

# Time-Frequency Domain Deconvolution based on Synchrosqueezing Generalized S Transform

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## ABSTRACT

Complex geological characteristics and deepening of the mining depth are the difficulties of oil and gas exploration at this stage, so high-resolution processing of seismic data is needed to obtain more effective information. Starting from the time-frequency analysis method, we propose a time-frequency domain dynamic deconvolution based on the Synchrosqueezing generalized S transform (SSGST). Combined with spectrum simulation to estimate the wavelet amplitude spectrum, the dynamic convolution model is used to eliminate the influence of dynamic wavelet on seismic records, and the seismic signal with higher time-frequency resolution can be obtained. Through the verification of synthetic signals and actual signals, it is concluded that the time-frequency domain dynamic deconvolution based on the SSGST algorithm has a good effect in improving the resolution and vertical resolution of the thin layer of seismic data.

**Keywords** : Synchrosqueezing Generalized S Transform, Time Frequency Analysis, Dynamic Deconvolution

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## I. INTRODUCTION

In order to obtain more accurate stratum information based on limited seismic data, experts and scholars have proposed high-resolution seismic data processing. Deconvolution is a common method to improve the resolution of seismic data. It has the advantages of simple processing and good processing effects. In pre-stack and post-stack seismic data processing. In 1940, Ricker first proposed the concept that seismic traces are composed of different components, and in 1953 he proposed that the presence of seismic wavelets in seismic signals affects the resolution of seismic data

[1,2]. On the basis of Ricker, Robinson proposed a convolution model in 1954, which regarded the seismic signal as the convolution result of the seismic wavelet and the reflection coefficient sequence. He assumed that the seismic wavelet has the minimum phase and the reflection coefficient sequence satisfies the characteristics of Gaussian white noise. According to this convolution model, the concept of predictive deconvolution is proposed [3]. Since then, more and more scientists have proposed different deconvolution methods. Robinson proposed predictive deconvolution in 1954 and compared its relationship with least squares deconvolution. Peacock and Treitel

further optimized it in 1969. The predictive deconvolution algorithm [4]. Oppenheim proposed homomorphic deconvolution in 1975 [5]. Wiggins first proposed minimum entropy deconvolution in 1978 [6]. Gulunay proposed f-x deconvolution in 1986, which uses the predictability of the f-x domain to attenuate multiple waves [7]. Milton proposed frequency domain hybrid phase deconvolution in 1988 [8]. Researchers such as Sacchi and Wang Xiaohua improved the minimum entropy deconvolution in 1995 and 1997, and obtained an improved frequency domain minimum entropy deconvolution [9].

Clarke first proposed the idea of deconvolution for non-stationary signals in 1968. It believed that the input of seismic wavelets was non-stationary and could not better reflect the changes of seismic signals on the time average. Therefore, for non-stationary processes, it can be directly passed Average over a region centered at time t to obtain some estimate of the best linear filter [10]. Gary Margrave proposed Gabor deconvolution in 2003, which realized time-frequency domain deconvolution [11]. And in 2011, Gabor deconvolution was improved again, and a time-frequency domain deconvolution based on the dynamic convolution model was proposed [12]. In 2007, Chen Wenchao and others constructed a wavelet transform using MBMSW wavelet as the mother wavelet to process actual seismic data [13]. Guo Tingchao et al. proposed a time-varying spectral simulation deconvolution method based on S transform in 2015 [14].

Based on the assumption that the wavelet shape is a smooth unimodal curve, we propose a time-frequency domain deconvolution based on the Synchrosqueezing Generalized S Transform (SSGST) [15], which aims to satisfy the actual seismic wavelet. The wavelet amplitude is estimated based on the characteristics of dynamic changes, and a dynamic deconvolution method that conforms to the

attenuation characteristics of seismic records is realized.

## II. METHODS

Affected by attenuated seismic wavelets, seismic records are non-stationary signals. Therefore, when processing seismic records, traditional Fourier transform cannot complete the transformation of seismic records. In 1946, Gabor first proposed the theory of time-frequency domain analysis. The model analyzes non-stationary signals in the time and frequency domains, and uses time and frequency to describe signal characteristics [16]. In this paper, we use SSGST to perform time-frequency analysis on seismic records to obtain the time-frequency spectrum of seismic records, and then use the spectral simulation algorithm to estimate the amplitude spectrum of dynamic seismic wavelets from the time-frequency spectrum. We can obtain the time-frequency spectrum of dynamic seismic wavelets, obtain the deconvolution operator according to the principle of dynamic deconvolution in the time-frequency domain, and perform deconvolution processing on the seismic record to obtain the processed time-frequency spectrum of the high-resolution seismic record, finally use iSSGST to obtain processed seismic records. The flow chart of the time-frequency domain dynamic deconvolution algorithm based on SSGST is as follows:

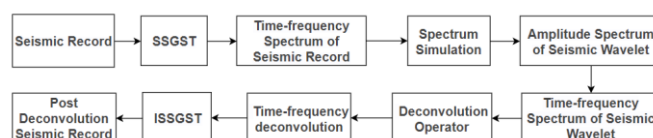


Figure 1: Flow chart of dynamic deconvolution based on SSGST

### A. The Synchrosqueezing Generalized S Transform

SSGST belongs to the post-processing process of Generalized S Transform (GST) [17], which overcomes the fixed frequency-dependent window used in Synchrosqueezing S Transform (SST) [18],

which is difficult to meet the actual situation. The Gaussian window is improved to a variable function containing three parameters, so that the size and shape of the window function can be flexibly changed to meet the high-resolution time-frequency analysis under different frequency conditions. The SSGST method compresses and reconstructs the complex coefficient spectrum of the GST result along the frequency direction, so that the energy distribution on the time spectrum is concentrated near the actual instantaneous frequency of the signal. Therefore, the time-frequency resolution can be improved. According to the time-frequency analysis result of the GST, we can get the instantaneous frequency representation of the original signal:

$$f_x(\tau, f) = f + \left[ i2\pi GST(\tau, f, \gamma_{HY}^B, \gamma_{HY}^F, \lambda_{HY}^2) \right]^{-1} * \frac{\partial GST(\tau, f, \gamma_{HY}^B, \gamma_{HY}^F, \lambda_{HY}^2)}{\partial \tau} \quad (1)$$

SST is used to compress and reconstruct the time-frequency spectrum of the GST along the frequency direction, so that the energy distribution of the time-frequency spectrum is concentrated near the actual instantaneous frequency, and the time-frequency representation of the energy concentration is obtained. We reassign its value according to the local oscillation represented by time-frequency. Combine SST and GST we name it SSGST, which is defined as:

$$SSGST_x(f_l, \tau) = L_f^{-1} * \sum_{f_k | |f_k - \tau| \leq \Delta f / 2} GST(\tau, f, \gamma_{HY}^B, \gamma_{HY}^F, \lambda_{HY}^2) \exp(i2\pi f_k \tau) f_k^{-1} \Delta f_k \quad (2)$$

Where  $f_l$  is the frequency of SSGST results.  $L_f$  is the half length of the frequency range centered on the frequency point  $f_l$ ,  $f_k$  represents the discrete frequency points in the GST frequency range and  $\Delta f_k = f_k - f_{k-1}$  [15]. The above formula shows that in the frequency range  $[f_l - L_f, f_l + L_f]$ , the energy is superimposed on the frequency point  $f_l$ , so that SSGST has a higher time-frequency resolution, that is, the frequency distribution of SSGST is close to the

instantaneous frequency of the real signal. Since SST and GST can perform lossless inverse transformation, the combined SSGST can also perform lossless inverse transformation in theory. Therefore, we can deduce the generalized inverse S transform of synchronous extrusion as:

$$x(t) = \text{Re} \left[ \left( C_\varphi C_\psi \right)^{-1} \sum_l SSGST(f_l, \tau) L_f \right] \quad (3)$$

$$C_\varphi = e^{i[2\pi fb + \phi(f, b)]} \quad (4)$$

$$C_\psi = \frac{1}{2} \int_0^\infty -\hat{\psi}(\zeta) \zeta^{-1} d\zeta \quad (5)$$

$$\zeta = f^{-1} \omega \quad (6)$$

### B. Dynamic Deconvolution Based on SSGST

First, we establish a dynamic convolution model of seismic data according to Clarke's [10] non-stationary convolution idea:

$$x_{non}(t) = w(t, \tau) * r(t) + n(t) = \int_{-\infty}^{+\infty} w(t - \tau, \tau) r(\tau) d\tau + n(t) \quad (7)$$

Where  $x_{non}(t)$  is the attenuated seismic signal,  $w(t - \tau, \tau)$  including reflection coefficient  $\omega(t)$  and  $a(\tau, f)$ ,  $a(\tau, f)$  represents the attenuation function of the seismic signal, and Q is the quality factor:

$$|a(\tau, f)| = \exp\left(\frac{-\pi f \tau}{Q}\right) \quad (8)$$

Therefore, the frequency domain expression of the dynamic convolution model can be expressed as:

$$x_{non}(\omega) = \int_{-\infty}^{+\infty} w(\tau, \tau) r(\tau) \exp(-i\omega\tau) d\tau + n(\omega) \quad (9)$$

$$x_{non}(\omega) = W(\omega) * R(\omega) + n(\omega) \quad (10)$$

Where  $x_{non}(\omega)$  is the seismic signal spectrum,  $W(\omega)$  is the time-varying seismic wavelet spectrum,  $R(\omega)$  is the reflection coefficient sequence spectrum, and  $n(\omega)$  is the noise spectrum. According to formula (9) and formula (10), we conclude that in order to obtain the reflection coefficient sequence, the seismic wavelet must be estimated first. According to the dynamic convolution model, we can conclude that the time spectrum of the attenuation seismic record is approximately equal to the results of the attenuation

function spectrum, the reflection coefficient spectrum, and the wavelet spectrum. Therefore, the relationship between their amplitudes can be expressed as:

$$|SSGST(\tau, f)| = |w(f)| |a(\tau, f)| |R(\tau, f)| \quad (11)$$

Where  $SSGST(\tau, f)$  is the time spectrum of the seismic record,  $w(f)$  is the time spectrum of the seismic wavelet,  $a(\tau, f)$  is the time spectrum of the attenuation function, and  $R(\tau, f)$  is the time spectrum of the reflection coefficient sequence. Rosa proposed in the article "Processing via spectral modeling" that it can be assumed that the seismic wavelet is a single-peak curve with a smooth amplitude spectrum, and its amplitude shape is similar to the Lake wavelet. The mathematical model is as follows [19]:

$$W(f) = |f|^k \exp\left(\sum_{n=0}^N a_n f^n\right) \quad (12)$$

Where  $w(f)$  is the amplitude spectrum of the seismic record,  $N$  is the fitting order,  $k$  is a constant, and  $a_n$  is the polynomial coefficient of  $f$ . The spectral simulation algorithm does not require that the reflection sequence coefficients meet the Gaussian white noise condition, but only needs to assume that the seismic wavelet is a zero-phase wavelet, so it has a larger application range.

After we estimate the frequency spectrum of the time-varying seismic wavelet, in order to restore the reflection coefficient sequence in the original seismic record, we need to construct an inverse operator to deconvolve the seismic record. The basic formula is as follows:

$$A(\tau, f) = |A(\tau, f)| e^{-i\varphi_a(\tau, f)} = \frac{1}{(|W_w(\tau, f) + \mu W_{\max}|)} * \exp(-i\varphi_w(\tau, f)) \quad (13)$$

Where  $A(\tau, f)$  is the deconvolution operator,  $W_w(\tau, f)$  is the seismic wavelet amplitude spectrum,  $\mu W_{\max}$  is the minimum value added to avoid zero value in the denominator,  $\mu$  is a small positive real number,  $W_{\max}$  is the maximum value of the seismic wavelet

amplitude spectrum, and  $\varphi_w(\tau, f)$  is the seismic wavelet Phase spectrum. Multiply the inverse operator and the seismic record time spectrum to obtain the time spectrum of the reflection coefficient sequence, and then perform the iSSGST on the time spectrum of the reflection coefficient sequence to realize the time-frequency domain dynamics based on SSGST The formula for deconvolution is as follows:

$$R_{SSGST}(\tau, f) = X_{SSGST}(\tau, f) * A(\tau, f) \quad (14)$$

$$r(\tau, f) = iSSGST(R_{SSGST}(\tau, f)) \quad (15)$$

Where  $R_{SSGST}(\tau, f)$  is the time-frequency spectrum of the seismic signal processed by deconvolution,  $X_{SSGST}(\tau, f)$  is the time-frequency spectrum of seismic recording,  $A(\tau, f)$  is the deconvolution operator,  $iSSGST()$  is the inverse synchrosqueezing generalized S transform, and is the seismic signal processed by the deconvolution.

### III. EXPERIMENTAL IMPLEMENTATION

In this section, we first synthesize a single-channel stationary seismic signal by using the minimum phase rake wavelet with a dominant frequency of 60 Hz and the reflection coefficient sequence. On the basis of the stationary signal, we add an attenuation factor of 60 to synthesize the attenuated seismic signal. The simulation method recovers the seismic wavelet amplitude spectrum from the synthesized signal, compares it with the original seismic wavelet amplitude spectrum, and deconvolves the seismic signal by calculating the inverse operator. The experimental results are shown in the figure below:

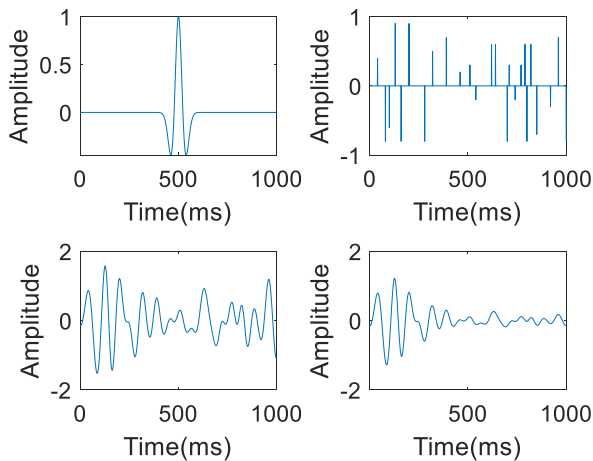


Figure 2: Synthetic seismic record (a. seismic wavelet b. reflection coefficient sequence c. stationary seismic signal d. attenuated seismic signal)

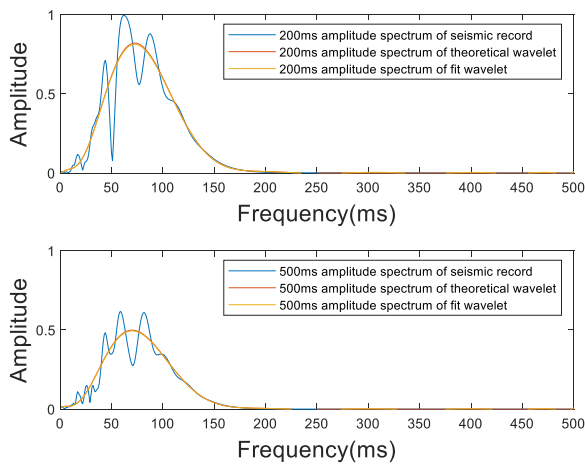


Figure 3: Attenuated seismic signal extracts seismic wavelet amplitude spectrum at different moments (a.200ms b.500ms)

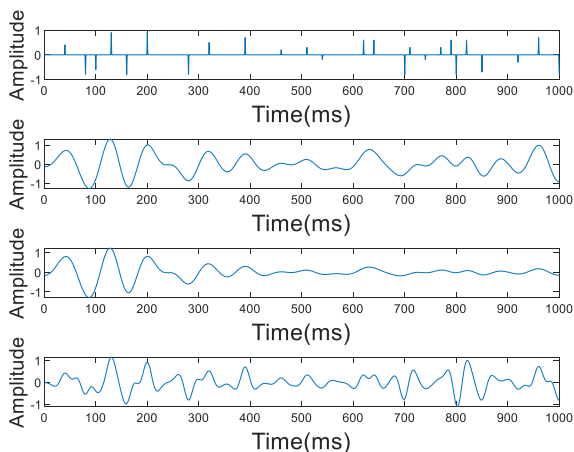


Figure 4: Time-frequency domain spectrum simulation deconvolution results (a. Reflection coefficient sequence b. Stationary seismic record c. Attenuation seismic record d. Seismic record after deconvolution)

Figure 2(a) and figure 2(b) respectively show the zero-phase rake wavelet and reflection coefficient sequence, and Figure 2(c) and figure 2(d) show the steady seismic record and attenuated earthquake using the combination of wavelet and reflection coefficient Record. Figure 3 is the amplitude spectrum of the seismic wavelet at 200ms and 500ms estimated by the time-frequency domain spectrum simulation algorithm. As time increases, the recovered seismic wavelet amplitude is also attenuated, which means that we can use the spectral simulation method to recover the time-varying seismic wavelet. According to the time-frequency spectrum dynamic deconvolution model, we use the estimated attenuation seismic wavelet to design a deconvolution operator, and perform deconvolution processing on the attenuation seismic record. The result is shown in Figure 4(d). Comparing Figure 4(b), Figure 4(c) and Figure 4(d), we can find that the attenuated seismic signal after deconvolution in the time-frequency domain can recover energy, distinguish thin layers, Eliminate the influence of part of the sub-wave side lobes on the reflection coefficient, so that the processed seismic record can more clearly reflect the specific characteristics of the reflection coefficient sequence. Therefore, we can consider that the dynamic deconvolution based on the simultaneous extrusion generalized S-transform has certain application value in identifying thin layers and restoring seismic energy attenuation.

In the previous section, we used synthetic seismic signals to verify that dynamic deconvolution based on SSGST can improve resolution, compensate for amplitude attenuation, and reduce the impact of seismic wavelets on seismic data when processing seismic records. In this section, we use actual seismic signals. Verify the performance of the algorithm again. This section first uses actual seismic signals from a certain area in the Ordos Basin as data samples. The geological characteristics of this area are thin reservoirs, rapid thickness changes and strong



heterogeneity. The analysis sampling time is 1000ms for a single seismic signal. The effect comparison before and after treatment is shown in the figure below:

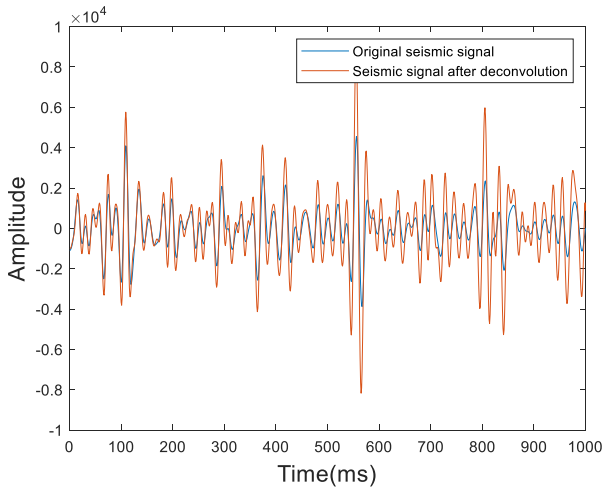


Figure 5: Original seismic signal and seismic signal after deconvolution

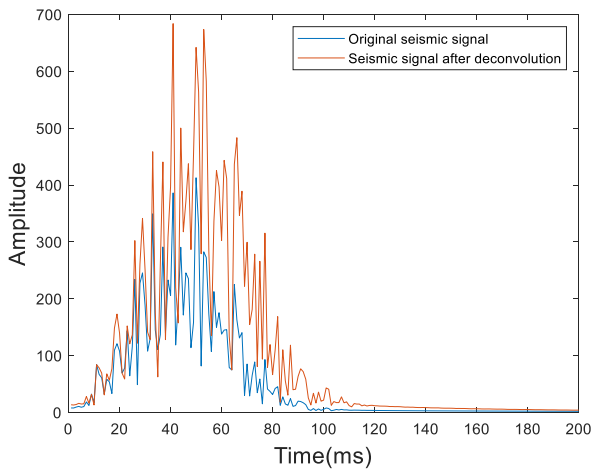


Figure 6: The spectrum of original seismic signal and The spectrum of seismic signal after deconvolution

Figure 5 is the time domain diagram of the original actual seismic signal and the signal after dynamic deconvolution based on SSGST. Figure 6 is the frequency spectrum of the two signals. By comparing the amplitude spectrum and frequency spectrum of the two signals, we can see that the seismic signal after dynamic deconvolution is more obviously compensated in amplitude. In some parts where the change is not obvious, such as 240ms and 320ms, the

processed signal changes more obviously, and it can be seen that the original signal is not displayed. The fluctuations that come out. And with the increase of time, the effect of compensation becomes more obvious. In terms of frequency spectrum, the amplitude of the processed signal in the main frequency part is increased obviously, and the effective bandwidth of the signal has been broadened, achieving the purpose of amplitude compensation and frequency compensation. Next, select a total of 500 channels of data in the same area, and the seismic section formed by seismic records with each data length of 1000ms for processing:

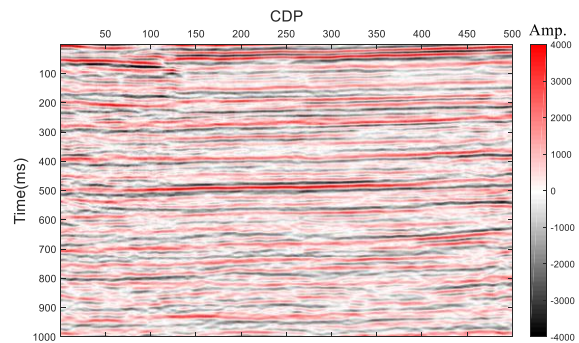


Figure 7: Original seismic section

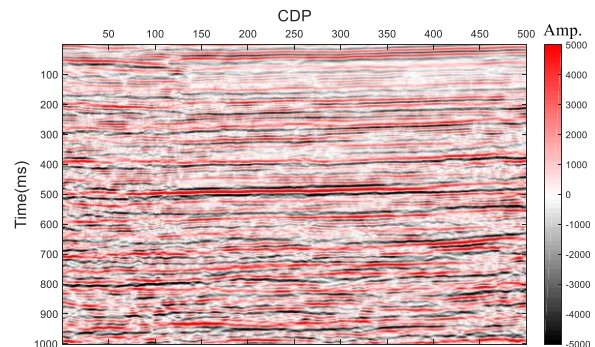


Figure 8: Seismic profile after dynamic deconvolution in time-frequency domain based on SSGST

Figure 7 is the original seismic section, and Figure 8 is the seismic section after SSGST-based dynamic deconvolution in the time-frequency domain. Comparing the two figures, we can see that the amplitude of the processed seismic profile has been significantly improved, especially at the position of 800ms-1000ms. The original actual profile is affected by attenuation and the stratum distribution is not

clear, but after deconvolution processing The maximum amplitudes of the sections have been improved, the stratification between the various strata has become more obvious, and the resolution has been improved. Especially in the circled part of the black circle, we can see that the resolution improvement effect of the signal processed by dynamic deconvolution based on SSGST is obvious. Part of the original hidden detail information can be restored, and the layering is not displayed in the original section. The conditions of the faults are shown in Figures 8, and the thin-layer resolution has been significantly improved

#### IV. CONCLUSION

This paper mainly combines the time-frequency analysis method with deconvolution, and proposes a time-frequency domain dynamic deconvolution based on Synchrosqueezing generalized S transform. This method mainly uses the characteristics of SSGST with high time-frequency resolution and high-energy focusing. The time-frequency spectrum of each moment can be obtained more accurately from the attenuation seismic record, and then the amplitude of each moment is fitted by the spectral simulation method. Obtain the time-varying amplitude spectrum of the seismic wavelet, obtain the wavelet time spectrum based on the zero phase assumption of the wavelet, estimate the attenuated seismic wavelet closer to the actual situation, and obtain the inverse operator in the deconvolution, according to Rick's proposal Dynamic deconvolution of the dynamic convolution model, which deconvolves seismic records in the time-frequency domain, reduces the impact of seismic wavelets on seismic records and improves the resolution of seismic data. Through the verification of synthetic seismic data and actual seismic data, we can conclude that the time-frequency domain dynamic deconvolution based on SSGST is better than traditional static deconvolution in improving the longitudinal resolution of seismic

data and improving the resolution of thin layers. Effect. And because SSGST has strict mathematical reasoning and can process signals of different frequencies, the dynamic convolution model is more in line with the actual signal model, so the time-frequency domain dynamic deconvolution based on SSGST is a practical and extensive High-resolution processing method of seismic data.

#### V. REFERENCES

- [1] Douglas, A. (1997). Bandpass filtering to reduce noise on seismograms: Is there a better way? *Bull. Seismol. Soc. Am.* 87, 770–777.
- [2] Al-Yahya, K. M. (1991). Application of the partial Karhunen–Loève transform to suppress random noise in seismic sections, *Geophys. Prospect.* 39, 77–93, 1991.tb00302.
- [3] Yilmaz, Ö. (2001). *Seismic Data Analysis: Processing, Inversion, and Interpretation of Seismic Data*, Second Ed., Society of Exploration Geophysicists, Tulsa, Oklahoma.
- [4] Djarfour, N., T. Aïfa, K. Baddari, A. Mihoubi, and J. Ferahtia (2008). Application of feedback connection artificial neural network to seismic data filtering, *Compt. Rendus Geosci.* 340, no. 6, 335–344.
- [5] Trickett, S. (2008). F-xy cadzow noise suppression, *SEG Tech. Program Expanded Abstr.* 27, 2586–2590.
- [6] Gibbons, S. J., and F. Ringdal (2006). The detection of low magnitude seismic events using array-based waveform correlation, *Geophys. J. Int.* 165, 149–166.
- [7] Hashemi, H., A. Javaherian, and R. Babuska (2008). A semi-supervised method to detect seismic random noise with fuzzy GK clustering, *J. Geophys. Eng.* 5, no. 4, 457–468.
- [8] Oropeza, V., and M. Sacchi (2011). Simultaneous seismic data denoising and reconstruction via multichannel singular spectrum analysis, *Geophysics* 76, V25–V32.

- [9] Bonar, D., and M. Sacchi (2012). Denoising seismic data using the nonlocal means algorithm, *Geophysics* 77, A5–A8.
- [10] Clarke, Kc G. Time-Varying Deconvolution Filters[J]. *Geophysics*, 1968, 33(6):936-944.
- [11] Margrave G F, long L, Gibson P C, et al. 2003. Gabor deconvolution: Extending wiener's method to nonstationarity[Z]. *The CSEG Recorder*, 28.
- [12] Margrave, G. F., M. P. Lamoureux, and D. C. Henley. 2011. Gabor deconvolution: Estimating reflectivity by nonstationary deconvolution of seismic data[J]. *Geophysics*, 2011, 76(3): w15-w30
- [13] Wenchao Chen, Jinhui Gao. 2007. Analysis of attenuation characteristics of seismic data based on improved best matching seismic wavelet [J]. *Journal of Geophysics*, 50(03):837-843.
- [14] Tingchao Guo, Wenjun Cao. 2015. Research on Time-Varying Spectrum Simulation Deconvolution Method [J]. *Petroleum Geophysical Prospecting*, 54(1): 36-42.
- [15] H. Chen, L. Lu and D. Xu. The Synchrosqueezing Algorithm Based on Generalized S-transform for High-Precision Time-Frequency Analysis[J]. *APPLIED SCIENCES-BASEL*, vol. 7, no. 8, pp. 769, Aug 2017.
- [16] Gabor D. Theory of communication[J]. *Iee Proc London*, 1946, 93(73):58.
- [17] Pinnegar C R, Mansinha L. The S-transform with windows of arbitrary and varying shape [J]. *Geophysics*, 2003, 68(1): 381-385
- [18] H. Chen, L. Lu and D. Xu. The Synchrosqueezing Algorithm Based on Generalized S-transform for High-Precision Time-Frequency Analysis[J]. *APPLIED SCIENCES-BASEL*, vol. 7, no. 8, pp. 769, Aug 2017.
- [19] Rose A L R,Ulrych T J. Processing via spectral modeling[J]. *Geophysics*, 1991, 56 (8) : 1244-1251.

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