Seismic Signal Denoising and Reconstruction Based on Multi-scale Geometric Analysis

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ABSTRACT

To solve the problems that the fast Fourier transform and wavelet transform could not detect contour, curve, and direction information of the signal, seismic signaldenoising and reconstruction methods based on multi-scale geometric analysis are proposed. The wavelet basis of traditional wavelet transform has the scale of point approaching line, which could not represent the anisotropy of the signals. The support interval of multi-scale geometric analysis is the desired rectangle. With the increase of scale, the final expression is the line approaching, which can reflect the anisotropy of the signal. Experimental results show that the multi-scale geometric analysis based methods have great advantages in denoising and reconstruction of low-dimensional and high-dimensional seismic signals.

Keywords: Multi-scale Geometric analysis; Wavelet transform; Fast Fourier transform; Seismic Signal

1. Introduction

Discrete Wavelet Transform (DWT) and Fast Fourier Transform (FFT) are traditional signal analysis methods[1]. These methods, however, could not detect the outline, curve and direction information of the signal so as not to effectively capture the key features of the signal. Based on the improvement of wavelet transform, dual density discrete wavelet transform and second harmonic complex wavelet transform obtains better results[2]. In recent years, new multi-scale geometric analysis techniques, such as Contourlet, Shearlet, and Curvelet, etc. have been widely used in signal processing and image processing [3-6].

Contourlet transform captures the direction information of discrete domain through dual filter bank structure to extract the smooth contour of the signal. Edge singularities at different scales of signals are obtained by Laplace pyramid (LP) firstly, and then high frequency subbands at each scale are converted by directional filter banks (DFB). The control coefficients are obtained from the points in each direction connected to the linear structure. Shearlet transformation is obtained by a series of mathematical operations. Because of the invariance of time-shift and the effectiveness of capturing direction information, these transforms can capture more detailed information than traditional fast Fourier transform and wavelet transform. It can be concluded that Contourlet transform and Curvelet transform decompose signals better than traditional wavelet transform and Fourier transform and could capture more information.

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2 Overview of Some Multi-scale Geometric Analysis methods

2.1 Discrete Wavelet Transform (DWT)

DWT developed by Stephane Mallat is a classical method of signal and image processing [7-8]. DWT can be applied at many levels, where thresholds could be used to reduce noise. When the signal is decomposed by Curvelet, four subbands would be formed at different levels. The first represents the approximate or low-frequency features. The other three represent the diagonal, vertical and horizontal details or high-frequency features. The low-frequency information shows approximate coefficients and contains most of the content of the signal, while the high-frequency information shows detail coefficients and contains details and noise, which means that when noise is eliminated, some details will be lost. Once the signal is decomposed, the signal is reconstructed by threshold and inverse transform. The diagram of the wavelet transform is shown in Figure 1 below.

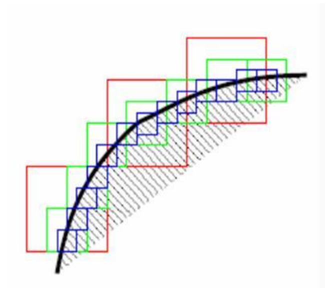


Fig.1 Wavelet Transform Approximation

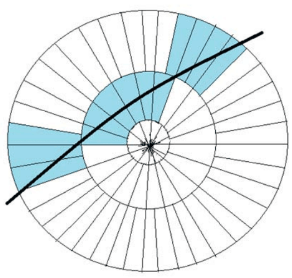
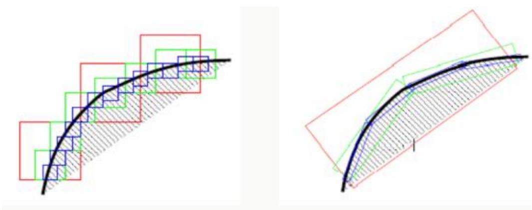


Fig.2 Curvelet Transform Approximation

2.2 Curvelet Transform

Based on Ridgelet transform, Candes and Donoho proposed the Curvelet transform in 1999 and constructed a tight framework of Curvelet[9]. If the objective function contains the singularity of the curve, the signal would be well represented by Curvelet transform. Curvelet transform is a higher dimensional generalization of the wavelet transform, which is usually used to represent images of different scales and angles. One of the problems of wavelet transform is that even on the small scales, the signal may exhibit large wavelet coefficients, which means that the mapping of the coefficients will see the edges of the signal repeatedly on multiple scales. Because of repetition, a large number of Curvelet coefficients should be used to achieve better reconstruction results, so that thresholds may become invalid. Curvelet does not track discontinuous shapes, but provides stable and effective representations of discontinuous smooth objects on smooth curves. Unlike wavelet, the degree of localization varies with the proportion. One advantage of curve wavelet is that it restores sparsity by reducing redundancy on scales, which provides sparse representations of smooth and straight functions. As for how to isolate different scales, only one spatial bandpass filter is needed. The schematic diagram is shown in Figure 2.



(a)Wavelet aransform approximation

(b) Contourlet transform approximation

Fig.3 Wavelet Transform Approximation and Contourlet Transform Approximation

2.3 Contourlet Transform

Minh N. Do and Martin Vetterli have created a filter bank structure similar to wavelet, which can effectively process segmental smooth images with smooth contours, which leads to an image extension of a directional multi-resolution analysis framework consisting of contour segments[10-12]. The transformation is to pass the signal through its dual filter bank structure to get the signal on different scales. Structurally, the Contourlet transform is a combination of two filter structures, Laplacian Pyramid (LP) and Directional Filter Banks (DFB). In essence, Contourlet uses wavelet transform similar to edge detection and local orientation transform similar to contour detection. Figure 3 shows the comparison between wavelet and Contourlet.

2.3.1 Laplacian Pyramid (LP) Decomposition

LP decomposition is similar to Fourier transform, except that the former is in the complex domain and the latter is in the real domain. After LP, the signal would be divided into high-frequency subband and low-frequency subband. The low-frequency subband would be further transformed by LP and automatically stop until achieving the appropriate level of decomposition.

LP image decomposition is related to Gaussian pyramid decomposition, which gets a series of Gaussian images from a series of approximate components through down-sampling and smoothing filtering. Laplace pyramid is achieved by subtracting the adjacent Gaussian images. The steps of LP decomposition are as follows:

(1) Firstly, through a series of sampling and filtering combinations the approximate component of the original signal is obtained.

(2) Then, the estimated signal is obtained by filtering and sampling the approximate components, which is contrary to the above step.

(3) Finally, high frequency subband signal could be obtained by subtracting the original signal and the predicted signal.

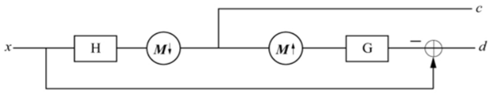


Fig.4 Laplacian Pyramid Decomposition of Signals

2.3.2 Directional Filter Banks

To generate smooth contours of images, filter banks should be applied. Multi-scale decomposition using LP is calculated into frequency doubling bands, and then DFB is applied to each band-pass channel. Because the combination of LP and DFB is inseparable, the Contourlet transform uses a multi-scale decomposition to eliminate low frequency. Therefore, the combination structure of LP and DFB is also called PDFB. DFB can recognize the direction of image contour and reconstruct the result into image. Contour transformation uses discrete regions and contour segments to construct multi-resolution, local and directional expansion of the image. PDFB decomposition has the following conservative functions of signal x:

$$\|x\|^2 = \sum_{j}^{J} \|d_j\|^2 + \|\alpha_j\|^2 \tag{1}$$

Among them, d_j is the directional coefficient, and α_j is the low-pass image of the band-pass image, j = 1, 2,…, J. The basic schematic structure of Contourlet transformation is shown in Fig. 5.

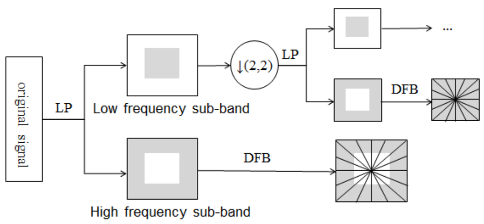


Fig.5 Basic Structure of Contourlet Transform

2.4 ShearletTransform

The following is the formulas of Shearlet transform [13-14]

$$SH_{f(x)}(a,s,t)=\left\langle f(x),\psi_{a,s,t}(x)\right\rangle \tag{2}$$

The Shearlet function has the following expression:

$$\psi_{a,s,t}(x)=\left\{a^{-3/4}\psi\left(\boldsymbol{M}^{-1}\boldsymbol{N}^{-1}(x-t)\right):a\in R^{+},s\in R,t\in R^{2}\right\} \tag{3}$$

where a , s , and t represent scale parameters, translation parameters and shear parameters respectively. By changing the values of the parameters a , s , t , different Shearlet coefficients could be obtained.

3. Application of Multi-scale Geometric Analysis on Seismic Signal Denoising and Reconstruction

Multi-scale geometric analysis is very suitable for denoising and reconstruction of seismic signals due to its excellent characteristics.

3.1 Denoisingof Seismic Signals

The Curvelet transform mostly uses the adaptive threshold method to achieve denoising. According to the characteristics of Curvelet coefficients in various situations, the appropriate methods can be used to minimize the total variation and reduce noise while preserving edges. Firstly, the appropriate Curvelet coefficients are obtained; the noise variance of each scale and direction, the signal variation of each scale and direction are then estimated; the threshold of each scale and direction are calculated afterwards; and the denoising signal is finally obtained by shrinking the constrained curve of total variation.

When used for seismic signal denoising, the following steps could be applied. After the Contourlet transform, the transform coefficients of signals with effective information are relatively large and correlated in Contourlet domain, while the coefficients of signals with noise in Contourlet domain are relatively small and the tangent correlation is relatively low. According to these characteristics, K-L transform is adopted. According to the advantages of K-L transform in classification and extraction, the coefficients can be modified in Contourlet domain, and the noisy coefficients can be removed in inverse transformation, so as to achieve denoising. The experimental results show the good performance compared to the classical wavelet transform. The steps are as follows.

(1) The input signal is transformed into Contourlet transform, and then the Contourlet coefficients with different scales and directions can be obtained through the dual filter bank structure to form the coefficient matrix C.

(2) The K-L transform is applied to each coefficient matrix C, and the corresponding feature representation is obtained.

(3) The energy percentage threshold function in the K-L transform domain is obtained.

(4) The K-L inversion is determined again.

(5) K-L inverse transformation is used to get a new Contourlet coefficient matrix after removing the coefficients containing noise.

(6) The new Contourlet coefficient matrix is inversely transformed by Contourlet

transform, and the signal after denoising can be obtained.

Fig. 6 shows the result of Curvelet transform and Contourlet transform.

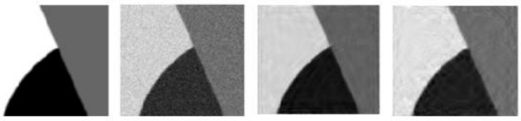


Fig.6 Comparison of Curvelet transform denoising and Contourlet transform denoising. (a) Original image; (b) Noisy image; (c) Curveletdenoising; (d) Contourletdenoising

3.2 Seismic signal reconstruction

Shearlet transform has been developed recently and has more advantages in direction than Contourlettransform. Seismic signals can be expressed more sparsely and reconstructed better based on compressed sensing. When using Shearlet transform to reconstruct seismic data, regularization method is used to correct the directional coefficients in Shearlet domain. Seismic data reconstruction can be achieved by designing sampling matrix according to the absence of seismic signals, sparsifying it in the sparse domain, and then using some algorithm to sparsify it in the sparse domain. Finally, the reconstructed seismic signal can be obtained by inverse Shearlet transform. The experimental results show that the seismic signals in Shearlet sparse matrix are more sparse than Fourier sparse matrix, discrete cosine sparse matrix, wavelet sparse matrix and Curvelet sparse matrix. Therefore, the reconstruction accuracy of Shearlet transform based on compressed sensing technology is higher than other transformations of traditional compressed sensing technology.

4. Existing problems and future research directions

(1) Choose an appropriate method. In some cases, some non-adaptive methods processed by simple hard thresholds have better non-linear approximation performance than complex adaptive methods. Therefore, researchers could continue to study the choice of methods.

(2) Continue to develop new methods. At present, there are many multi-scale geometric analysis methods, but better methods are stilled needed to achieve different manifestations.

(3) Typically, good algorithms are achieved at the expense of other costs. The better the effect of the transform, the longer the operation time, and the less perfect it can be. Therefore, how to achieve a balance between the two could be the goal of the next researches.

(4) Establish a high-dimensional signal processing model. Current processing is within low dimension, but high-dimensional processing maybe become simple when low-dimensional processing is not convenient, so it is necessary to establish a suitable high-dimensional model.

5 Conclusions

Multi-scale geometric analysis has been widely used in the field of image processing. Applying these methods to the field of seismic signal processing in an appropriate way will make great contributions to the reconstruction and denoising of seismic signals. The real value of seismic signal would be shown in high dimensional processing. Multi-scale geometric analysis of high dimensional seismic signal is one of the key research points in the next stage.

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