge the coefficients in an appropriate way so that a high-quality fused image can be obtained.

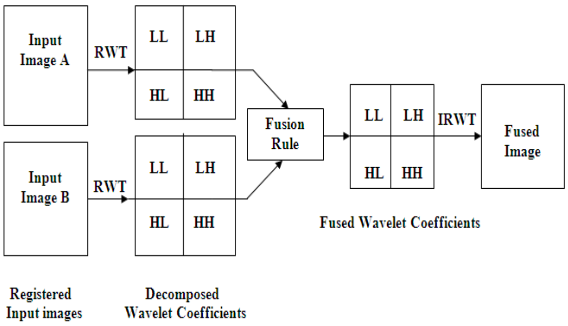

Fig. 1 Block diagram for Wavelet based image fusion [3]

The wavelet approach provides an advantage of identifying the detailed information in the image. Redundant Wavelet Transform of the image gives four different coefficients of the image such as approximation, horizontal, vertical, diagonal. Since each coefficient is separately obtained, specific fusion operation can be done easily. These coefficients of both low and high-frequency bands are then performed with fusion rule. In this paper, for a low frequency band, a maximum selection rule is used to select the coefficients. This rule selects the largest absolute wavelet coefficient at each location from the input images. Since the details of an image are mainly included in the high frequency bands, the high frequency coefficients are processed with morphological operators [14], [15] followed by maximum selection rule.

In morphological processing, a structuring element is applied to the decomposed detailed images (LH, HL, and HH) and creates the output images with same size. This process compares the corresponding pixel in the input image with its neighbors to produce pixel value in the output image. The dilation and erosion are the basic morphological operations. The rule is used to process the corresponding pixel and its neighbors in the input image. In dilation operation, the output pixel value is the maximum value of all the pixels in the input pixel's neighborhood. In erosion operation, the output pixel value is the minimum value of all the pixels in the input pixel's neighborhood. After morphological processing, Inverse Redundant Wavelet Transform is applied to the fused wavelet coefficients.

The procedures of our method can be summarized as follows.

1. Decompose the images to one wavelet plane.
2. The wavelet coefficients of the low frequency components are performed by MS rule and the wavelet coefficients of the high frequency components are processed with morphological operator followed by using the MS rule.
3. Perform the Inverse Redundant Wavelet Transform with the combined coefficients obtained from step (3).

III. Experimental Results and Analysis

In this section, the performance of the proposed algorithm is compared with the fusion results obtained from pixel averaging method [10], PCA and conventional DWT method with maximum selection rule [12]. The algorithm has been implemented using MATLAB R2010a.The CT and MRI images are taken as source images. Like most of the literatures [1], [3], we assume that input images taken are in perfect registration.

The simulation of fusion methods have been conducted with an Intel core 2 Duo processor T6600 (2.2 GHz, 800 MHz FSB). For simulating PCA method, source code available in [16] is used. For wavelet based methods, we use the daubechies-8(db8) with single level of decomposition as the wavelet basis for DWT and the proposed methods. For quantitative and qualitative evaluation of the proposed algorithm, simulations are performed on six pairs of medical images.

To evaluate the performance of above fusion methods, the following performance parameters are defined.

A. Mean Value (μ)

The mean value of an image I (m, n) with size of M × N is defined as

$$\mu = \frac{1}{MXN} \sum_{m=1}^{M} \sum_{n=1}^{N} I(m,n) \tag{1}$$

where I(m, n) denotes the gray level of a pixel with coordinate (m, n). It represents the average intensity of an image.

B. Standard Deviation (σ)

The standard deviation of an image I (m, n) with size of M ×N is defined as [3]:

$$\sigma = \sqrt{\left(\frac{1}{MXN} \sum_{m=1}^{M} \sum_{n=1}^{N} (I(m,n) - \mu)^2\right)} \tag{2}$$

where μ is the mean value of the image. It is used to evaluate how widely spread the gray values in a fused image. If the standard deviation is large, the result is better.

C. Average Gradient

The average gradient of an image I (m, n) with size of M × N is defined as [3]:

$$Avg = \frac{1}{(M-1)(N-1)} X \sum_{m=1}^{M-1} \sum_{n=1}^{N-1} \sqrt{\frac{\left[\left(\frac{\partial I(m,n)}{\partial m}\right)^2 + \left(\frac{\partial I(m,n)}{\partial n}\right)^2\right]}{2}} \tag{3}$$

where I(*m*, *n*) is the same meaning as in the standard deviation. The average gradient reflects the clarity of the fused image. The larger average gradient means sharper the image.

D. Spatial Frequency (SF)

Spatial frequency gives how much the image is perceivable to human eye. If its value is high in fused image, the information content of the image is high. The spatial frequency of the image I(m, n) with size of M × N is defined as [11]:

$$\mathrm{SF} = \sqrt{(\mathrm{RF})^2 + (CF)^2} \tag{4}$$

where

$$RF = \sqrt{\frac{1}{MXN}\sum_{m=1}^{M}\sum_{n=2}^{N}[\,\mathrm{I(m,n)} - \mathrm{I(m,n-1)}]^2}$$

$$CF = \sqrt{\frac{1}{MXN}\sum_{n=1}^{N}\sum_{m=2}^{M}[\,\mathrm{I(m,n)} - \mathrm{I(m-1,n)}]^2}$$

E. Edge Based Similarity Measure ($Q^{AB/F}$)

It is used to evaluate the edge information present in a fused image. It is defined as [17]:

$$Q_F\mathrm{AB/F} = \frac{\sum_{n=1}^{N}\sum_{m=1}^{M} Q^{AF}(n,m)w^{A}(n,m) + Q^{BF}(n,m)w^{B}(n,m)}{\sum_{n=1}^{N}\sum_{m=2}^{M}[\,w^{A}(n,m) + w^{B}(n,m)]} \tag{5}$$

where A,B and F represent the input and fused images respectively. The $Q^{AF}(n,m)$ and $Q^{BF}(n,m)$ are defined as

$$Q^{AF}(n,m) = Q^{AF}{}_{g}(n,m) \text{ X } Q^{AF}{}_{\alpha}(n,m)$$
$$Q^{BF}(n,m) = Q^{BF}{}_{g}(n,m) \text{ X } Q^{BF}{}_{\alpha}(n,m)$$

where $Q^{AF}{}_{g}(n,m)$, $Q^{BF}{}_{g}(n,m)$ and $Q^{AF}{}_{\alpha}(n,m)$, $Q^{BF}{}_{\alpha}(n,m)$ are the edge strength and orientation preservation values at location (n,m) respectively for images A,B.

The visual results of the proposed fusion algorithm and conventional fusion algorithms Pixel averaging, PCA and DWT are shown in Figs. 2 to 7. These figures clearly show that proposed fusion algorithm outperforms the conventional methods. The detailed quantitative evaluation is given in Tables I to VI. From Tables, we can observe that values of the Standard deviation, Mean, Average Gradient, Spatial frequency, Edge based Similarity Measures of the proposed method are larger than the values generated by pixel averaging, PCA, DWT methods, which means the proposed fusion method can get more image information.

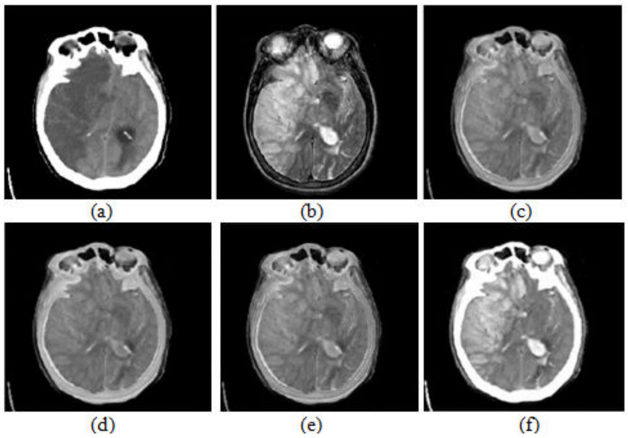

Fig. 2 Fusion results of the CT and MRI images with different methods.(a) Original CT image; (b) original MRI image; (c) fused image by pixel averaging; (d) fused image by PCA; (e) fused image by DWT; (f) fused image by the proposed method

TABLE I
QUANTITATIVE EVALUATION RESULTS OF THE FOUR DIFFERENT FUSION METHODS IN FIG. 2

Fusion Methods	Pixel Averaging	PCA	DWT	Proposed method
Spatial Frequency	18.7235	19.3416	22.0123	**22.5613**
Mean Value	58.0289	59.4784	58.0422	**79.6441**
Standard Deviation	65.8200	68.6807	66.2105	**92.1347**
Average Gradient	12.9995	14.3652	14.6996	**22.2292**
$Q^{AB/F}$	0.4229	0.4183	0.4346	**0.5471**

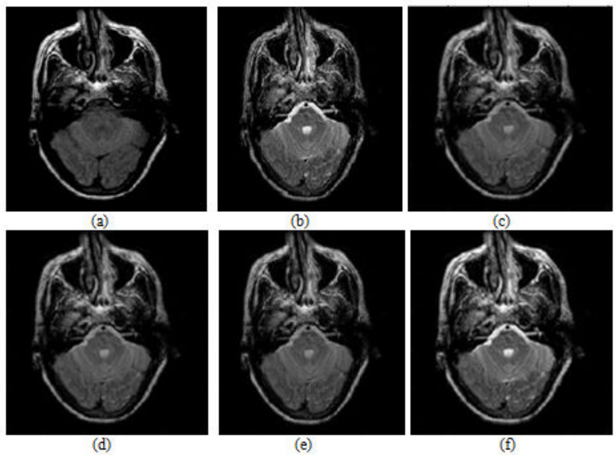

Fig. 3 Fusion results of the MRI T1 weighted and MRI T2 weighted images with different methods. (a) Original MRI T1 weighted image; (b) original MRI T2 weighted image; (c) fused image by pixel averaging; (d) fused image by PCA; (e) fused image by DWT; (f) fused image by the proposed method

TABLE II
QUANTITATIVE EVALUATION RESULTS OF THE FOUR DIFFERENT FUSION METHODS IN FIG. 3

Fusion Methods	Pixel Averaging	PCA	DWT	Proposed method
Spatial Frequency	14.0513	14.0646	16.7513	**17.3918**
Mean Value	28.7916	28.9470	28.7916	**36.5860**
Standard Deviation	41.6798	41.7700	41.9846	**51.8716**
Average Gradient	15.3750	15.4020	16.0809	**19.8413**
$Q^{AB/F}$	0.5315	0.5371	0.5198	**0.6020**

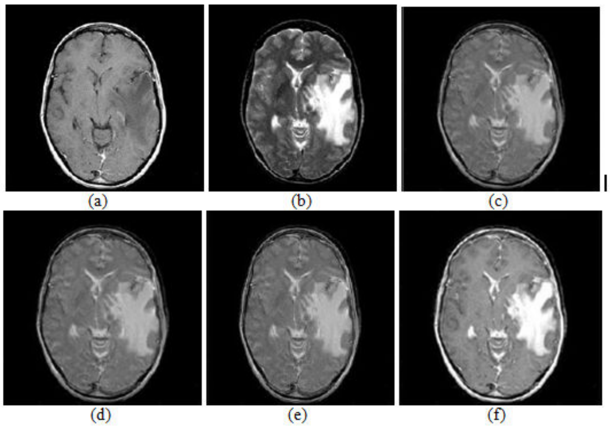

Fig. 4 Fusion results of the MRI T1 weighted and MRI T2 weighted images with different methods. (a) Original MRI T1 weighted image; (b) original MRI T2 weighted image; (c) fused image by pixel averaging; (d) fused image by PCA; (e) fused image by DWT; (f) fused image by the proposed method.

TABLE III
QUANTITATIVE EVALUATION RESULTS OF THE FOUR DIFFERENT FUSION METHODS IN FIG. 4

Fusion Methods	Pixel Averaging	PCA	DWT	Proposed method
Spatial Frequency	14.7059	14.9426	19.4460	**21.3148**
Mean Value	51.9848	52.1706	51.9983	**69.4087**
Standard Deviation	60.5301	60.5821	61.0269	**79.9568**
Average Gradient	11.8668	11.9473	13.3635	**18.0499**
$Q^{AB/F}$	0.3540	0.3626	0.3759	**0.5268**

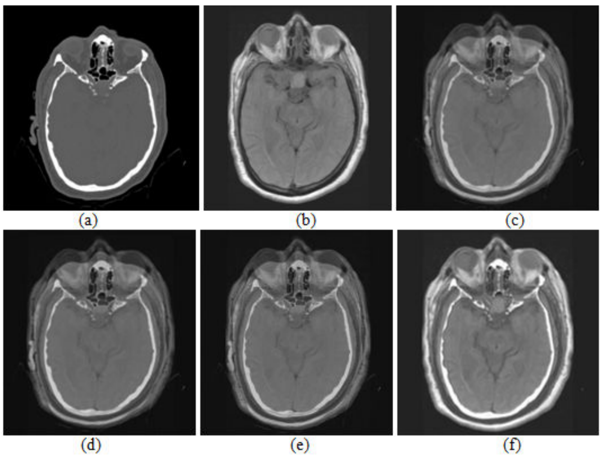

Fig. 5 Fusion results of the CT and MRI images with different methods. (a) Original CT image; (b) original MRI image; (c) fused image by pixel averaging; (d) fused image by PCA; (e) fused image by DWT; (f) fused image by the proposed method

TABLE IV
QUANTITATIVE EVALUATION RESULTS OF THE FOUR DIFFERENT FUSION METHODS IN FIG.5

Fusion Methods	Pixel Averaging	PCA	DWT	Proposed method
Spatial Frequency	10.7924	11.3062	12.7537	**16.0416**
Mean Value	64.9179	62.2015	64.9179	**88.9646**
Standard Deviation	47.3289	48.2632	47.4959	**56.7950**
Average Gradient	11.5072	11.7082	12.3039	**18.0471**
$Q^{AB/F}$	0.4364	0.4207	0.4454	**0.6629**

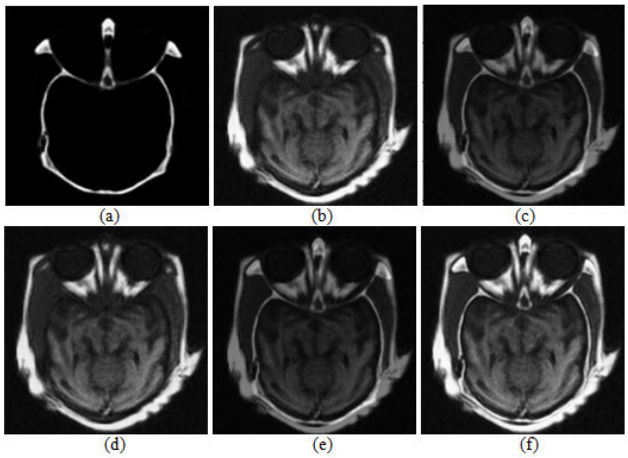

Fig. 6 Fusion results of the CT and MRI images with different methods. (a) Original CT image; (b) original MRI image; (c) fused image by pixel averaging; (d) fused image by PCA; (e) fused image by DWT; (f) fused image by the proposed method

TABLE V
QUANTITATIVE EVALUATION RESULTS OF THE FOUR DIFFERENT FUSION METHODS IN FIG. 6

Fusion Methods	Pixel Averaging	PCA	DWT	Proposed method
Spatial Frequency	10.2684	13.7405	11.0306	**17.8738**
Mean Value	32.0971	51.8182	32.0969	**59.7314**
Standard Deviation	34.8846	54.1606	34.9653	**61.5611**
Average Gradient	13.7396	19.4630	13.9444	**23.9953**
$Q^{AB/F}$	0.4261	0.6512	0.4295	**0.7758**

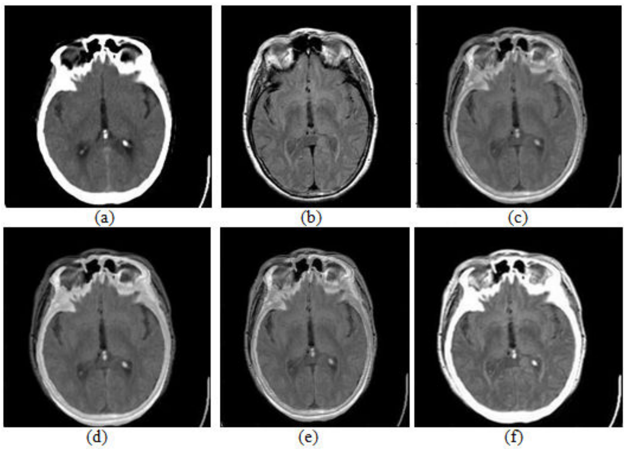

Fig. 7 Fusion results of the CT and MRI images with different methods. (a) Original CT image; (b) original MRI image; (c) fused image by pixel averaging; (d) fused image by PCA; (e) fused image by DWT; (f) fused image by the proposed method

TABLE VI
QUANTITATIVE EVALUATION RESULTS OF THE FOUR DIFFERENT FUSION METHODS IN FIG. 7

Fusion Methods	Pixel Averaging	PCA	DWT	Proposed method
Spatial Frequency	15.8738	16.9745	19.9984	**23.3396**
Mean Value	53.4626	54.0789	53.4634	**72.0759**
Standard Deviation	59.2605	62.8146	59.6508	**84.3274**
Average Gradient	15.3218	16.2382	16.6339	**25.3206**
$Q^{AB/F}$	0.3789	0.3748	0.3953	**0.5375**

IV. Conclusion

In this paper, we have presented a new wavelet based fusion algorithm for fusion of multimodality Medical images. The images to be fused are decomposed by Redundant Wavelet Transform (RWT). The low frequency bands are fused by maximum selection rule whereas high frequency bands are fused by morphological operator followed by maximum selection rule. Finally, the fused image is reconstructed with the Inverse Redundant Wavelet Transform (IRWT). In our experiment, different pairs of medical images are fused using conventional fusion algorithms and proposed algorithm. The statistical and visual comparisons demonstrate that the proposed algorithm enhances the details of fused image than the conventional algorithms.

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