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Performance Comparison Of Medical Image Fusion Methods Based On Redundant Discrete Wavelet Transform, Wavelet Packet Transform And Contourlet Transform

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Abstract

Image fusion is the process of combining relevant information from two or more images into a single fused image. The resulting image will be more informative than any of the input images. The fusion in medical images is necessary for efficient diseases diagnosis from multimodality, multidimensional and multi parameter type of images. This paper describes a multimodality medical image fusion system using different fusion techniques and the resultant is analysed with quantitative measures. Initially, the registered images from two different modalities such as CT (anatomical information) and MRI - T2, FLAIR (pathological information) are considered as input, since the diagnosis requires anatomical and pathological information. Then the fusion techniques based on Redundancy Discrete Wavelet Transform (RDWT), Wavelet Packet Transform and Contourlet Transform are applied. Further the fused image is analyzed with quantitative metrics such as Standard Deviation (SD), Entropy (EN), and Signal to Noise Ratio (SNR) for performance evaluation. From the experimental results it is observed that RDWT method provides better information quality for SD and SNR metric and the Contourlet Transform method provides better information quality using EN metric.

Keywords— Contourlet Transform,Entropy, SD, SNR.

I. INTRODUCTION

Image fusion aims at synthesizing information from multiple source images to obtain a more accurate, complete and reliable fusion image for the same scenes or targets. Compared with original inputs, the fused image are more suitable for observation, analysis, understanding and recognition. Structural images like Magnetic Resonance Imaging (MRI), Computed Tomography (CT), Ultrasonography (USG), Magnetic Resonance Angiography (MRA) etc. provide high resolution images with anatomical information. On the other hand, functional images such as Position Emission Tomography (PET), Single-Photon Emission Computed Tomography (SPECT) and functional MRI (fMRI) etc. provide low-spatial resolution images with functional information. A single modality of medical image cannot provide comprehensive and accurate information. As a result, combining anatomical and functional medical images to provide much more useful information through image fusion (IF), has become the focus of imaging research and processing.

In the research of fusion techniques, many approaches are proposed and implemented. Some of these methods are available in Fusion Tool of Matlab5.0 namely are Filter- Subtraction-Decimate Pyramid (FSD), Gradient Pyramid, Laplacian Pyramid, Principle Component Analysis, Morphological Pyramid, Ratio Pyramid, Contrast Pyramid and so on[1]. In all the above methods each approach has its own limitation in fusion process. With the evolution of Discrete Wavelet Transform (DWT), many fusion techniques based on DWT was also proposed. One of the major drawbacks of DWT is that the transformation does not provide shift invariance. This causes a major change in the wavelet coefficients of the image even for minor shifts in the input image. Redundant discrete wavelet transform (RDWT) another variant of wavelet transform, is used to overcome the shift variance problem of DWT [2]. It has been applied in different signal processing applications but it is not well researched in the field of medical image fusion. Recently, a multi-dimensional signal processing theory called Multiscale Geometric Analysis (MGA) has been developed, which includes ridgelet , curvelet, bandelet and brushlet, etc. Since 2001, the latest MGA tool contourlet proposed by M.N. Do and M. Vetterli has been paid widely attention[3]. Contourlet offers a highly efficient image representation for its good properties : multiresolution, localization, directionality and anisotropy, etc. on the fused image.

The remaining sections of this paper are organized as follows. In Section II, the system design is briefly reviewed. Section-III describes quantitative metrics and Section IV deals with the experimental results and evaluates the performance of the proposed methods based on the quantitative metrics.

II. SYSTEM DESIGN

In this system initially the two different types of modality CT (anatomical) and MRI (pathological) are given as input. Then the fusion techniques are applied to the registered images to find a more informative fused image. The fused image is validated using quantitative measures

A. Redundant Discrete Wavelet Transform And Wavelet Packet Transform

Here the same algorithm is used for both RDWT based and wavelet packet transform based image fusion.Let A1 and B1 be the registered images of different modalities (CT and T2) or (CT and T1). Three levels of RDWT decomposition is done using Daubechies filters on both the images.

In the first stage I_1 image is decomposed into I_1^a, I_1^v, I_1^d, and I_1^h, be the RDWT subbands and also I_2^a, I_2^v, I_2^d, and I_2^h, be the corresponding RDWT sub bands from I_2 image. To extract the features from both the images, coefficients from approximation band of I1 and I2 are averaged.

$$I_F^{\,a} = \text{mean}\left(I_1^{\,a}, I_2^{\,a}\right) \qquad (1)$$

where I_F^a is the approximation band of the fused image.

In the next stage each sub band namely LH, HL, HH is divided into blocks of size 3 * 3 and the entropy of each block is calculated, as in equation below

$$e_i^{\,jk} = \ln\sqrt{\frac{\mu_i^{\,jk} - \sum_{x,y=1}^{3,3} \frac{I_i^{\,jk}(x,y)}{\sigma_i^{\,jk}}^{2}}{m^2}} \qquad (2)$$

where j (= v, d, h) denotes the sub bands, m = 3 (size of each block), k represents the block number, and i (= 1,2) is used to differentiate the two multimodal images I1 and I2. Using the entropy values, the detail sub bands for the fused image IFv, IFd, and IFh are generated, as in (3). The derive a fused image block IF^{jk}, RDWT coefficients from I1 is selected if the entropy value of the specific block of I1 image is greater than the specific block of I2 image, otherwise $I2^{jk}$ is selected.

$$I_F^{\,jk} = I_1^{\,jk} \quad if \quad (e_1^{\,jk} > e_2^{\,jk})$$
$$= I_2^{\,jk} \quad if \quad (e_1^{\,jk} <= e_2^{\,jk}) \qquad (3)$$

Finally inverse transform is applied to all the four sub bands to obtain the resultant fused image.

B. Contourlet Transform

The Contourlet transform is a multi-resolution and a multidirectional transform that is powerful for providing sparse expansions of images containing smooth contours by applying a double filter bank structure named Pyramid Directional Filter Bank (PDFB). Implementation of the CT is achieved via two major steps: First, the Laplacian pyramid is used to capture the points discontinuities. Second, the Directional Filter Bank (DFB) is utilized to link the discontinues into linear structures[3]. Therefore, the directional filter bank is designed to capture the high frequency components representing directionality, while the Laplacian pyramid is used to avoid leaking of low frequency components into several directional sub bands. Therefore, the directional information is captured efficiently[6].

Laplacian Pyramid

The Laplacian Pyramid (LP), as introduced by Burt et al. in, is a multiscale decomposition filter bank, which produces two output images at each decomposition level. The first output image represents the low frequency components (lowpass) of the original image. The second image is the difference between the original input image and the prediction as illustrated in Figure1 . The input image is processed with the two filters (H and G), which are the analysis and synthesis filters respectively. The LP decomposition produces two output images (a1 and a2), where a1 is the coarse approximation and a2 is the difference between the original image and the prediction. Also from the figure 1, the LP avoids the scrambled frequencies by only down sampling the output of the lowpass filter. This process is iterated to produce the next decomposition level.

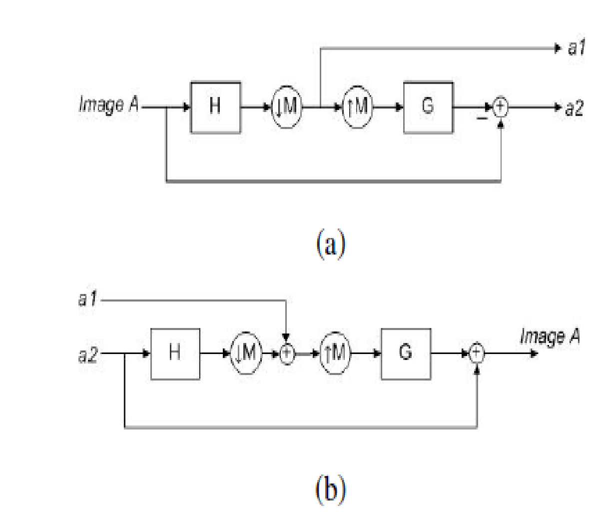


Figure.1 Laplacian Pyramid. (a) One level of decomposition. (b)Reconstruction.

Directional Filter Bank

In 1992, Bamberger and Smith constructed a 2D-DFB that can be maximally decimated while achieving perfect reconstruction. It is used in the second stage of CT to link the edge points into linear structures, which involves modulating the input image and using quincunx filter banks (QFB) with diamond-shaped filters. An *l*-level tree structured DFB is equivalent to a 2*l* parallel channel filter bank with equivalent filters and overall sampling matrices as shown in Fig. 4.2. As shown in Fig. 4.2, corresponding to the sub bands indexed, the equivalent analysis and synthesis filters are denoted using *Hk* and *Gk*, $0 \le k < 2m$. An *l*-level DFB generates a perfect directional basis for discrete signal in *l2(Z2)* that is composed of the impulse responses of 2*l* directional synthesis filters and their shift.

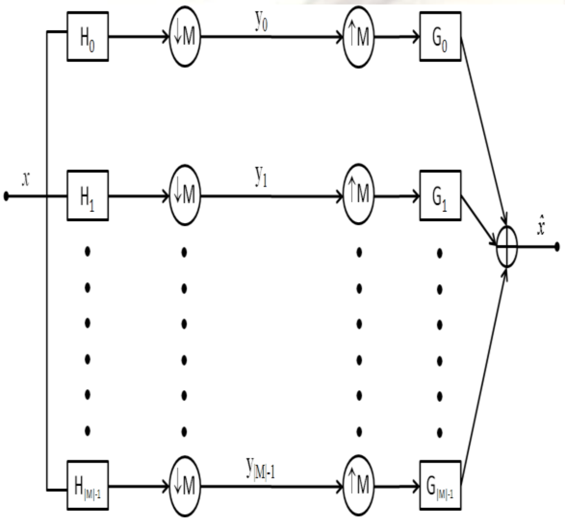


Figure 2 Construction of DBF.

The main advantage of the CT is the flexibility in choosing the number of directions at each level. Also, the utilization of the iterated filter banks increases its computational efficiency. CT based techniques successfully deal with images containing contours and textures as the CT exhibits very high directionality and anisotropy. These characteristics are very important when processing remote sensing images, which contain contours and lines (i.e., roads).

Here image A and B denotes the input source images CT and MRI respectively. F is the final fused outcome after inverse Contourlet transform. In Contourlet transform based image fusion method, the local energy is developed as the measurement, then the selection and averaging modes are used to compute the final coefficients . The same rule is used for both low frequency fusion and high frequency sub band fusion. The local energy E(x,y) is calculated centering the current coefficient in the sub band a, which is

$$E(x,y) = \sum_m \sum_n a_j(x+m,y+n)^2 W_L(m,n) \qquad (4)$$

where (x,y) denotes the current contourlet coefficient, WL(m,n) is a template of size 3*3

$$W_L = 1/9 * \begin{matrix} 1 & 1 & 1 \\ 1 & 1 & 1 \\ 1 & 1 & 1 \end{matrix}$$

Then the salience factor is calculated to determine whether the selection mode and averaging mode to be used in the fusion process.

$$M_j^{AB}(x,y) = 2\sum_m \sum_n (a_j^A(x+m,y+n)a_j^B(x+m,y+n))/(E^A(x,y)+E^B(x,y))$$
(5)

where $a_j^x(x,y)$; x=A,B denotes the contourlet coefficients (low pass or high pass) of the source image A or B *and* Mj ^{AB}(x,y) is the salience factor. Salience factor reflects the similarity of the low pass or high pass sub bands of the two source images. Then this value is compared to a predefined threshold TL (TL=1). If $M_j^{AB}(x,y) > TL$, averaging mode is selected for fusion.

$$a_j^F = \alpha_A a_j^A(x,y) + \alpha_B a_j^B(x,y) \qquad (6)$$

Where $a_j^F(x,y)$ is fused result at position (x,y). The α_A and α_B are selected based on the condition specified, as below

$$\alpha_A = \begin{cases} \alpha_{min} & \text{for } E^A(x,y) < E^B(x,y) \\ \alpha_{max} & \text{for } E^A(x,y) \ge E^B(x,y) \end{cases}$$
(7)

Where $\alpha_B = 1-\alpha_A$, α_{min} € (0,1) $\alpha_{min} + \alpha_{max} = 1$

The selection mode is chosen for the condition $M_j^{AB}(x,y) <= TL$, with the fusion rules denoted as below

$$a_j^F(x,y) = a_j^A(x,y) \quad \text{for } E^A(x,y) \ge E^B(x,y)$$
$$= a_j^B(x,y) \quad \text{for } E^A(x,y) < E^B(x,y)$$
(8)

The fused image is constructed from $a_j^F(x,y)$ (contourlet coefficients of the sub bands of the fused image)using inverse contourlet decomposition method.

III. QUANTITATIVE ANALYSIS

The quantitative measurement is done on the fused images using some objective and subjective quality measures. It helps better in assessing the information of images. This section explains the quantitative metrics used in the analysis of this system.

A. Entropy

$$EN = -\sum_{i=0}^{L-1} P_F(i)\log_2 P_F(i) \quad (9)$$

where P_F is the normalized histogram of the fused image to be valuated, *L* is the maximum gray level for a pixel in the image. In our tests, *L* is set to 255[8].

B. Standard Deviation (SD)

The standard deviation defines the contrast information of an image. The image with more contrast has high value of standard deviation where as low value for minimum contrast images.

$$\sigma = \sqrt{1/N \sum_{i=1}^{N} (xt - x)^2} \quad (10)$$

where x is defined as a summation

$$x = \frac{\sum_{i=1}^{N} x_i}{N} = x_1 + x_2 + \cdots + x_N / N \quad (11)$$

C. Signal To Noise Ratio (SNR)

It is defined as the ratio of mean pixel value to that of standard deviation of the corresponding pixel values[8].

SNR = Mean / Standard Deviation (12)

IV. EXPERIMENTAL RESULTS AND DISCUSSION

The fusion algorithms based on redundant discrete wavelet transform, wavelet packet transform and contourlet transform are simulated using Matlab 7.10. Simulation results of the fusion techniques are analysed with three input datasets. The input images consists of CT images and three different MRI images (T1, T2 and PD). All images have the same size of 256 * 256 pixels, with 256- level gray scale.

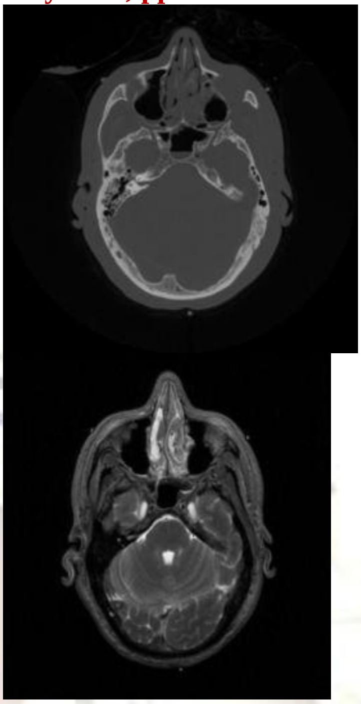
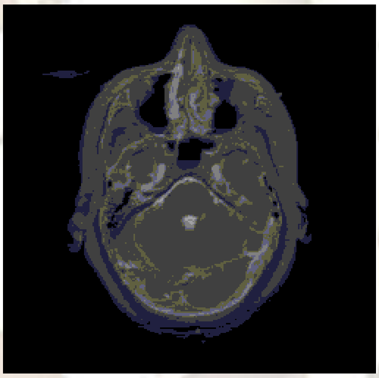
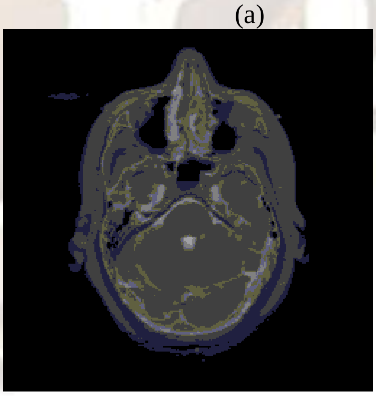


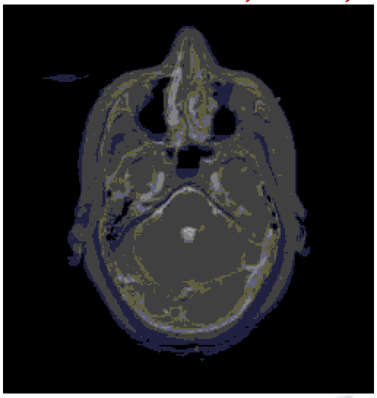
Figure 3 Input Data Set



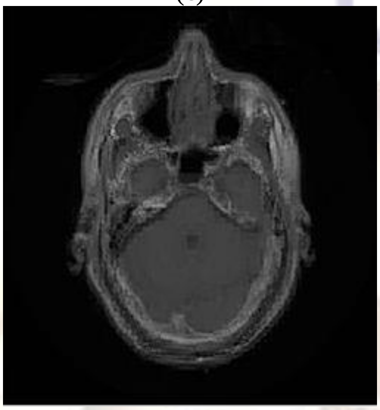
(a)



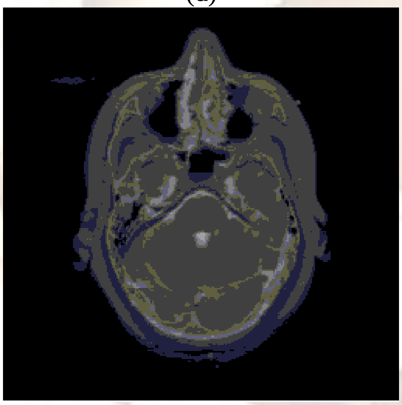
(b)



(c)



(d)



(e)

Figure 4 Fused image a)RDWT Level 1 b) RDWT Level 2 c)RDWT Level 3 d)Wavelet packet e)Contourlet Transform

Table 1. Entropy values for different data sets

	IMAGE SET 1	IMAGE SET 2	IMAGE SET 3
RDWT LEVEL1	4.7280	4.8399	5.0479
RDWT LEVEL2	4.7554	4.8945	5.1204
RDWT LEVEL 3	4.7708	4.8972	5.1306
WAVELET PACKET TRANSFORM	4.7520	4.8705	5.1178
CONTOURLET TRANSFORM	5.1108	5.2986	5.6416

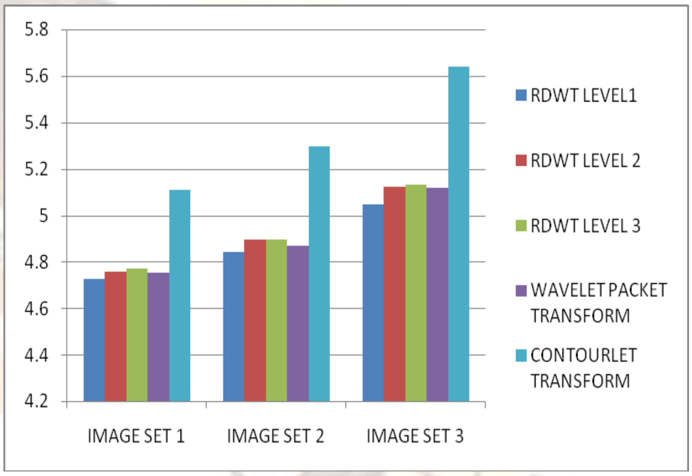


Figure 5. Plot of entropy values for different data sets

Table 2. Standard Deviaiton values for different data sets

	IMAGE SET 1	IMAGE SET 2	IMAGE SET 3
RDWT LEVEL1	15.4551	14.8417	22.5408
RDWT LEVEL2	15.5789	14.9842	22.7693
RDWT LEVEL 3	15.4195	14.8318	22.5586
WAVELET PACKET TRANSFORM	15.7578	15.1322	23.0472
CONTOURLET TRANSFORM	16.4829	16.1886	26.5253

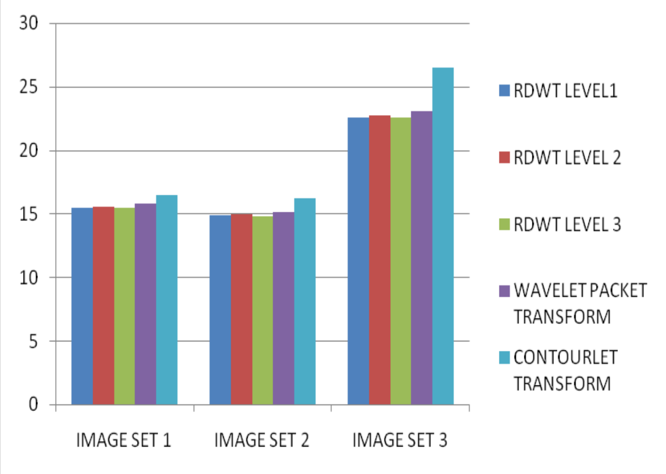


Figure 6. Plot of standard deviation values for different data sets

Table 3. SNR values for different data sets

	IMAGE SET 1	IMAGE SET 2	IMAGE SET 3
RDWT LEVEL1	1.7242	1.7635	1.7503
RDWT LEVEL2	1.7105	1.7467	1.7327
RDWT LEVEL 3	1.7281	1.7646	1.7488
WAVELET PACKET TRANSFORM	1.6911	1.7296	1.7118
CONTOURLET TRANSFORM	1.6885	1.7057	1.6798

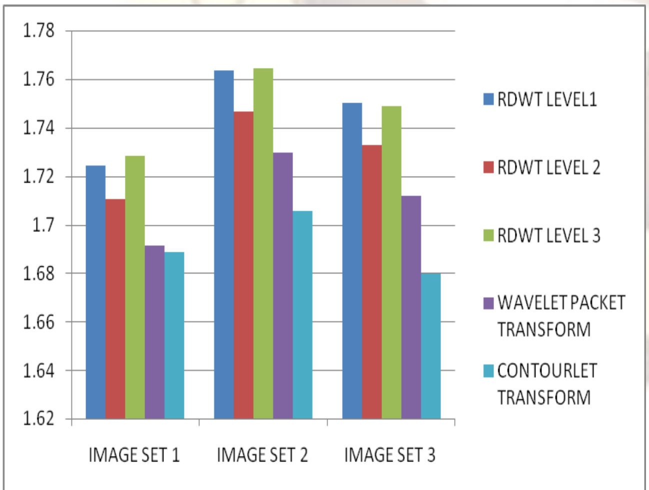


Figure 7. Plot of SNR values for different data sets

CONCLUSION

In this paper, we have compared medical image fusion algorithms based on three transforms viz, redundant discrete wavelet transform, wavelet packet transform and contourlet transform. From the experimental results it is observed that the contourlet transform provides better fused image in terms of entropy metric and also in the visualization of the fused image event though it has poor signal to noise ratio than the other two transforms.

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