Fusion of MRI and CT Images using Multi-Wavelet Based Image Fusion

D. Ranjith kumar and S. Nelson

Abstract--- *At this paper we reviewed the application of the Multi-Wavelet Transform (Haar wavelet) in the fusion of different modality medical images such as Computed Tomography (CT) and Magnetic Resonance (MR) are fused forming a new image with highly improved information content for diagnosis. In our Proposed Method, an algorithm for image fusion based on the MWT was implemented, analyzed and compared with existed Wavelet-based fusion algorithm. And further results were evaluated and provided with better efficiency measures of performance in – the ENTROPY (H), ROOT MEAN SQUARE ERROR (RMSE), PEAK SIGNAL TO NOISE RATIO (PSNR) AND CORRELATION COEFFICIENT (CC). The quantitative performance measure parameters have shown that the MWT based image fusion algorithm provides a slightly better fused image than the Wavelet algorithm.*

Keywords--- *Image Fusion, Multi-Wavelet Transform, Wavelet Transform, Entropy, Root Mean Square Error (RMSE), Peak Signal to Noise Ratio (PSNR)*

I. INTRODUCTION

IMAGE fusion is the process of combining the meaningful visual information from two or more images into a single high informative image. Image fusion finds its application in various fields such as Satellite Imaging, Remote sensing and Medical imaging. Initially, image fusion was used in the Satellite imaging and then is application extended over various areas namely robotics, medical imaging, remote sensing and so on. Several algorithms were proposed for enhancing the image fusion. Algorithms such as the Intensity-Hue-Saturation (IHS) and the Wavelet Transform were successfully used in the Satellite image fusion. IHS belongs to color image fusion algorithms [1].Image fusion based on the wavelet transform succeeded in both Satellite and Medical image fusion applications [2,3,4].

Medical imaging involves obtaining high resolution images in order to improve the accuracy of the diagnosis .It is known that there are several medical imaging techniques. MR and CT imaging are the two commonly used imaging techniques used for diagnostic purposes. CT imaging technique express more information about the bone structures and less information about soft tissues [5,6]. But MR imaging gives more information about the soft tissues and less information about rigid bone structures [7,8].So the fusion of CT and MR images result in an integrated image with more information content. Several attempts have already been made by researchers in the field of fusion of different modality medical images. Most of the attempts are towards the application of the Wavelet Transform.

The rest of the paper is discussed as follows: Section II describes the Wavelet Fusion algorithm. Section III reviews the Multi-Wavelet Transform. Section IV presents the image fusion methods and reviews the proposed medical image fusion algorithm. Section V presents the performance measures for image fusion. Section VI reviews Experimental Results. Finally Section VII gives the concluding remarks.

II. WAVELET TRANSFORM FOR IMAGE FUSION

Discrete Wavelet Transform (DWT) using Haar Wavelets is a kind of fusion method being widely used in the recent years [9,10]. In this method, initially each source image is decomposed into a multi-scale representation using discrete wavelet transform. Then a composite wavelet pyramid is constructed from the source representations and a fusion rule. Finally the fused image is obtained by taking an inverse discrete wavelet transform of the composite multi-scale representation. The DWT is also a multi-resolution analysis of source image.

DWT offers directional information and provides a non-redundant pyramid representation of the original images while pyramid representation does not introduce any spatial information in the decomposition process [11]. Moreover using the same fusion rule, images generated by wavelet based fusion method have better signal-to-noise ratio than the images generated by pyramid image fusion method .

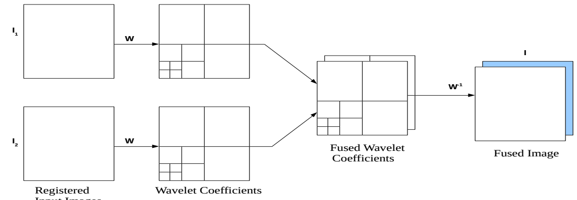


Figure 1: Fusion of Wavelet Transforms of Two Images

Like all the transform-domain fusion techniques, the transformed images are combined in the wavelet domain using a predefined fusion rule, then transformed back to the spatial domain resulting in the formation of the fused image. The Wavelet transform fusion is defined by considering the wavelet transforms W of the two registered input images $I_1(x,y)$ and $I_2(x,y)$ together with the fusion rule φ. Then the

D. Ranjith kumar, RVS College of Engineering and Technology, Dindigul. E-mail:ecranjith083@gmail.com

S. Nelson, RVS College of Engineering and Technology, Dindigul. E-mail:ecnel68@gmail.com

inverse wavelet transform W^{-1} is computed and the fused image I(x, y) is reconstructed and given by

$$I(x,y) = \omega^{-1}(\varphi(\omega(I_1(x,y)),\omega(I_2(x,y)))) \quad (1)$$

This process is explained in the above figure 1.

III. MULTI-WAVELET TRANSFORM

Multi-Wavelet Transformation is a new concept of wavelet transform architecture and has been used extensively for many applications in the recent years. Time-frequency localization is one of the main properties of singular wavelet functions. However there is a limitation in the time-frequency localization property of the singular wavelet functions. Multiwavelet has two or more scaling and wavelet functions [12]. The first polynomial wavelet was constructed by Alpert and later Geronimo, Hardin and Massopust constructed a multi-scaling function with 2 components using fractal interpolation. Multiwavelet has several applications in image processing such as image compression, watermark processing, image pattern recognition and so on. For notational convenience, the multiscaling function is defined from the set of scaling functions as

$$\Phi(t)=[\varphi_1(t)\ \ \varphi_2(t)\ \ \ldots\ \ \varphi_r(t)\ ]^T \quad (2)$$

Similarly the Multiwavelet function is defined from the set of wavelet functions as

$$\Psi(t) = [\psi_1(t)\ \ \ \psi_2(t)\ \ \ldots\ \ \psi_r(t)]^T \quad (3)$$

Where **r** > 1 is an integer. When r =1, is called a scalar wavelet or simply wavelet. When r =2, is called a Multiwavelet. In the GHM multi wavelet, they translate of the scaling and wavelet functions are orthogonal and both the scaling and wavelet functions are symmetric [12]. The Multiwavelet two scale equations resemble those for scalar wavelets

$$\varphi(t) = \sum_{k=0}^{m-1} G_k \varphi(2t-k) \quad (4)$$

$$\psi(t) = \sum_{k=0}^{m-1} H_k \psi(2t-k) \quad (5)$$

The pair $\{G_K, H_K\}$ is called a Multiwavelet filter bank. G_K is called a matrix low pass filter and H_K is called a matrix high pass filter. They are r×r matrices for each integer k, and m is the number of scaling coefficients [13]. The application of Multiwavelet requires the input signal to be first victimized, namely pre-processing (which is crucial point known as Multiwavelet initialization or pre-filtering).Pre-filtering process generate multiple (vector) streams from a given scalar source stream and results in the initial expansion coefficients of the given Multiwavelet system. To construct an efficient pre-filter, the nature of the components of the multiscaling functions should be taken into account.

In the case of scalar wavelet, during a single level of decomposition the 2-D image is decomposed into four blocks corresponding to the sub bands in the representing either low pass or high pass filtering in both dimensions. These sub bands are illustrated in Figure 2(a)

Figure 2 Image sub band after a single level decomposition, for (a) scalar wavelets and (b) Multiwavelet

The Multiwavelet have r scaling functions and the Multiwavelet used here have 2 channels (r=2), so that there will be two sets of wavelet and scaling coefficients. Since the multiple iterations over low pass data are desired, the scaling and wavelet coefficients of the two channels are stored together. The Multiwavelet decomposition is described in fig.2 (b). In this case, 4 sub band images obtained from the single level decomposition of 2-D image are once again decomposed into 16 more sub band images and they can be divided into 4 blocks. For example LH sub band obtained from single level decomposition of 2-D image is again decomposed into L1H1, L_1H_2, L_2H_1 and L_2H_2. L_1H_1 corresponds to the data from the first channel high pass filter in the horizontal direction and the first channel low pass filter in the vertical direction. Multiwavelet have remarkable properties like orthogonally, symmetry, short support and vanishing moments which are known to be important in image processing.

IV. RELATIVE WORK

Many image fusion techniques using transforms are proposed. These methods focus mainly on improving the fusion rate and not concentrating on using different fusion techniques in order to improve the information content in the fused image. In our proposed work, we have used minimum data sets and different fusion techniques so that more information can be made available to the radiologists.

4.1. Image Fusion Methods

Due to the limited focus depth of the optical lens, it is not possible to obtain a single image that contains all the relevant information about the objects in focus. There are many image fusion methods available, among which we have chosen the methods which have contributions in the area of image processing. Some of the image fusion methods are presented below:

1. Maximum selection method
2. Minimum selection method
3. Simple Average method
4. Principal Component Analysis (PCA) method
5. Laplacian Pyramid

We have used all the above image fusion methods in our proposed method.

4.2. Multiwavelet Transform for Image Fusion Algorithm

The specific operational procedure for the Multiwavelet based image fusion approach is now summarized as follows:

1. The two input images are first registered.
1. The Multiwavelet transform steps are performed for both images (each input image is analyzed and a set of Multiwavelet Coefficients are generated).
2. The maximum frequency fusion rule or any other rule (minimum, Average, PCA, Laplacian pyramid) is used for the fusion of the coefficients [14,15].
3. The inverse Multiwavelet transform step is performed (The fused coefficients are subjected to the inverse Multiwavelet transform) to obtain the fused image.

These steps are expected to merge the details in both images into a single image with much more details.

V. PERFORMANCE MEASURES FOR IMAGE FUSION

The widespread use of image fusion methods has led to an increasing need for pertinent performance or quality assessment tools in order to compare results obtained with different algorithms or to obtain an optimal setting of parameters for a given fusion algorithm [16]. In recent years, several objective performance measures for image quality analysis were proposed. In the present work four performance measures were used to evaluate the performance of the Multi-Wavelet fusion algorithm and to compare it with wavelet fusion algorithm.

5.1. Entropy (H)

The Entropy (H), of an image is a measure of information content [8]. It is the average number of bits needed to quantize the intensities in the image. An image with high information content would have high entropy. If entropy of fused image is higher than parent images then it indicates that the fused image contains more information.

It is defined as

$$H = -\sum_{g=0}^{L-1} p(g)\log_2 p(g) \tag{6}$$

5.2. Root Mean Square Error (RMSE)

A commonly used reference based assessment metric is the Root Mean Square Error (RMSE). The RMSE between a reference image, R, and a fused image, F, is given by the following equation:

$$RMSE = \sqrt{\frac{1}{MN}\sum_{m=1}^{M}\sum_{n=1}^{N}(R(m,n)-F(m,n))^2} \tag{7}$$

where R(m, n) and F(m, n) are the reference (CT or MR) and fused images, respectively, and M and N are image dimensions. Smaller the value of the RMSE, better the performance of the fusion algorithm.

5.3. Peak Signal to Noise Ratio (PSNR)

PSNR is the ratio between the maximum possible power of a signal and the power of corrupting noise that affects the fidelity of its representation. The PSNR of the fusion result is defined as follows:

$$PSNR = 10 \times \log\left(\frac{(f_{\max})^2}{RMSE^2}\right) \tag{8}$$

Where f_{max} is the maximum gray scale value of the pixels in the fused image. Higher the value of the PSNR, better the performance of the fusion algorithm.

5.4. Correlation Coefficient (CC)

The correlation coefficient measures the closeness or similarity in small size structures between the source and the fused images. The CC value varies between -1 and +1. Higher value of correlation means that more information is preserved. The ideal value is one when the reference and fused image are exactly alike and it will be less than one when the dissimilarity increases. Values close to +1 indicate that the original and fused images are highly similar, while the values close to -1 indicate that they are highly dissimilar. The correlation coefficient is given by equation

$$CORR = \frac{2C_{rf}}{C_r + C_f} \tag{9}$$

Where

$$C_r = \sum_{i=1}^{M}\sum_{j=1}^{N} I_r(i,j)^2$$

$$C_f = \sum_{i=1}^{M}\sum_{j=1}^{N} I_f(i,j)^2$$

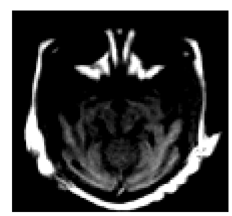
$$C_{rf} = \sum_{i=1}^{M}\sum_{j=1}^{N} I_f(i,j) I_r(i,j)$$

C_r is the reference image and C_f is the fused image respectively.

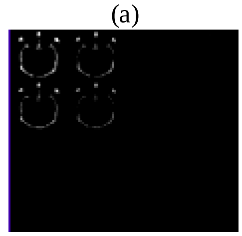
VI. THE EXPERIMENTAL RESULTS

The proposed algorithm for the fusion of MR and CT images is tested and compared with the traditional wavelet fusion algorithm.MR image is taken as the reference image for calculating the metric values. Two experiments are conducted for this purpose. For the evaluation purpose, the visual quality of the obtained fusion result as well as the quantitative analysis is used.

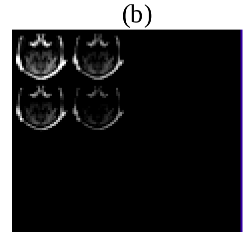
(a)



(b)



(c)



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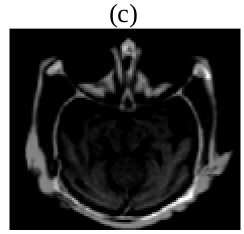

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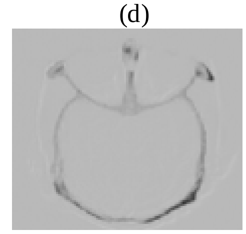

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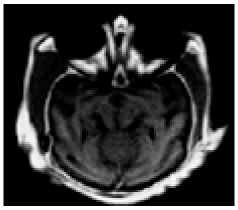
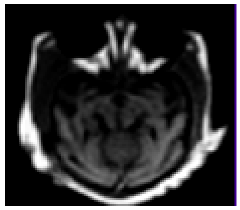
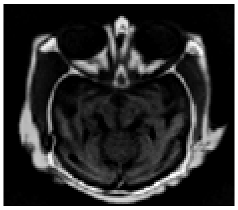


(g)



(h)



(i)

Fig. 3: Source Images: (a) CT Image; (b) MR Image , ((c),(d)) Multi-wavelet Transform Applied in CT & MR Image, (e) Average Output , (f) Minimum Output , (g) Maximum Output , (h) PCA Output , (i) Laplacian Pyramid Output

Table I: Statistic Results of Different Fusion Methods using DWT

Fusion method	Metrics			
	Entropy	RMSE	PSNR	CC
Select Maximum	6.7560	2.8549	39.0189	0.9099
Select Minimum	1.3884	15.0013	24.6082	0.1265
Simple Average	5.91955	12.2084	26.3976	0.8507
Principal Component Analysis	6.418	7.0367	31.1834	0.9967
Laplacian Pyramid	6.2270	13.4232	25.5737	0.8269

From the Table I, Entropy value holds the highest value in the case of the Select Maximum method, followed by PCA and Laplacian method and least value is observed in the Select Minimum method. In the case of PSNR value, the value is maximum in the Select Maximum, PCA method and minimum in the Select Minimum method. In the case of RMSE, methods Select Maximum and PCA have lower values and Select Minimum method has the higher PSNR value. Considering the Correlation Coefficient value, PCA and Select Maximum methods have higher values closer to 1 and value is least in Select Minimum method.

Table II Statistic Results of Different Fusion Methods using MWT

Fusion method	Metrics			
	Entropy	RMSE	PSNR	CC
Select Maximum	6.7756	1.0722	47.5249	0.9116
Select Minimum	1.5285	15.0268	24.5935	0.2369
Simple Average	5.9335	12.2346	26.379	0.8506
Principal Component Analysis	6.4157	7.0539	31.1622	0.9966
Laplacian Pyramid	5.9898	13.8933	25.2747	0.8292

From the Table II, Select Maximum and PCA methods have higher Entropy, PSNR, CC values and lower RMSE values. Select Minimum method has lower metric values compared to all the fusion methods. Laplacian Pyramid and Simple Average methods have better performance measure values compared to the Select Minimum fusion method.

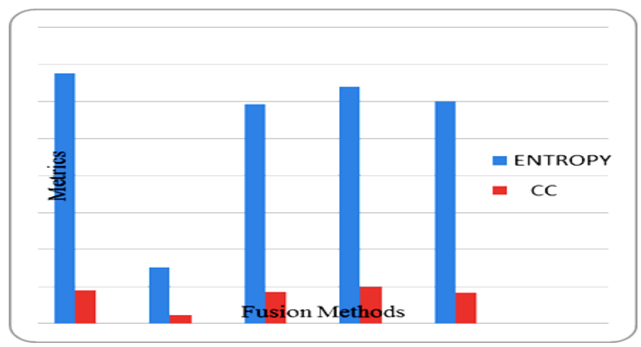


Figure 5: Entropy and CC Plot for MWT

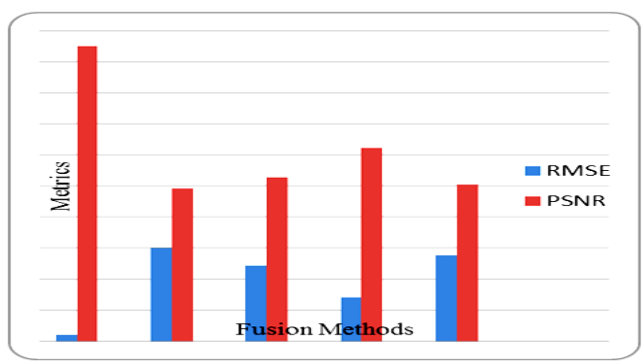


Figure 6: Root Mean Square Error and Peak Signal to Noise Ratio plot for MWT

VII. CONCLUSION

Using our proposed Multiwavelet Transform(Haar Wavelet) with the Image fusion algorithm We improver the four meaningful performance measures namely entropy, Peak Signal to Noise Ratio, Root Mean Square Error and Correlation Coefficient used to assess the effectiveness of the two image fusion algorithms. Results have proved that there is a slight difference in the performances of the Existence fusion algorithms. It has been shown also that the best performance criterion should be linked with the specific application. According to visual perception, the fused image has been significantly improved the content information in the Silde using both fusion techniques.

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