Image Fusing using Transformation Approach

Ankur Upadhyay
Department of Electronic Engineering
PIIT, New Panvel,

Ujwal Harode
Department of Electronic Engineering
PIIT, New Panvel,

ABSTRACT
Now-a-days, almost all areas of medical diagnosis are impacted by the digital image processing. When an image is processed for visual interpretation, the human eye is the judge of how well a particular method works. Clinical application demanding Radiotherapy plan, for instance, often benefits from the complementary information in images of different modalities. For medical diagnosis, Computed Tomography (CT) provides the best information on denser tissue with less distortion. Magnetic Resonance Image (MRI) provides better information on soft tissue with more distortion. With more available multimodality medical images in clinical applications, the idea of combining images from different modalities become very important and medical image fusion has emerged as a new promising research field. Wavelet transform fusion is more formally defined by considering the wavelet transforms of the two registered input images together with the fusion rule .Then, the inverse wavelet transform is computed, and the fused image is reconstructed. The wavelets used in image fusion can be classified into three categories Orthogonal, Bi-orthogonal and A'trous'wavelet. Although these wavelets share some common properties, each wavelet has a unique image decompression and reconstruction characteristics that lead to different fusion results. A Novel multi-resolution fusion algorithm is proposed in this paper, which combines aspects of region and pixel based fusion. Normally, when a wavelet transformation alone is applied the results are not so useful for analysis. However if a wavelet transform and a traditional transform such as Principal Component Analysis(PCA) transform is integrated, better fusion results may be achieved. Hence a new novel approach is introduced in this work to improve the fusion method by integrating with PCA transforms. In this paper the fusion results are compared visually and statistically to show that wavelet integrated method can improve the fusion result, reduce the ringing or aliasing effects and make image smoother.

Keywords
Computed Tomography (CT), Magnetic Resonance Image (MRI), Fusion, Wavelets, PCA Transform.

1. INTRODUCTION
Image fusion is a data fusion technology which keeps images as main research contents. It refers to the techniques that integrate multi-images of the same scene from multiple image sensor data or integrate multi-images of the same scene at different times from one image sensor [1].

The image fusion algorithm based on Wavelet Transform which faster developed was a multiresolution analysis image fusion method in recent decade [2]. Wavelet Transform has good time frequency characteristics. It was applied successfully in image processing field [3]. Nevertheless, its excellent characteristic in one-dimension can't be extended to two dimensions or multi-dimension simply. Separable wavelet which was spanning by one-dimensional wavelet has limited directivity [4].

Aiming at these limitation, E. J. Candes and D. L. Donoho put forward Curvelet Transform theory in 2000 [5]. Curvelet Transform consisted of special filtering process and multi-scale Ridgelet Transform. It could fit image properties well. However, Curvelet Transform had complicated digital realization, includes sub-band division, smoothing block, normalization, Ridgelet analysis and so on. Curvelet's pyramid decomposition brought immense data redundancy [6]. Then E. J. Candes put forward Fast Curvelet Transform(FCT) that was the Second Generation Curvelet Transform which was more simple and easily understanding in 2005[7]. Its fast algorithm was easily understood. Li Huihui's researched multi-focus image fusion based on the Second Generation Curvelet Transform [8]. This paper introduces the Second Generation Curvelet

Transform and uses it to fuse images, different kinds of fusion methods are compared at last. The experiments show that the method could extract useful information from source images to fused images so that clear images are obtained.

2. TYPES OF WAVELET TRANSFORMS

A. Orthogonal wavelet
The dilations and translation of the scaling function Øj, k(x) constitute a basis for Vj, and similarly k(x) for Wj, if the Øj, k(x) and k(x) are orthonormal, they include the following property [9].

Vj perpendicular Wj

B. Biorhogonal wavelet
For biorthogonal transform, perfect reconstruction is available. Orthogonal wavelets give orthogonal matrices and unitary transforms; biorhogonal wavelets give invertible matrices and perfect reconstruction. For biorthogonal wavelet filter, the Low – pass and high – pass filters do not the same length. The low pass and high pass filters do not have the same length. The low – pass filter is always Symmetrical, while high pass filter could be either symmetric or anti – symmetric.

C. A 'trous 'wavelet (non – orthogonal wavelet)
A trous is a kind of non – orthogonal wavelet that is different from orthogonal and bi orthogonal. It is a 'stationary' or redundant transform, i.e. decimation is not implemented during the process of wavelet transform, while the orthogonal or biorthogonal wavelet can be carried out using either decimation or undecimation mode.

3. WAVELET BASED IMAGE FUSION TECHNIQUES

1. Additive wavelet based image fusion method

The process can be divided into four steps.

a) Histogram match.

b) Wavelet decomposition.

c) Details information combination.

d) Inverse wavelet transform.

Apply the histogram match process between panchromatic image and different bands of the multispectral image respectively, and obtain three new panchromatic images

PANR, PANG, PANB.

· Use the wavelet transform to decompose new panchromatic images and different bands of multispectral image twice, respectively.

· Add the detail images of the decomposed panchromatic images at different levels to the corresponding details of different bands in the multispectral image and obtain the new details component in the different bands of the multispectral image and obtain the new details component in the different bands of the multispectral image.

· Perform the wavelet transform on the bands of multispectral images, respectively and obtain the fused image.

2. Integration of substitution method

The integration of substitution method is divided in two parts.

a. Refers to substitution fusion method.

b. Refers to the wavelet passed fusion method.

The process consists of following steps

· Transform the multispectral image into the PCA components.

· Apply histogram match between panchromatic image and intensity component and obtain new panchromatic image.

· Decompose the histogram matched panchromatic image and intensity component to wavelet planes respectively.

· Replace the LLP in the panchromatic decomposition with the LL1 of the intensity decomposition, add the detail images in the panchromatic decomposition to the corresponding detail image in the panchromatic decomposition to the corresponding detail images of the intensity and obtain LL1, LHP, HHP and HLP. Perform an inverse wavelet transform, and generate a new intensity. Transform the new intensity together with hue, saturation components or PC1, PC2, PC3 back. Into RGB space.

4. CURVELET TRANSFORM

Curvelet Transform was proposed by Cands and Donoho in 2000, it derived from Ridgelet Transform. They constructed a new Curvelet frame in 2005, it didn't bring Ridgelet Transform different from traditional Curvelet Transform, but gave expression forms of Curvelet basis in the frequency domain; it was true Curvelet Transform. As a new geometric multi-scale transform in sparse representation, curvelet is more suitable for the analysis of image edges such as curve and line characteristics than wavelet. The key features of curvelet lies in it can divide the frequency plane into a series of "parabolic" wedges, and in spatial domain, each of the wedge corresponds to a particular curvelet at a given scale, spatial position and angle (orientation), which reveal the highly anisotropy and directional property of the curvelet transform. The principle and implementation of curvelet has been investigated by many researchers. In our work, we use the implementation of the second generation curvelet, which is simpler, faster, and less redundant.

5. THE CURVELET-BASED SPECKLE DENOISING METHOD IN IMAGES

In the past few decades, ultrasonography has been considered as one of the most powerful medical imaging modalities, especially capable of imaging soft tissues structures in the internal anatomy of the human body. The major advantages of medical ultrasound image outperform the other medical diagnostic techniques, lies in its noninvasive, harmless to the human body, and relatively low-cost. Because of these advantages, ultra-sonography has become the most popular imaging modality and made

great contributions in medical diagnosis fields.

However, medical ultra-sonography also suffers from a disadvantage, the speckle noise, which significantly degrades image visual quality and makes great negative effects in the task of clinical diagnosis. As a result, speckle reduction is a critical presupposition for the clinical application of the medical ultrasound images.

In this paper, we use the second generation curvelet transform and apply it to echocardiographic images despeckling research. Our goal is to achieve a better speckle suppression effect. The architecture of our denoising method is then as follows:

(1) Conduct a multi-scale decomposition of the observed image using curvelet transform to obtain the curvelet coefficients at all scales and angles (orientations).

(2) For each curvelet coefficient at a given scale and angle, compute the shrinkage parameters. Generally, the effect of the shrinkage is heavily dependent on the choice of the shrink parameter. In this step, we use GCV (generalized cross validation) approach to estimate the shrinkage values. The main features of the GCV method is that the function only rely on the input and the output, no estimation of the noise, such as the standard deviation, is necessitated, nor is the prior knowledge of the true signals.

(3) Perform the shrinkage of the curvelet coefficients. In this paper, the observed data are the echocardiographic images, and the interests of medical experts are the detail anatomy information, such as the movement and the position of the muscles and the heart valves. In the view of that, we choose the Soft threshold algorithm, which is capable of preserving the detail features in the images, to shrink the curvelet coefficients.

(4) Curvelet reconstruction process, the estimated image is reconstructed by performing the inverse curvelet transform of the processed coefficients to recover the images.

(5) For the most of the multi-scale algorithm, even unexceptional as the curvelet transform, the multiresolution decomposition process may cause the mild ringing artifacts around the edges of the images. As a powerful tool for artifacts suppression, the use of the nonlinear diffusion technique to overcome the ringing artifacts is already well accepted in the literature [10]. In this paper, we apply total

variation (TV) strategy to reduce the artifacts after the curvelet shrinkage [11].

6. RESULTS

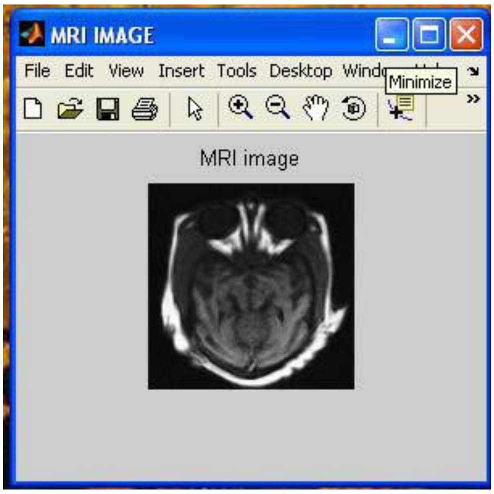

Figure1: MRI Image of Brain

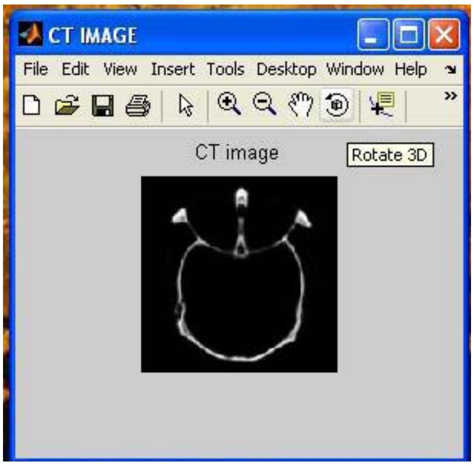

Figure2: CT Image of Brain

Figure1and figure2 represents the MRI and CT images of Brain of same person respectively. In the MRI image the inner contour missing but it provides better information on soft tissue. In the CT image it provides the best information on denser tissue with less distortion, but it misses the soft tissue information.

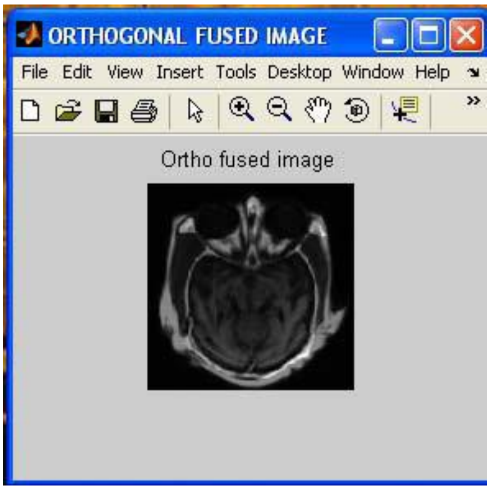

Figure3: Orthogonal fused image

The figure3 image is the result of orthogonal wavelet fusion technique which is by combining of MRI and CT images .The orthogonal wavelet fused image have information of both images but have more aliasing effect.

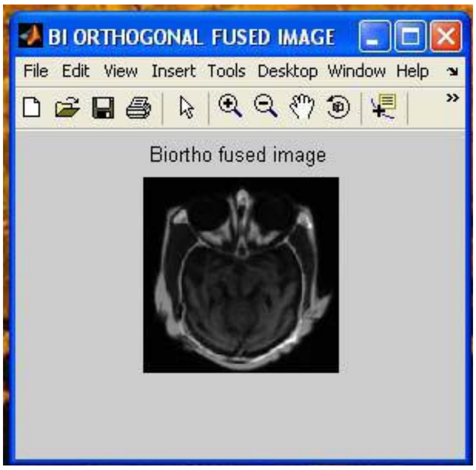

Figure 4: Biorthogonal fused image

The figure.4 image is the result of Biorthogonal wavelet fusion technique. When compare Biorthogonal wavelet with orthogonal wavelet it shows soft tissues information which are not shown in above figure i.e. at the left and right side of the inner part.

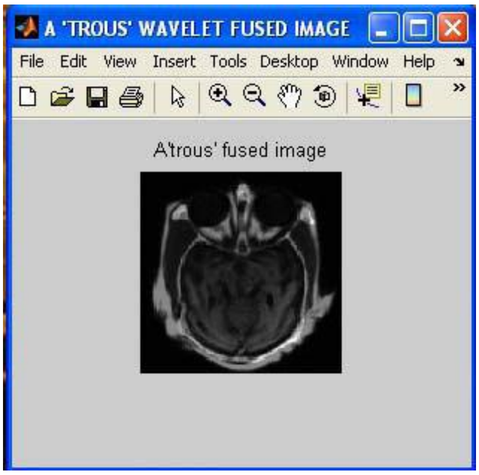

Figure5: 'A trous 'wavelet fused image

The figure.5 image is the result of 'A trous' wavelet (non-orthogonal wavelet) based fusion. The fusion results of non-orthogonal wavelet have information on soft tissues and denser tissues.

Table 1. Statistical parameters for various methods

Method || Parameter	Orthogonal	Biorthogonal	Trous
Mean	32.8347	32.8347	32.8347
Standard Deviation	30.2884	30.2884	30.2884
Entropy	6.0039	6.0042	6.0043
Covariance	2.0293	2.0293	2.0293
Correlation Coefficient	0.0526	0.5675	0.5675

The above table consists of Mean, Standard deviation, Entropy, Covariance, Correlation Coefficients of different methods like Orthogonal, Biorthogonal, A'trous'wavelet and Wavelet \Principal Component Analysis. From the above table the mean and covariance is same for all the methods but the standard deviation is less and entropy, correlation coefficient is more for proposed method.

7. CONCLUSION

In this paper Comparison between wavelet based and wavelets integrated fusion methods visually and statistically. Wavelet based fusion extracts spatial details from high resolution bands; resultant image appears similar to a high pass filtered image. But from the statistical result analysis wavelet integrated method improves the fusion result reduce the ringing or aliasing effects and making the image smoother.

This paper puts forward an image fusion algorithm based on Wavelet Transform and the Second Generation Curvelet Transform. It includes multiresolution analysis ability in Wavelet Transform, also has better direction identification ability for the edge feature of awaiting describing images in the Second Generation Curvelet Transform. This method could better describe the edge direction of images, and analyzes feature of images better. According to it, this paper uses Wavelet and the Second Generation Curvelet Transform into fusion images, then makes deep research on fusion standards and puts forward corresponding fusion projects. At last, these fusion methods are used in simulation experiments of multifocus and complementary fusion images. In vision, the fusion algorithm proposed in this paper acquires better fusion result.

8. REFERENCES

[1] Chao Rui, Zhang Ke , Li Yan-jun. An image fusion algorithm using Wavelet Transform[J]. Chinese Journal of Electronics , 2004, 32(5):750-753.

[2] Li, H., Manjunath, B.S., Mitra, S.K., 1995. Multisensorimage fusion using the Wavelet Transform. Graphical Models Image Process. 57 (5),235–245.

[3] Li, S., Wang, Y., 2000. Multisensor image fusion using discrete multiWavelet Transform. In: Proc. 3rd Internat. Conf. on Visual Computing, pp. 93–103.

[4] Li, H., Manjunath, B.S., Mitra, S.K., 1995. Multisensor image fusion using the Wavelet Transform. Graphical Models Image Process. 57 (5), 235–245.

[5] E. J. Candes, D. L. Donoho. Curvelets : A surprisingly effective nonadaptive representation for objects with edges[J]. In:C. Rabut A. Cohen , L. L. Schumaker. Curves and Surfaces. Nashville , TN: Vanderbilt University Press , 2000. 105-120.

[6] E. J. Candes, D. L. Donoho. New tight frames of curvelets and optimal representations of objects with singularities[J]. Commun. On Pure and Appl. Math.2004, 57(2):219-266.

[7] E. J. Candes , L. Demanet D. L. Donoho et al.. Fast Discrete Curvelet Transforms[R]. Applied and Computational Mathematics. California Institute of Technology , 2005.1.

[8] LiHui-hu,i GuoLe,i LiuHang. Research on image fusion based on the second generation curvelet transform [J]. Acta Optica Sinica, 2006,26(5): 657 ~662.

[9] L.J. Chipman, T.M. Orr, and L.N. Lewis. Wavelets and image fusion. IEEE Transactions on Image Processing, 3:248–251.

[10] P. Perona and J. Malik, "Scale-space and edge detection using anisotropic diffusion," IEEE Trans. Pattern Anal. March. Intell., vol. 12, no. 7, pp. 629-639, Jul. 1990

[11] Rudin L I, Osher S, Fatemi E Nonlinear total variation based noise removal algorithm s[J]. Physica D, 1992, 60: 259-268