Curvelet Based Multi-Focus Medical Image Fusion Technique: Comparative Study With Wavelet Based Approach

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***Abstract*—Limited depth of focus of optical lenses results in blurred representation of some of the relevant objects in any image. Multi focus image fusion is used to solve this problem. Both curvelet based and wavelet based image fusion methods are implemented and compared in this paper. Comparison is done based on various parameters called "fusion performance index". Wavelet and curvelet coefficients are calculated and represented in the form of images . Experiments showed that curvelet decomposition based fusion increases the quality of obtained fused images.**

***Keywords* - image fusion, wavelet transform, curvelet transform.**

Introduction

Image fusion can be described as a process of combining the information from two or more images to produce a new image that has superior properties over the individual input images. Medical image fusion is the process of integration complementary information of a particular organ focused by the different types of sensors. In present day technology, images acquired from single sensor may not always give accurate to represent all required information of a particular organ, whereas the images obtain from different sensors carry complimentary but important information. For example, MR-T1 gives a greater detail about the anatomical structure and MR-T2 gives greater contrast between the normal and abnormal tissues [3]. Moreover, dose calculation is based on the computed tomography (CT) data, and PET images describe the metabolic process of the organs, like blood flow, food activity etc with low space resolution [15]. Hence it is very important and natural to integrate different modalities of medical images together to increase the examination accuracy and evaluation specificity.

The concept of multi-focus images is to combine or fuse the sharply focused regions from different sensors to take a better decision than the single source only [13]. The data fusion is an important step for systems analysis and complex situations [4],[9].

In past, many image fusion methods have been proposed for combining different modality images by different authors. Some of techniques are based on Bayesian approaches [8]. Hurn et al. suggested a hierarchical frame work for estimating a fused classification of medical images by combining registered data images at different resolution. The authors not only proposed fusion process for the functional images representing the metabolic activities, also included structural images to incorporate anatomical properties [5].

The multiresolution image fusion schemes are widely acknowledged as the most efficient and promising image fusion algorithms. Pyramid [14] and wavelet [11] are the most widely studied and used multi-resolution image fusion schemes. There are many types of pyramid and wavelet decomposition algorithms in recent years; however, not much research has been conducted on fusion rules.

The basic idea of wavelet based methods is to perform decompositions on each source image, and then fuse all these decomposed images to obtain composite representation, from which the final fused image can be recovered by finding inverse transform. This method is found to be effective. However, wavelets transform can only reflect "through" edge characteristics, but can not express "along" edge characteristics. At the same time, the wavelet transform cannot precisely show the edge direction since it adopts isotropy. To overcome the limitation of the wavelet transform, Donoho et al. has proposed the concept of Curvelet transform, which uses edges as basic elements, possesses maturity, and can adapt well to the image characteristics. Moreover, Curvelet Transform has anisotropy and has better direction, can provide more information to image processing [16][17].

The rest of the paper is organised as follows. The section II and section III give the relevant theory and algorithms associated with wavelet transform fusion and curvelet fusion respectively. The experiment is shown in section VI. The paper is concluded in section VII.

Wavelet based Image Fusion

Wavelets are finite duration oscillatory functions with zero average value. The irregularity and good localization properties make them better basis for analysis of signals with discontinuities. Wavelets can be described by using two functions viz. the scaling function $f(t)$, also known as 'father wavelet' and the wavelet function or 'mother wavelet'. 'Mother' wavelet $\psi(t)$ undergoes translation and scaling operations to give self similar wavelet families as in (1).

$$\psi_{a,b}(t) = \frac{1}{\sqrt{a}}\psi\left(\frac{t-b}{a}\right), \quad (a, b\epsilon R), a > 0 \qquad (1)$$

Practical implementation of wavelet transforms requires discretisation of its translation and scale parameters by taking,

$$a = a_0^j, \qquad b = ma_0^j b_0 \quad j, m\epsilon Z \qquad (2)$$

Thus, the wavelet family can be defined as:

$$\psi_{j,m}(t) = a_0^{-\frac{j}{2}}\psi\left(a_0^{-j}t - mb_0\right) \quad j, m\epsilon Z \qquad (3)$$

Wavelet transform has good spatial and frequency localization characteristics which shows itself mainly at three aspects: frequency feature compression (feature compression in the frequency domain), space compression feature and structure similarity of wavelet coefficients among different scales.

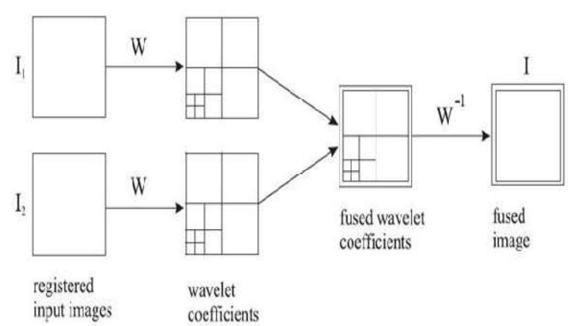


Figure 1. Image Fusion using Wavelet Transform

The original concept and theory of wavelet-based multiresolution analysis came from Mallat [6].Frequency compression feature means that the energy of original image concentrates at low frequency sub-band. Space compression feature indicates that the energy of high frequency sub-band mainly distributes at the corresponding positions of the edges of original image. Structure similarity of wavelet coefficients refers to the general consistence of the distributions of wavelet coefficients in high frequency sub-bands of the same orientation.

Actually, wavelet transform can be taken as one special type of pyramid decompositions. After one level of decomposition, there will be four frequency bands, namely Low-Low (LL), Low-High (LH), High-Low (HL) and High-High (HH). The next level decomposition is just apply to the LL band of the current decomposition stage, which forms a recursive decomposition procedure. Thus, an N-level decomposition will finally have $3N + 1$ different frequency bands, which include $3N$ high frequency bands and just one LL frequency band. The $2 - D$ DWT will have a pyramid structure. The frequency bands in higher decomposition levels will have smaller size.

Therefore, the basic idea of image fusion based on $2 - D$ DWT can be expressed as the images to be fused are firstly performed by a multiresolution decomposition, the coefficients of both the low frequency band and high frequency bands are then performed with a certain fusion rule. The widely used fusion rule is maximum selection scheme. This simple scheme just selects the largest absolute wavelet coefficient at each location from the input images as the coefficient at the location in the fused image. After that, the fused image is obtained by performing the IDWT for the corresponding combined wavelet coefficients. Therefore, the detailed fusion steps based on DWT can be summarized below.

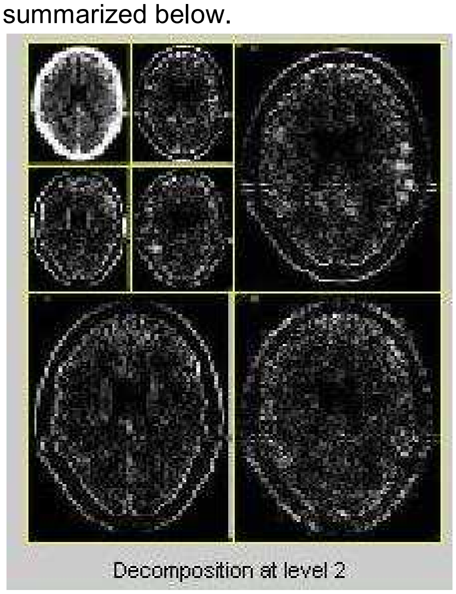


Fig 2-Wavelet Decomposition at level 2 (wavelet coefficients)

Step 1: The images to be fused must be registered to assure the corresponding pixels are aligned.
Step 2: These images are decomposed into wavelet transformed images respectively, based on DWT. The transformed images with K - level decomposition will include one low frequency portion and $3K$ high frequency portions.
Step 3: The transform coefficients of different portions or bands are performed with a certain fusion rule.
Step 4: The fused image is constructed by performing the IDWT based on the combined transform coefficients from step 3.

Curvelet based Image Fusion

Here we are using wrapping algorithm based curvelet decomposition. The wrapping discrete curvelet transform is implemented using the following steps :
Step 1:FFT of the image is taken and the resulting Fourier samples is divided into collection of digital corona tiles as shown in "Figure.4".
Step 2: For each corona tile, the tile is translated to the origin.
Step 3: The parallelogram shaped support of the tile is wrapped around a rectangle centered at the origin.
Step 4: The Inverse FFT of the wrapped support is determined and finally the resulting curvelet array is added to the collection of curvelet coefficients.

The scheme of Image Fusion

Several methods were proposed for various applications utilizing the directionality, orthogonality and compactness of wavelets. Fusion process should conserve all important analysis information in the image and should not introduce any artifacts or inconsistencies while suppressing the undesirable characteristics like noise and other irrelevant details. Fusion can be performed on pixel, feature or decision level. The complexity of pixel based algorithms is lesser than other methods. The advent of region based image fusion can be attributed to the inefficiencies faced by pixel algorithms in cases where the salient features in images are larger than one pixel. Region based rules are more complicated than simple pixel algorithms and used when pixel spacing of images are different.

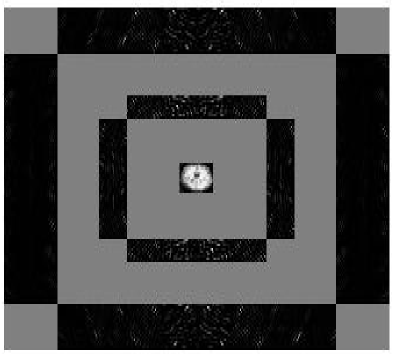


Fig 3 Curvelet Decomposition of MRT1(curvelet coefficients)

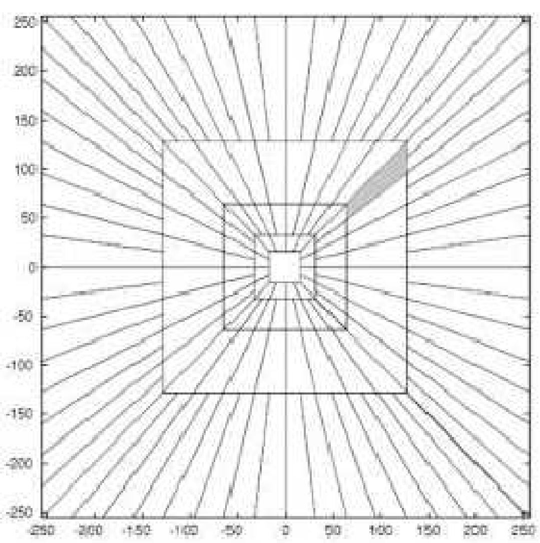


Figure 4 Frequency spectrum coverage by curvelet(Digital Corona of the frequency domain)

Fusion Performance Index

We select the mean, standard deviation , mutual information, and the entropy to evaluate the effect of the fused images.

For image in size of M * N, the mean is defined as equation [4]

$$\mu = \frac{1}{M * N} \sum_{i,j} f(i,j) \tag{4}$$

Where $\mathrm{f}\,(\mathrm{i},\mathrm{j})$ is the pixel gray value of point $(\mathrm{i},\mathrm{j}\,)$.

For image in size of M * N, the variance is defined as [5]

$$\sigma^2 = \frac{1}{M * N - 1} \sum_{i,j} [f(i,j) - \mu]^2 \tag{5}$$

Where $f\,(i,j)$ is the pixel gray value of point $(i,j\,)$.

The standard deviation is the square root of variance.

Mutual Information (MI) is a basic concept from information theory, measuring the statistical dependence between two random variables or the amount of information that one variable contains about the other. The definition of the mutual information of two images A and B combines the marginal entropy, $p_A(a)$ and $p_B(b)$ and joint entropy $p_{A,B}(a,b)$ of the images in the following manner:

$$I(A,B) = \sum_{a,b} p_{AB} \;\; log \frac{p_{AB}(a,b)}{p_A(a) \;\; p_B(b)} \tag{6}$$

MI is related to entropy by the equation

$$I(A,B) = \; H(A) + \; H(B) - \; H(A,B) \tag{7}$$

with $H(A)$ and $H(B)$ being the marginal entropy of A and B, respectively, and $H(A,B)$ be their joint entropy. The entropy is defined as equation [8] .

$$H\,(A) = \; -\sum_{\mathrm{a}} \mathrm{p_A}\,(\mathrm{a}) \;\; \log \mathrm{p_A}\,(\mathrm{a}) \tag{8}$$

EXPERIMENTAL RESULTS

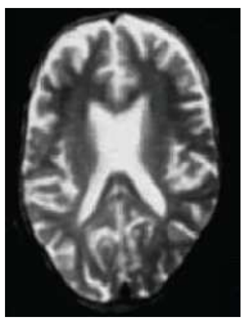
In present work authors report the experimental results using MR (T1 & T2) and CT brain images to test the proposed fusion scheme. Fusion method we are using here is selection based fusion rule. The experiments are performed using MATLAB.

TABLE- I

MR T1 vs. MR T2 Fusion (Figure 5)

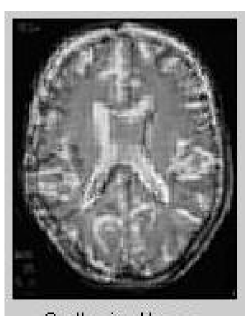
Image	Mean	Standard Deviation	Entropy	MI
Wavelet Based	93.95	63.14	7.28	3.13
Curvelet Based	99.04	64.38	7.43	3.27

5(a)



5(b)

5(c)



5(d)

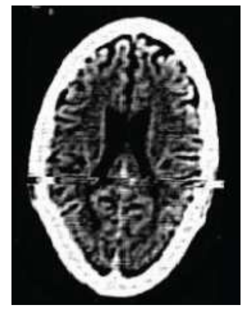
Figure. 5: (a) MR T1 , (b) MR T2, (c) Fused Image using Curvelet Based Fusion Technique, (d) Fused Image using Wavelet basedFusion Technique.

TABLE- II

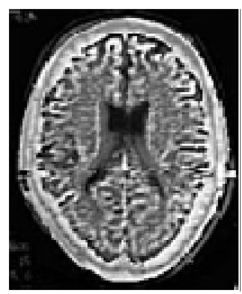
MR T2 vs. CT Fusion (Figure 6)

Image	Mean	Standard Deviation	Entropy	MI
Wavelet Based	93.95	68.46	7.46	2.98
Curvelet Based	94.98	74.38	7.64	3.4005

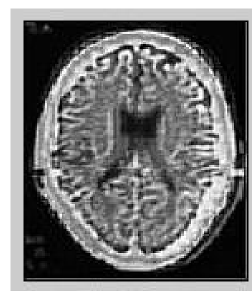
6(a)



6(b)



6(c)



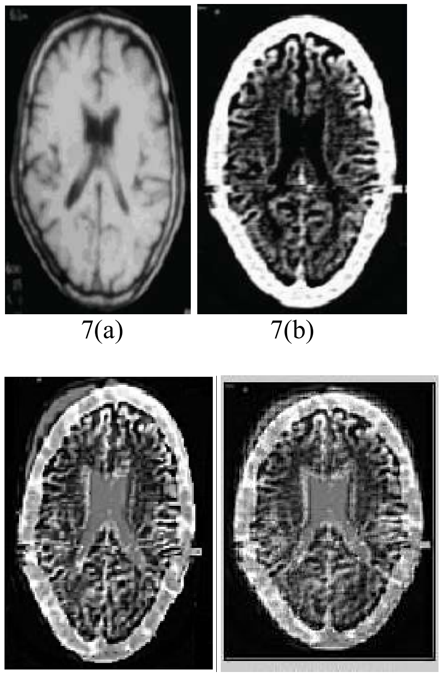
6(d)

Figure. 6: (a) MR T2, (b) CT, (c) Fused Image using Curvelet Based Fusion Technique,
(d) Fused Image using Wavelet based Fusion Technique.

TABLE- III

MR T1 vs. CT Fusion (Figure 7)

Image	Mean	Standard Deviation	Entropy	MI
Wavelet Based	84.36	70.64	7.29	3.04
Curvelet Based	84.87	77.26	7.38	3.40



7(a) 7(b)

7(c) 7(d)

Figure. 7: (a) MR T1, (b) CT, (c) Fused Image using Curvelet Based Fusion Technique,
(d) Fused Image using Wavelet based Fusion Technique.

CONCLUSIONS AND FUTURE WORK

This paper presented the detailed implementation of both wavelet and curvelet decomposition and also represented wavelet and curvelet based coefficients in the form of a image. In this paper, an experimental study was conducted by applying the wavelet based and curvelet based image fusion techniques on medical images. The high value of mean, standard deviation, entropy, and mutual information for curvelet based method confirms that it is better than wavelet based method.

Our future work includes application of different evolutionary algorithms based fusion techniques for both of these transformations. The wrapping algorithm is used for curvelet decomposition in this paper other algorithms can also be used for the decomposition.

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