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Image Fusion Based On Wavelet And Curvelet Transform

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Abstract : *In this paper we have put forward an image fusion algorithm based on wavelet transform and second generation curvelet transform. The wavelet transform does not represent the edges and singularities well. So the second generation curvelet transform is performed along with the wavelet transform and the image fusion is done. Finally, the proposed algorithm is applied to experiments of multi focus image fusion and complementary image fusion. The proposed algorithm holds useful information from source multiple images quite well.*

Keywords - *Image fusion, Wavelet transforms, Second Generation Curvelet Transform*

I. 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 dimension 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. This method could extract useful information from source images to fused images so that clear images are obtained.

II. WAVELET BASED IMAGE FUSION SCHEMES

The general procedure of wavelet-based image fusion algorithm is shown in Fig. 3.1. Where I_1 and I_2 denote the source images to be fused, and are assumed to be well registered. *L* denotes the wavelet decomposition level. F is the final fused image. I_1, and I_2 are first decomposed by the Lth level wavelet transform into 3L horizontal, vertical and diagonal detail sub-images at each of the *L* resolution levels and a gross approxirnation of the image at the coarsest resolution level.. Couple subimages of I_1, and I_2 are then combined, respectively. The final fused image is reconstructed by inverse wavelet transform from the modified coefficients

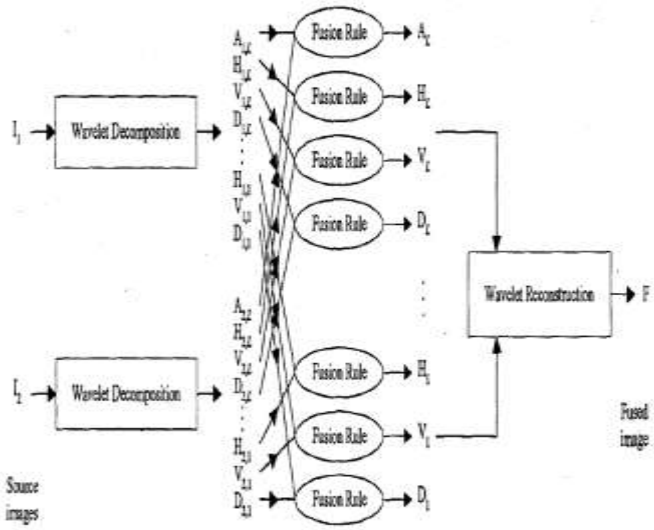

Fig.1 Wavelet based Image Fusion Procedure

III. 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.

3.1 Why Curvelets?

On images with *C*2 boundaries, non-optimal systems have the rates.

Fourier Approximation: $$||f - f_m^F||_{L_2}^2 \asymp O\left(m^{-\frac{1}{2}}\right) \quad (1)$$

Wavelet Approximation: $$||f - f_m^W||_{L_2}^2 \asymp O\left(m^{-1}\right) \quad (2)$$

Curvelet Approximation: $$||f - f_m^C||_{L_2}^2 \asymp O\left((\log m)^3 m^{-2}\right) \quad (3)$$

As seen from the m-term approximations, the Curvelet Transform offers the closest m-term approximation to the lower bound. Therefore, in images with a large number of C^2 curves (i.e. an image with a great number of long edges), it would be advantageous to use the Curvelet Algorithm.

3.2 Continuous Curvelet Transform

The Continuous Curvelet Transform has gone through two major revisions. The first Continuous Curvelet Transform used a complex series of steps involving the ridgelet analysis of the radon transform of an image. Performance was exceedingly slow. The algorithm was updated in 2003. The use of the Ridgelet Transform was discarded, thus reducing the amount of redundancy in the transform and increasing the speed considerably. In this new method, an approach of curvelets as tight frames is taken. Using tight frames, an individual curvelet has frequency support in a parabolic-wedge area of the frequency domain.

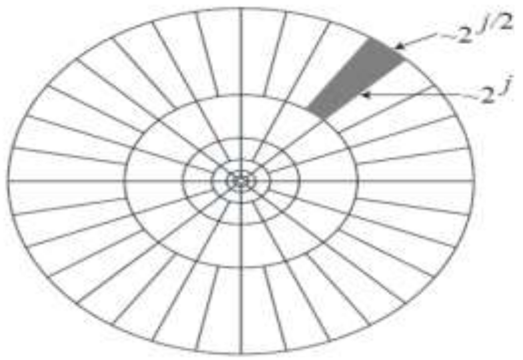

Fig. 2 Continuous Curvelet support in the frequency domain

A sequence of curvelets are tight frames if there exists some value for *A* such that :

$$A\,||f||_{L^2}^2 = \sum_{j,l,k} |\langle f, \gamma_{j,l,k}\rangle|^2 : \forall f \in L^2 \tag{4}$$

where each curvelet in the space domain is defined as:

$$\gamma_{j,l,k} = 2^{\frac{2j}{3}}\gamma\left(D_j R_\theta x - k_\delta\right) \tag{5}$$

Using the property of tight frames, the inverse of the curvelet transform is easily found as:

$$f = \sum_{j,l,k} \langle f, \gamma_{j,l,k}\rangle\, \gamma_{j,l,k} \tag{6}$$

(where Dj = Parabolic Scaling matrix, R_θ = Rotation matrix, k = translation parameter).

3.3 Discrete Curvelet Transform – Wrapping

Using the theoretical basis in (where the continuous curvelet transform is created), two separate digital (or discrete) curvelet transform (DCT) algorithms are introduced. The first algorithm is the Unequispaced FFT Transform, where the curvelet coefficients are found by irregularly sampling the fourier coefficients of an image. The second algorithm is the the Wrapping transform, using a series of translations and a wraparound technique. Both algorithms having the same output, but the Wrapping Algorithm gives both a more intuitive algorithm and faster computation time. Because of this, the Unequispaced FFT method will be ignored in this paper with focus solely on the Wrapping DCT method.

The Discrete Curvelet Transform is defined as follows :

$$c(j,l,k) = \int \hat{f}(w)\tilde{U}_j(S_{\theta_l}^{-1}w)\exp[i\langle b, S_{\theta_l}^{-T}w\rangle]dw = \int \hat{f}(S_{\theta_l}w)\tilde{U}_j(w)\exp[i\langle b, w\rangle]dw \tag{7}$$

The Wrapping Algorithm has faster computation time. The two implementations essentially differ by the choice of spatial grid used to translate curvelets at each scale and angle.

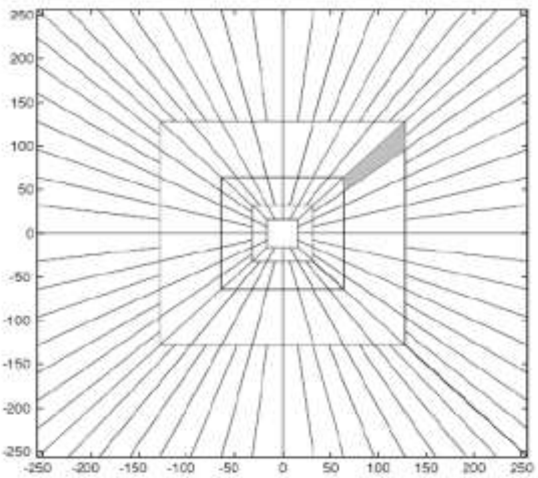

Fig. 3 Digital Corona of the Frequency Domain

IV. Image Fusion Algorithm Based On Wavelet And Curvelet Transform

First, we need pre-processing, then cut the same scale from awaiting fused images according to selected region. Subsequently, we divide images into sub-images which are different scales by Wavelet Transform. Afterwards, local Curvelet Transform of every sub-image should be taken, its sub-blocks are different from each others on account of scales' change. The steps of using Curvelet Transform to fuse two images are as follows:

• Resample and registration of original images, we can correct original images and distortion so that both of them have similar probability distribution. Then Wavelet coefficient of similar component will stay in the same magnitude.

• Using Wavelet Transform to decompose original images into proper levels. One low-frequency approximate component and three high-frequency detail components will be acquired in each level.

• Curvelet Transform of individual acquired low frequency approximate component and high frequency detail components from both of images, neighborhood interpolation method is used and the details of gray can't be changed.
• According to definite standard to fuse images, local area variance is chose to measure definition for low frequency component. Regional activity is defined as a fusion standard of high-frequency components.
• Inverse transformation of coefficients after fusion, the reconstructed images will be fusion images.

V. Image Fusion

5.1 Multi-Focus Image Fusion

We use multi-focus images to this algorithm. Fig. 4 shows right-focus image. Fig. 5 shows left-focus image. Three fusion algorithms are adopted in this paper to contrast fusion effects. We separately use Discrete Wavelet Transform(DWT), the Second Generation Curvelet Transform that is Discrete Fast Curvelet Transform(DFCT) which is proposed in this paper. According to DWT, we use different fusion standard in different sections. Average operator is used as a fusion standard for low-frequency sub-band.
Choosing the fusion operator based the biggest absolute value is used as a fusion standard for three high-frequency sub-band from the highest scale. Choosing the fusion operator based the biggest local area variance is used as a fusion standard for high-frequency sub-band from other scales. In fig.6 the result of DWT looks worse by contrast; we can see evident faintness in edges. We can acquire the best subjective effect in DFCT. The fused image is the clearest, and detail information are kept as more. We adopt Entropy of fused image, correlation coefficient C_{CC} and r.m.s. error E_{rms} [8] to evaluate the fused quality.

Fig.4 Right focus image

Fig. 5. Left Focus Image

Fig. 6 Fused Image of DWT

5.2 Complementary Image Fusion

In medicine, CT and MRI image both are tomographic scanning images. They have different features. Fig. 7 shows CT image, in which image brightness related to tissue density, brightness of bones is higher, and some soft tissue can't been seen in CT images. Fig. 8 shows MRI image, here image brightness related to amount of hydrogen atom in tissue, thus brightness of soft tissue is higher, and bones can't been seen. There is complementary information in these images. We use the methods of fusion forenamed in medical images, and adopt the same fusion standards.

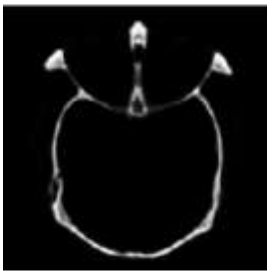

Fig.7 CT image

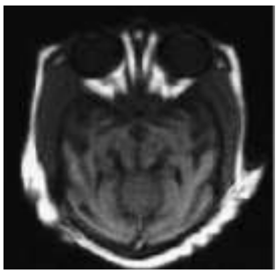

Fig. 8 MRI Image

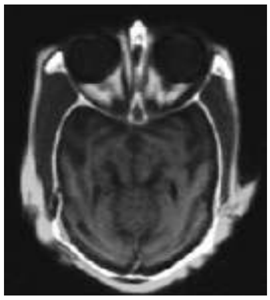

Fig. 9 Fused Image of DWT

We make simulation experiments by above fusion methods in comparison.

VI. Conclusion

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 multi-focus and complementary fusion images. In vision, the fusion algorithm proposed in this paper acquires better fusion result.

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