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Generalized S Transform with Adaptive Optimized Window and its Application in Seismic Signal Analysis

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Abstract: A method used to optimize the width of the window function by measuring energy concentration of S transform is discussed in the study which is called adaptive optimized generalized S-transform (AOGST). Adaptive parameter which can adjust the width of window function adaptively in frequency domain according to the different component in signal and achieve the optimized time-frequency distribution is induced in S transform. The optimization scheme has been proposed and a set of test signals have been evaluated. The results indicated that the method can provide much improved energy concentration in time-frequency domain, compared with standard S transform, short Fourier transform and its adaptive forms. Finally, the method has been used to analyze the time-frequency distribution of seismic signal and demonstrated its effectiveness.

Key words: Time-frequency, generalized S-transform, window width, adaptive optimization, energy concentration, seismic signal

INTRODUCTION

The frequency-domain analysis of signal can illustrate many characteristics that are difficult to visualize only in the time domain, in which the signal is mapped into the frequency domain determines the amount of new information that can be obtained, but it can’t describe time-varying spectral characteristics, especially for non-stationary signal which is often needed in practical application. Since, time-frequency mapping is a non-unique process, various methods exist for time-frequency analysis of non-stationary signals. Short-Time Fourier Transform (STFT) is to make signal multiply a time limited window function and assume that signal is stationary in the window. A group of local spectrum can be obtained by moving the window in time axis which express the time varying characteristics (Cohen, 1995).The wavelet transform has been applied in various branches of science and engineering, Mallat (1999) bring up multi-resolution analysis and fast algorithm which unifies the different forms of wavelet transform and makes wavelet transform have stronger practicability, but wavelet transform establishes time-scale spectrum, instead of time-frequency spectrum.

The effective time-frequency transform should detect the non-stationary change of frequency with time which can combine the time domain and frequency domain characteristics at the same time and reveal the essence of signal. S transform induced by Stockwell is the extension of continuous wavelet transform whose kernel function is the product of simple harmonic wave and Gaussian function (Stockwell, 1999). S transform combines the advantage of STFT and wavelet transform, where the reciprocal of frequency decides the width of window function and has the characteristic of multi- resolution analysis. In addition, phase factor is contained in S transform which can maintain absolutely phase of frequency and its basic transform need not to suffice for admissibility. Now, the S transform has already been used in power quality analysis, machinery fault diagnosis, seismic signal process and pattern recognition (Hasheminejad *et al*., 2012; Mohamad and Abidin, 2012; Li *et al*., 2012; Zhong *et al*., 2012; Liu *et al*., 2012).

Even though the S transform is becoming an effective method used in the analysis of signals, in some cases, its application is limited because the shape of the basic transform function is fixed. Different generalized S transform have been reported in the literature recently (Pinnegar and Mansinha, 2003; Lin and Xiaofeng, 2012). For example, the f of the Gaussian window is replaced by f/γ_{GS}. The smaller value of γ_{GS} can improve time resolution which sacrifices the frequency resolution and γ_{GS} need to determine artificially in signal analysis. Sejdic *et al.* (2008) discussed a window width optimized S-transform in time domain and used the method to analyze engine knock signal. A new scheme is introduced to adjust the parameter of window adaptively in frequency domain in this study, where the parameter controls the window

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width and is optimized adaptively corresponding to every frequency. Therefore, the method is referred to as Adaptive Optimized Generalized S Transform (AOGST).

The method has been verified by using synthetic seismic signals and its performance is compared with the standard S-transform and the Short-Time Fourier Transform (STFT). The results have shown that the method can enhance the energy concentration better. Finally, the proposed algorithm is used to analyze the time-frequency distribution of seismic signals in order to improve the profile resolution ability of thin-bed.

THE PROPOSED SCHEME

Standard S-transform: S-transform can be deduced from the STFT. The spectrum X (f)of a time series x (t) is given by standard Fourier analysis as:

$$X(f)=\int_{-\infty}^{+\infty}x(t)\exp(-i2\pi ft)\,dt \qquad (1)$$

If the time series x(t) is windowed by a window function g(t),then the resulting spectrum is:

$$X(f)=\int_{-\infty}^{+\infty}x(t)\,g(t)\exp(-i2\pi ft)\,dt \qquad (2)$$

The S-Transform can be found by first defining a particular window function, a normalized Gaussian:

$$g(t)=\frac{1}{\sigma\sqrt{2\pi}}\exp\left(-\frac{t^2}{2\sigma^2}\right) \qquad (3)$$

and then allowing the Gaussian to be a function of translation τ and dilation (or window width) σ:

$$S(\tau,f,\sigma)=\int_{-\infty}^{+\infty}x(t)\frac{1}{\sigma\sqrt{2\pi}}\exp\left(-\frac{(t-\tau)^2}{2\sigma^2}\right)\exp(-i2\pi ft)\,dt \qquad (4)$$

which, with a particular value of σ, is similar in definition to the STFT. The Gaussian window is chosen because it is the most compact in time and frequency. Because this is a function of three independent variables, it is impractical as a tool for analysis. Simplification can be achieved by adding the constraint restricting the width of the window to be proportional to the inverse of the frequency:

$$\sigma(f)=\frac{1}{|f|} \qquad (5)$$

Then, S-transform is:

$$ST(\tau,f)=\int_{-\infty}^{+\infty}x(t)\frac{|f|}{\sqrt{2\pi}}\exp\left(-\frac{(t-\tau)^2f^2}{2}\right)\exp(-i2\pi ft)\,dt \qquad (6)$$

As the width of the window is modulated by the frequency, the window is wider in the time domain at lower frequencies and narrower at higher frequencies. So, the window provides good localization in the frequency domain for low frequencies while providing good localization in time domain for higher frequencies. It can satisfy the analysis of non-stationary signal and overcome the default of STFT where the time-frequency resolution is invariant and it is a Multi-resolution analysis method.

Adaptive optimized generalized S transform (AOGST): In fact, if the window function is adopted the formula (5), the time-frequency distribution maybe not optimized for some signals. For example, for a single sinusoid signal, the time-frequency localization can be considerably improved by using the narrow window in the frequency domain. But for signals containing only an impulse, the wider window can lead to better time-frequency localization.

A method to reform the standard S-transform is to modify the standard deviation of the window:

$$\sigma(f)=\frac{1}{|f|^p} \qquad (7)$$

where, p = p (f) which is adaptive regulation factor corresponding to frequency f. Then the adaptive generalized S transform can be represented as:

$$GST^p(\tau,f)=\int_{-\infty}^{+\infty}x(t)\frac{|f|^p}{\sqrt{2\pi}}\exp\left(-\frac{(t-\tau)^2f^{2p}}{2}\right)\exp(-i2\pi ft)\,dt \qquad (8)$$

Parameter p controls the width of the window, the adaptive generalized S-transform can be realized by determining the optimized value of p for a given signal and the adaptive generalized S-transform also can be represented as:

$$GST^p(\tau,f)=\int_{-\infty}^{+\infty}X(\alpha+f)\exp\left(-\frac{2\pi^2\alpha^2}{f^{2p}}\right)\exp(-i2\pi\alpha\tau)\,d\alpha \qquad (9)$$

The corresponding discrete calculation formulas:

$$X\left(\frac{m}{NT}\right)=\frac{1}{N}\sum_{k=0}^{N-1}x(kT)\exp\left(-i\frac{2\pi}{N}mk\right) \qquad m=0,1,2,\cdots,N-1$$
$$GST^p\left(jT,\frac{n}{NT}\right)=\sum_{m=0}^{N-1}X\left(\frac{m+n}{NT}\right)\exp\left(-\frac{2\pi^2m^2}{n^{2p}}\right)\exp\left(i\frac{2\pi}{N}mj\right) \qquad n=0,1,2,\cdots,N-1$$
$$(10)$$

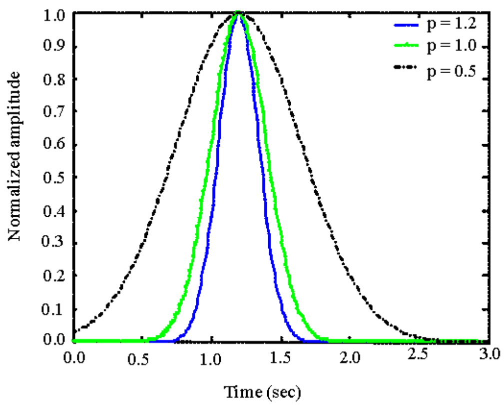

Fig. 1: Normalized Gaussian window for different values of p in time domain

Different value of p corresponds to different width of the window which results to different time-frequency concentration. The window functions with three different values of p are shown in Fig. 1, the three dimension distribution of different p are shown as Fig. 2, where the vertical axis is the dimensionless value of normalized amplitude in the two Fig. 1-2. where, p = 1 corresponds to the standard S-transform window. For p<1, the window width of time domain becomes wider and narrows in frequency domain. The situation is the opposite for p>1. Therefore, different value of p cause to different concentration effect for a specific signal. For the determination of the value of p, a simple measure for distributions concentration. The measure minimizes the energy concentration for any time-frequency representation based on the automatic determination of some time-frequency distribution parameter and it is defined as (Stankovic, 2001):

$$M(p) = \int_{-\infty}^{+\infty}\int_{-\infty}^{+\infty} \left|GST^p(\tau, f)\right| d\tau df \qquad (11)$$

where, M (p) stands for the concentration measure:

$$GST^p\left(jT, \frac{n}{NT}\right)$$

Eq. 10 is abbreviated GST^p (j, n). The AOGST algorithm for determining the optimized value of p is defined through the following steps:

Step 1: For p selected from a set 0<p#1 and p = k×1, 2, 3, ÿK, is the length of sampled signal X (n), compute S-transform GST^p (j, n) of the signal using Eq. 10.

Step 2: For each p, normalize the energy of the S-transform result, so that all of the representations have the equal energy:

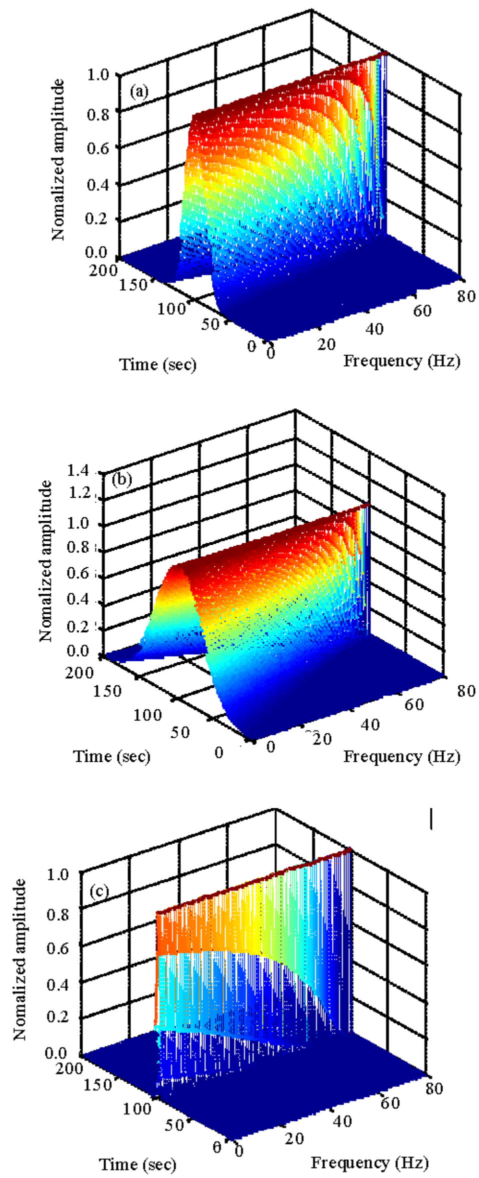

Fig. 2(a-c): Change of the window width for different value of p (a) p = 1.0, (b) p = 1.2 and (c) p = 0.5 in frequency domain

$$\overline{GST^p(j,n)} = \frac{GST^p(j,n)}{\left(\sum_{n=1}^{N}\sum_{j=1}^{N}\left|GST^p(j,n)\right|^2\right)^{\frac{1}{2}}} \qquad (12)$$

Step 3: For every frequency n, compute the concentration measure according to each p, that is:

$$M(n,p) = \sum_{n=1}^{N}\sum_{j=1}^{N}\left|\overline{GST^p(j,n)}\right| \qquad (13)$$

Step 4: The minimum of M (n, p) correspond to the optimized value of p in the frequency n and p is corresponding to k0, so the optimized value of p is:

$$p\ (n) = k_0.1/K \quad (14)$$

Step 5: Repeat the step 2-4 until for all the n, then the optimized regulation factor p is the function of frequency p (n).

Step 6: AOGST:

$$GST^p\ (j, n) = GST^{p(n)}\ (j, n)$$

It is important to note that the value of p is limited to the range [0,1]. If p<0, it would make the window wider as frequency increases. Similarly, if p>1, it may be too narrow in the time domain. For p>0, the AOGST is degenerated into STFT with a Gaussian window with unit standard deviation.

PERFORMANCE ANALYSIS

Here, a set of synthetic test signals is examined to estimate the performance of AOGST, standard S-transform, STFT and its adaptive form (ASTFT).The sampling period of the synthetic signals used in the simulations is Ts=1/256 seconds. The ASTFT is calculated according to the concentration measure given by Eq. 11. In addition, the result of STFT and AOGST are normalized. σ is the standard deviation of the Gaussian window and it is used as the optimizing parameter. The window is defined as:

$$w_{STFT}(t) = \frac{1}{\sigma\sqrt{2\pi}} \exp\left(-\frac{t^2}{2\sigma^2}\right) \quad (15)$$

The optimization of σ for synthetic signals is performed on the set of values defined by:

$$\sigma_{opt} = \{n/128, 1 \leq n \leq 128\} \quad (16)$$

The first test signal is shown in Fig. 3a. It has the following analytical expression:

$$x\ (t) = \cos\ (68\pi t\text{-}20\pi t^2)\text{+}\cos\ (2\pi \sin\ (5\pi t)\text{+}120\pi t)\text{+} \cos\ (168\pi t\text{+}28\pi t^2) \quad (17)$$

where, the sampling period in the simulation is $\Delta t = 1/256$, $t = n\Delta t$, (n = 0, 1, 2,..., 255).The signal consists of linear frequency modulation and sinusoidal modulation components (Fig. 3a). It is analyzed using the STFT, ASTFT with the optimum value of the width of the window, standard S-transform, generalized S transform and the proposed algorithm. A Gaussian window is also used in the analysis by the STFT, with standard deviations equal to 0.15. The optimum value of standard deviation for the ASTFT is calculated to be 0.266.

It can be seen from the results that STFT has better time-frequency concentration for the linear frequency modulation component of the signal and has poor concentration for the sinusoidal modulation components (Fig. 3b). The ASTFT shows a noticeable improvement for all the components (Fig. 3c). The STFT provides better energy concentration than the standard S-transform. S transform has higher frequency resolution for the low-frequency components, but with the increasing of the frequency, the resolution debases obviously and appears the frequency aliasing of different signal components (Fig. 3d). AOGST obtains very high resolution for the high frequency, linear frequency modulation and sinusoidal modulation components (Fig. 3e). The relation between the optimized regulation factor p and frequency is shown in Fig. 3f.

From the results of the time-frequency representations shown in Fig. 3, it can be seen that the proposed algorithm achieves higher concentration among the considered representations. The concentration measure by Stankovic (2001) is also used to verify this. A more concentrated representation will produce a smaller value. The time-frequency representation is normalized during measure. For the test signal, the performance measure for STFT, ASTFT, standard S-transform and AOGST is follows: STFT: 8.2965e+3; ASTFT: 7.9668e+3; Standard S-transform: 1.1185e+4; AOGST: 7.6243e+3.

Another important class of signals is those with crossing components that have fast frequency variations. A representative signal is given by:

$$x\ (t) = \cos\ (20\pi t \ln\ (10t\text{+}1)\text{+}\cos\ (48\pi t\text{+}8\pi t^2)) \quad (18)$$

In the signal, it exist the crossing components. The representation is demonstrated in Fig. 4, which are obtained by STFT, ASTFT, S-transform, AOGST, respectively.

The representation obtained by the STFT and ASTFT have similar concentration performance while ASTFT maybe better than STFT for lower frequency. The standard S-transform is capable of providing better concentration for the high frequencies. From the time-frequency representation obtained by the AOGST, it is obvious that the concentration is preserved not only at high frequencies, but also at low frequency. The performance measure implemented in the previous

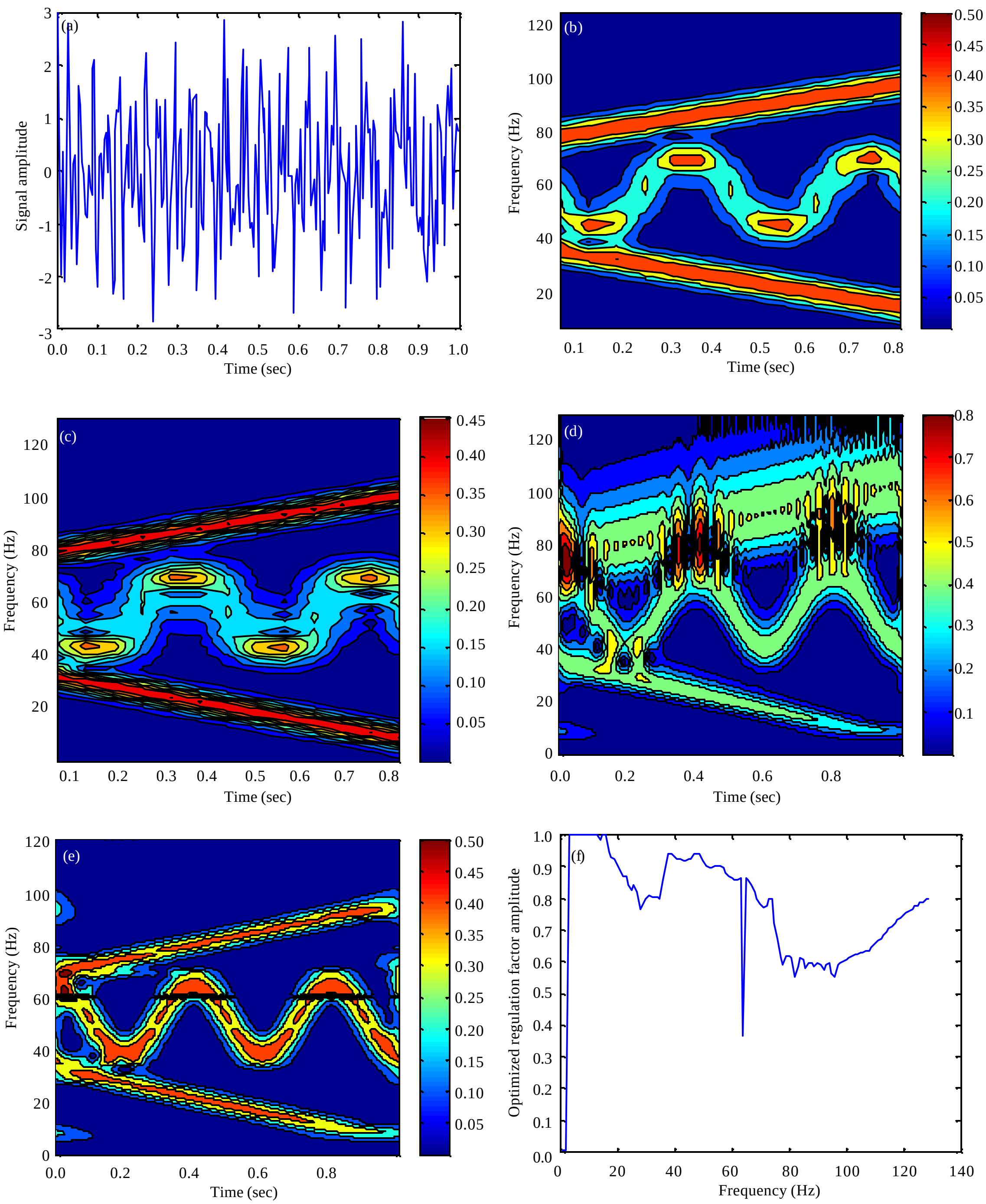

Fig. 3(a-f): (a) The first test signal, (b) Is its STFT, (c) Is its ASFT, where the optimized value p = 0.266, (d) Is its S-transform, (e) Is its AGOST, (f) is the optimized regulation factor p in AGOST

examples is used again and the results are shown follows: STFT: 3.4756e+3; ASTFT: 3.4042e+3; ST: 3.6654e+3; AOGST: 2.8483e+3. By comparing the values of the performance measure for different time-frequency transforms, these values confirm that AOGST produces more concentrated time-frequency representation.

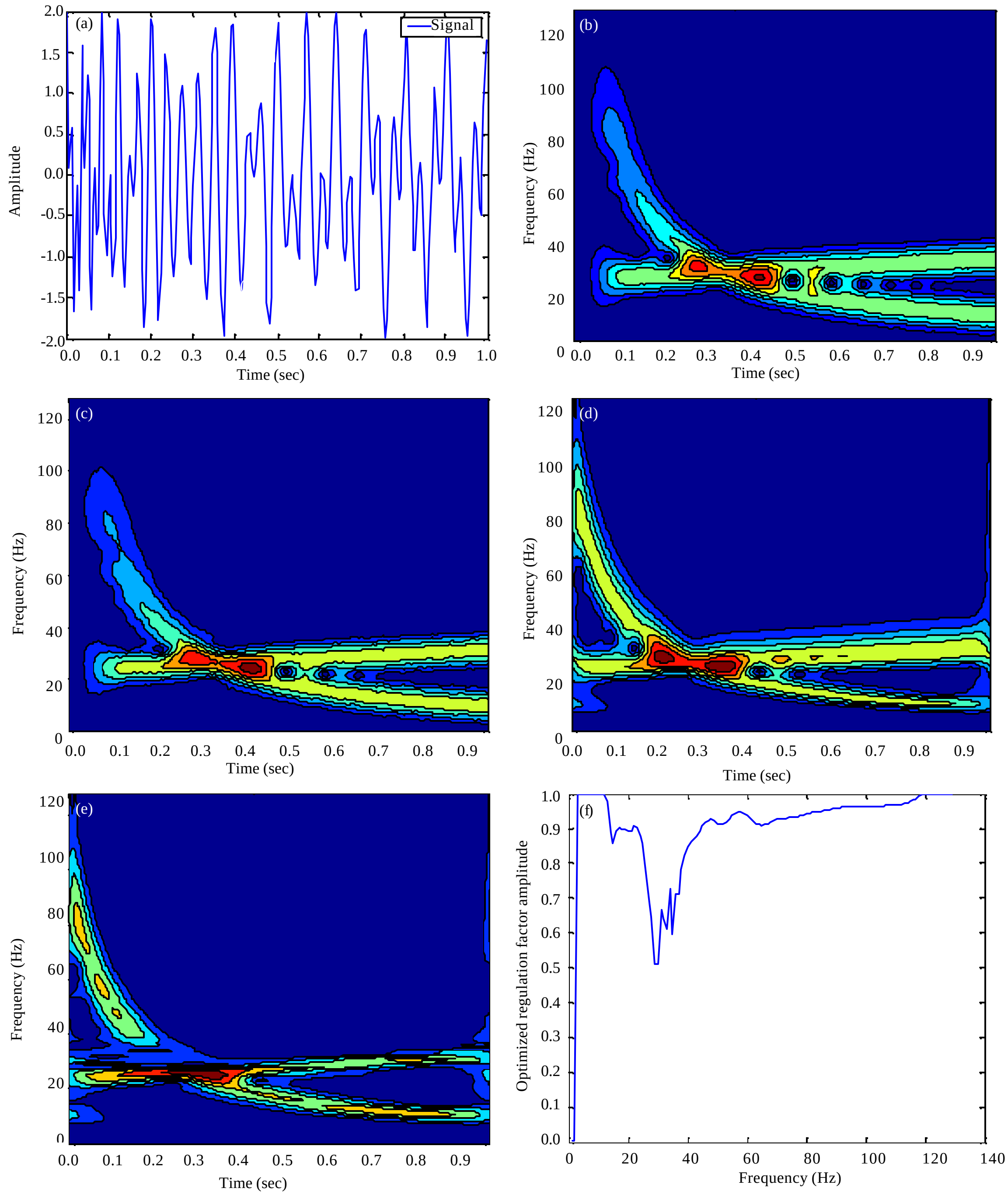

Fig. 4(a-f): (a) The second test signal, (b) Is its STFT, (c) Is its ASFT, where the optimized value p = 0.11, (d) is its S-transform and (e) is its AGOST, (f) is the optimized regulation factor p in AGOST

SEISMIC SIGNAL PROCESS

Because of the complexity of the underground medium, seismic signal is a typical non-stationary signal. Time-frequency analysis is a effective method to process seismic signal. With the oil and gas exploration, The structural oil and gas reservoir easy to identify is less and less, it is the main goal to find the concealed lithologic oil and gas reservoir trap and describe thin and interbedded lithologic oil and gas reservoirs. Now, thin-bed identification and characteristic analysis is an important research direction for petroleum geology field. The different frequency components of the seismic wave will have varying degrees attenuation with the propagation time (or depth) extension, especially the high frequency components attenuate more seriously which leads to the spectrum of the seismic signal distributing in low frequency band. The attenuation of the different frequency components propagating is related with the oil and gas content of reservoir which can be used to ascertain the characteristic, structure and location of the reservoir. Time-frequency analysis method has better effectiveness than the pure frequency domain analysis to describe characteristic of thin-bed which ca n not only realize frequency characteristic analysis of seismic signal, but also analyze the time varying characteristics in detail to reveal the internal information of the data. All of these are more conducive to the realization of fine treatment of seismic data.

A wedge model is shown in Fig. 5. The top and bottom reflection coefficient is 0.1 and -0.1, respectively. From the first trace, the time depth of the thin-bed is 2 msec and every trace increase progressively 2 msec, the total number of the trace is 31. The dominant frequency of Ricker wavelet is 40 Hz. Then the synthetic records can be obtained by convolution computation.

The performance of the proposed scheme is evaluated by comparing it with that of the STFT, ASTFT and the standard S-transform. The energy spectrums in different frequency are shown in Fig. 6-8, where the vertical coordinate is interval of sample points corresponding (msec) and horizontal coordinate is the number of trace. According to the thin bed tuning thickness and amplitude energy relations, when the thin-bed thickness is 1/4 of the seismic wave length, the amplitude of seismic wave is maximum and the reflective energy is strongest. With the increasing of frequency, the thinner stratum can be distinguished from the single frequency profile, the resolution of thin-bed is also improved. The location of strongest energy in single frequency profile moved toward the thin stratum. Thus, when the frequency of the single frequency profile is increased, the wave length is shorter, the strong energy spectrum is also moved to thinner stratum. From the Fig. 6-8, it can be seen that the results of STFT, ASTFT, ST and AOGST, comply with the principle, but the AOGST has better effect than other time-frequency representation. When the single frequency is 120 Hz, the strong energy in AOGST separates two parts and the time thickness of the strong energy is estimated 6 msec.

When the seismic wave propagate through stratum, especially through the petroliferous strata, the high frequency components attenuate quickly which causes the stratum information decrease. But as the high resolution characteristic of high frequency components, it also can be used for oil and gas geological fine structure description. Figure 9 is the seismic profile from the Xingshugang area in Daqing oil field. The sample interval is 1 msec, sample points is 1001, the total number of trace is 601. AGOST algorithm is used to process the seismic data. During the course, the frequency range is 0-255 Hz and the frequency interval is 1 Hz. Figure 10 demonstrate the different frequency slices by using AGOST, where the vertical coordinate is sample points corresponding to the time 0-1 sec in Fig. 9 and horizontal coordinate is the number of trace. From the results, it can be seen that the

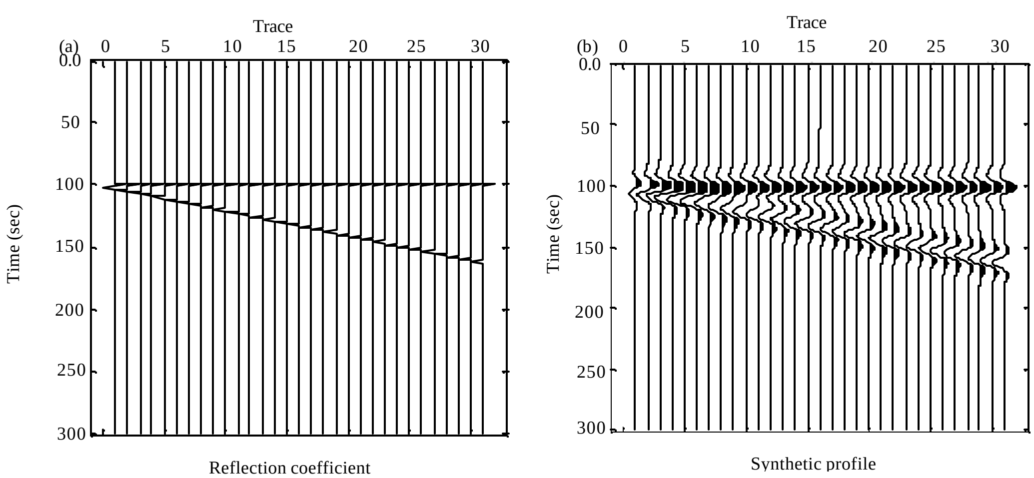

Fig. 5(a-b): Synthetic seismic signal (a) Reflection coefficient and (b) Synthetic profile

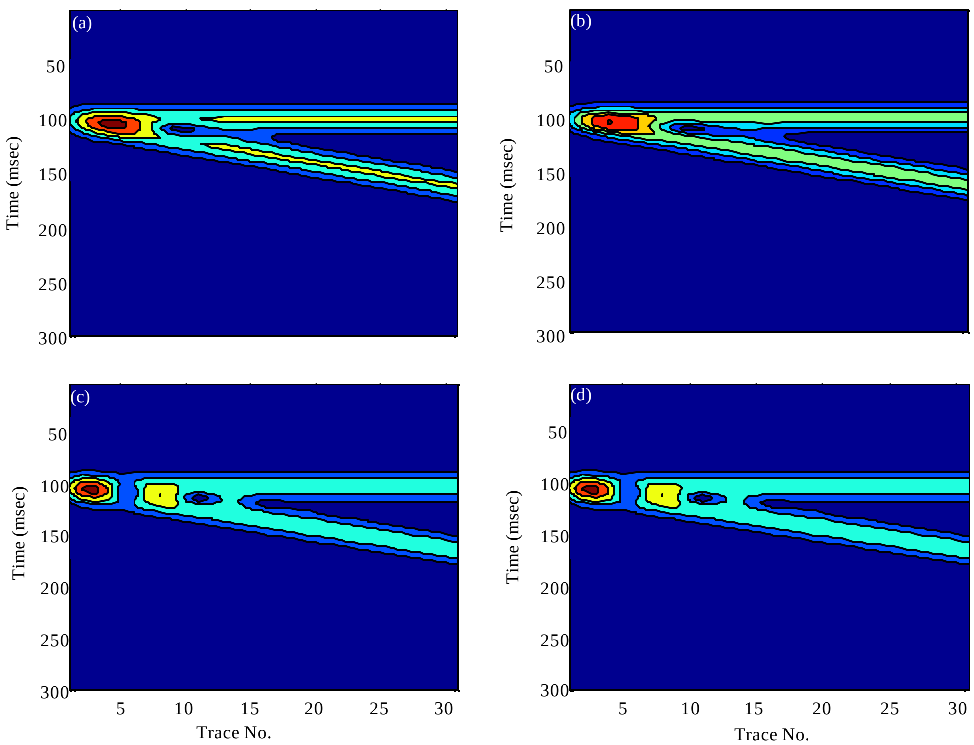

Fig. 6(a-d): Forty hertz frequency slice of Fig. 5b, (a) STFT, (b) ASTFT, (c) ST and (d) AOGST

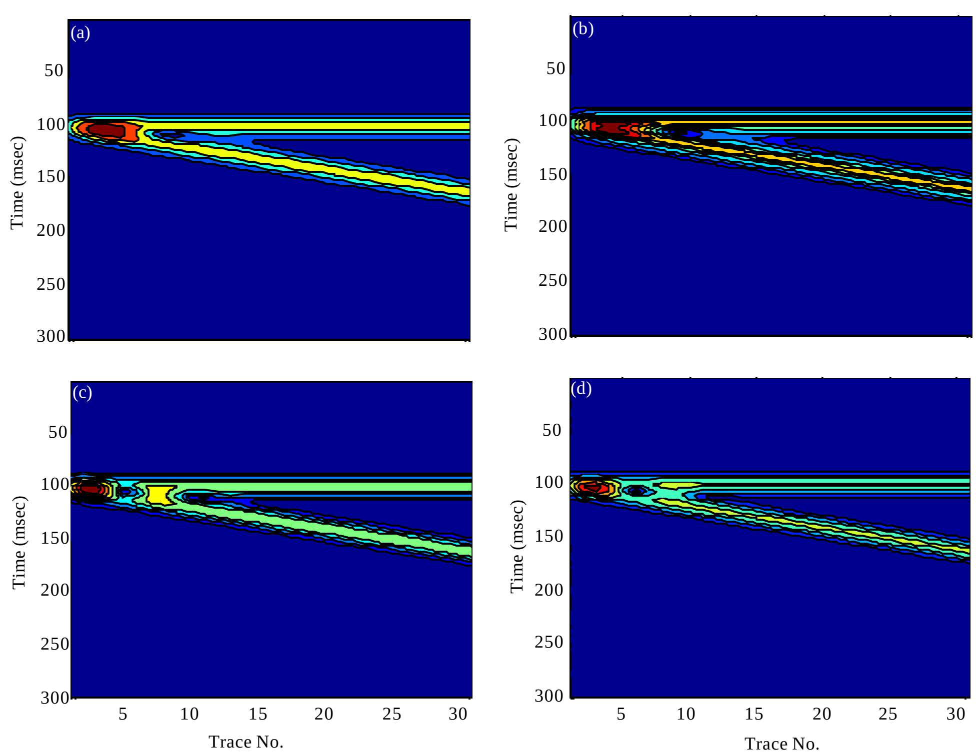

Fig. 7(a-d): Eighty hertz slice of Fig. 5b, (a) STFT, (b) ASTFT, (c) ST and (d) AOGST

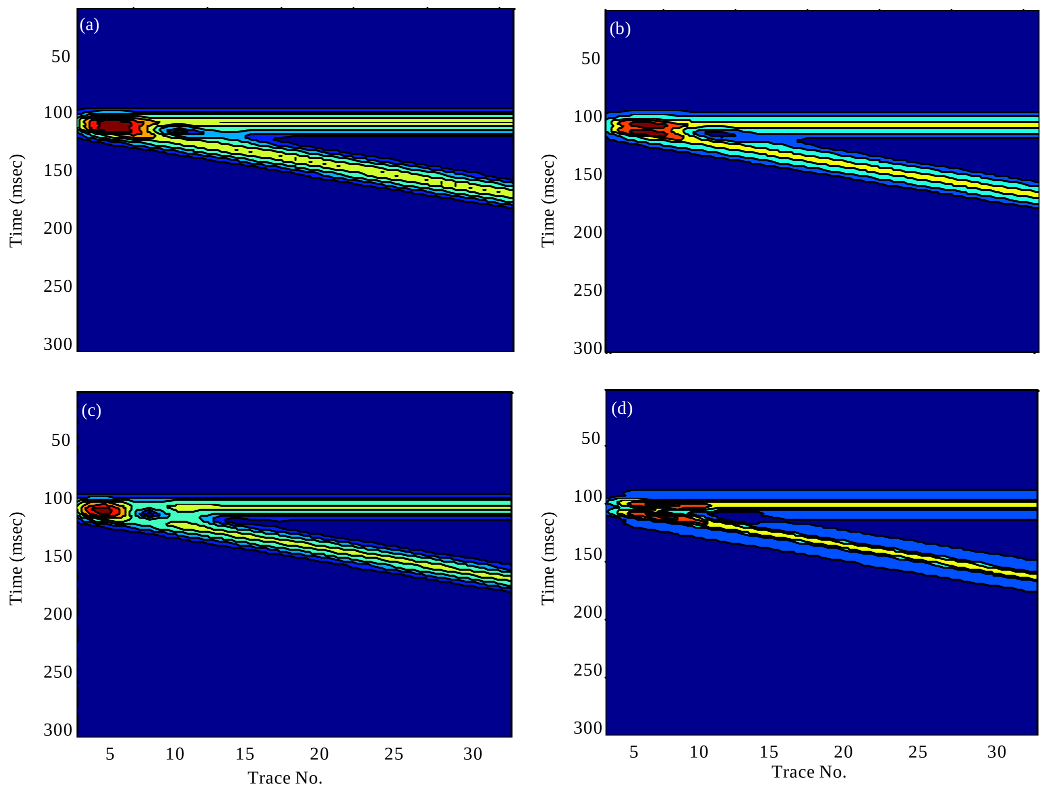

Fig. 8(a-d): One hundred and twenty hertz frequency slice of Fig. 5b, (a) STFT, (b) ASTFT, (c) ST and (d) AOGST, where horizontal coordinate is trace number and vertical coordinate is time (msec)

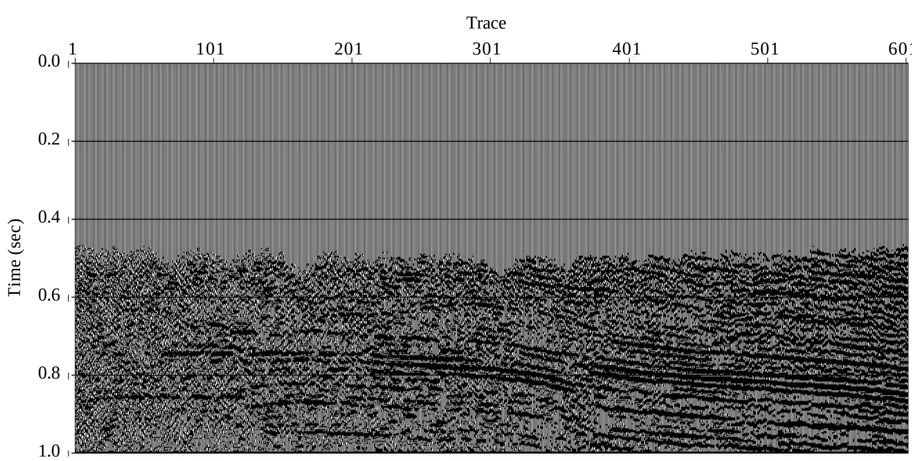

Fig. 9: Seismic profile

resolution of the thin-bed is improved with the extraction of single frequency profile frequency increasing. In the single frequency profile of 20-50 Hz (Fig. 10a-d), the resolution of time-frequency distribution is lower and the fault and thin-bed contained in red frame area can't be distinguished clearly. When the frequency is 60 and 80 Hz (Fig. 10e, f), some detail information can be distinguished, but it still is not very clear. While the frequency is 100 Hz (Fig. 10g), the fault between 300-400th trace can be clearly distinguished and the information of thin-bed is also shown. Figure 11 is the optimized value corresponding to the different frequency according to the AOGST for 100th

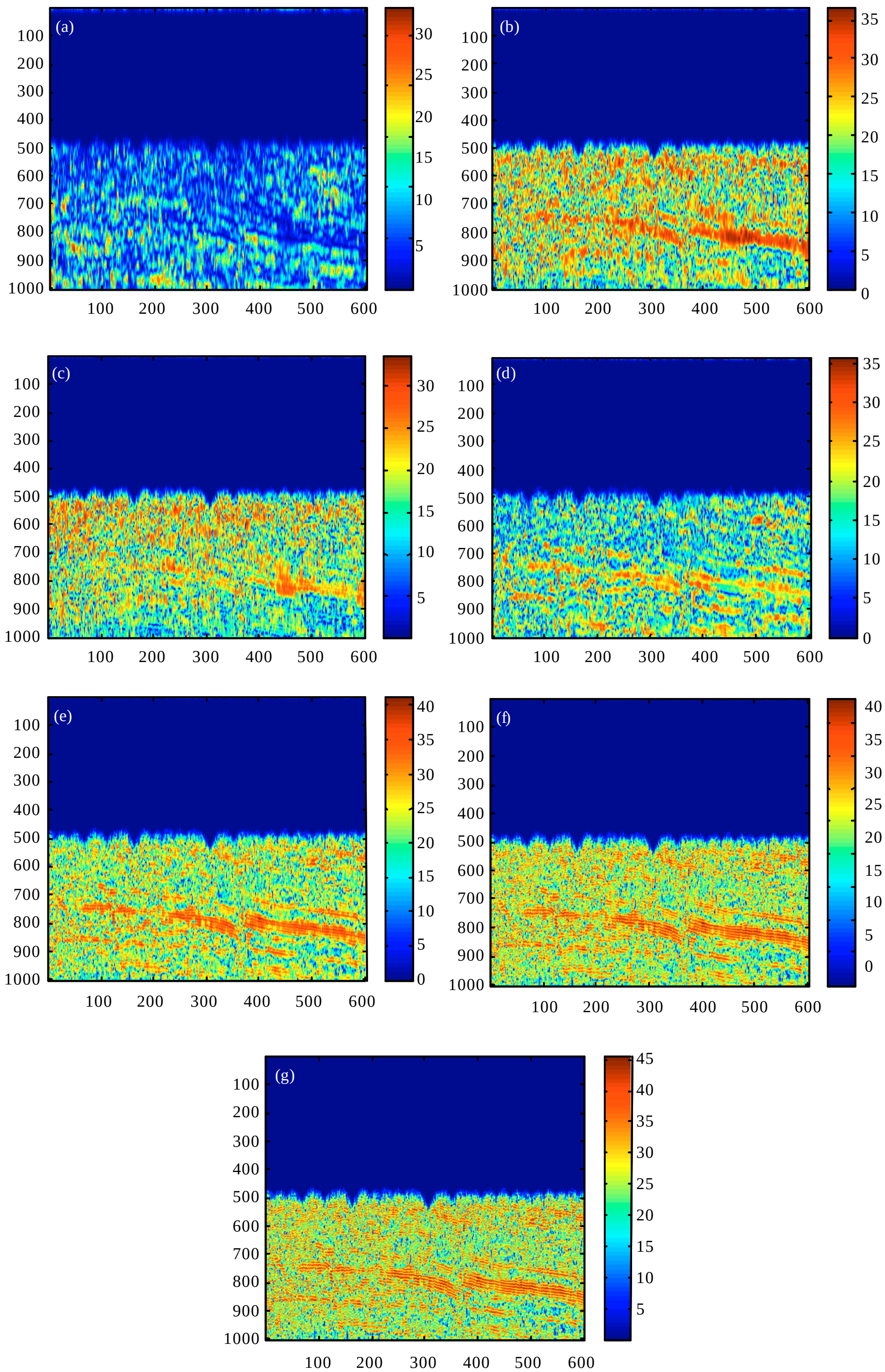

Fig. 10(a-g): Different frequency slices of Fig. 9 by using AGOST: (a) 20 Hz, (b) 30 Hz, (c) 40 Hz, (d) 50 Hz, (e) 60 Hz, (f) 80 Hz and (g) 100 Hz

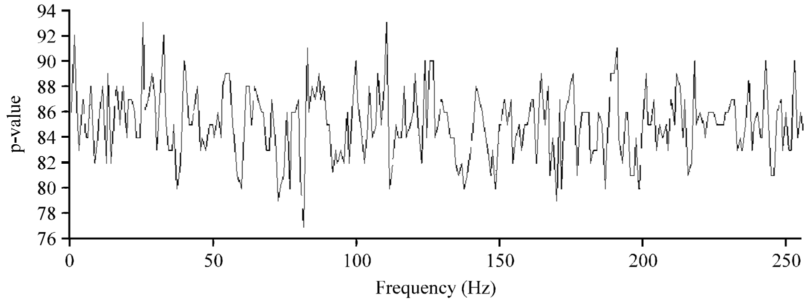

Fig. 11: The optimized value of p for 100th trace

trace. The phenomenon such as fault, sequence deposition etc. can be displayed clearly. Different single frequency profile can also be extracted according to different purpose, for example low frequency shadow analysis, attribute analysis and high resolution profile reconstruction.

CONCLUSIONS

A scheme for improvement of the energy concentration of the S-transform has been developed in the paper. The method is based on the adaptive optimization of the window width according to the characteristic of the different frequency components in the signals. The optimization is carried out by the way of a newly introduced parameter which is referred to as adaptive optimized generalized S transform (AOGST).The proposed scheme is evaluated and compared with the standard S-transform by using a set of synthetic test signals. The results show that the AOGST can achieve better energy concentration. Furthermore, the proposed method has also been applied to thin-bed analysis of seismic signal and the results indicate that it can provide a consistent improvement in seismic frequency slice extraction.

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