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High-resolution time-frequency decomposition with adaptive filter

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ABSTRACT

The success of seismic attributes analysis depends on the resolution of calculated attributes and robustness of the method against noise-contaminated data. Conventional methods are sensitive to errors in data, which demands the filtering process. Conventional filtering methods try to increase the SNR at the cost of losing spectral bandwidth. The challenge of having a high-resolution and robust signal processing tool motivated us to propose a sparse time-frequency decomposition which is stabilized for random noise normal distribution. The procedure begins by using Sparsity-based, adaptive S-transform to regularize abrupt variations in the frequency content of the non-stationary signals. An adaptive filter is then utilized to the previously sparsified time-frequency spectrum. The proposed zero adaptive filter enhances the high amplitude frequency components while suppressing the lower ones. The performance of the proposed method is compared to the sparse S-transform and the robust window Hilbert transform in the estimation of instantaneous attributes through studying synthetic signals. Seismic attributes estimated by the proposed method are superior to the conventional ones in terms of robustness and high-resolution viewpoint.

Keywords: Seismic attributes analysis, Time-frequency decomposition, zero adaptive filter

INTRODUCTION

Instantaneous seismic attributes benefit the complex trace in order to extend the definitions of simple harmonic oscillation and they have been adopted in the interpretation of structural features. Seismic attributes are analysed to determine stratigraphic and geological properties (Taner et al. 1979); they provide quantitative measures of phase, frequency, and reflector amplitude (e.g. the distribution of reef complexes, which can be explained by the instantaneous phase (Zheng et al. 2007). Although complex seismic attributes are applicable when defining complex structures, they are problematic in noisy data due to their sensitivity to noise. To address this problem, Luo et al. (2003) presented a generalised version of the Hilbert transform (HT). Lu and Zhang (2013) introduced the windowed Hilbert transform (WHT), a TFR form of HT accompanied by a zero-phase adaptive filter to enhance the resolution of instantaneous complex attributes. Despite the efficiency of filtering to remove the undesired frequency components in complex trace analysis, loss of the original data is the main concern. Regarding this fact, Sattari (2017) proposed a fast sparse S-transform (SST) to achieve sparse WHT by applying the optimised windows in the frequency domain. Although the resolution of the seismic attributes improved via the SST, the presence of random noise remains unsolved. Therefore, to obtain stable and high-resolution instantaneous spectral attributes, the SST is enhanced by the robust adaptive WHT (RAWHT) to obtain robust sparse s-transform (RSST), which concerns the abrupt changes in the frequency content of the signal and is less sensitive to the noise.

In this paper, a modified calculation of analytic signals is presented to provide a robust Hilbert transform which is of higher resolution, less sensitive to noise, and provide a better estimation of instantaneous attributes rather than traditional HT.

Analytic signal using SST

The main difference between the standard ST proposed by Stockwell et al. (1996) and the adaptive SST proposed by Sattari (2017) is that the latter uses frequency dependent window parameters that are reversely proportional to the amplitudes of various frequency components, while the former utilizes a window-length that is inversely proportional to frequency, while windowing the frequency domain input signal. The strategy used to obtain the adaptive SST relies on the fact that frequency components with higher amplitude are forced to dominate the time-frequency lattice by being localised through translation using high and short windows. The low amplitude harmonics need to be smeared in the time-frequency domain by using low and wide windows, while being translated. The adaptive SST is not only superior to the standard ST in terms of adaptivity and higher resolution, but also it is very efficient in that it adds no extra computation to the translation and modulation processes required for the spectral decomposition. Due to this properties, the SST even performs better than the alternative energy concentration (ECM) methods used for adaptivity enhancement of Fourier-based spectral decomposition. However, under the low SNR, the SST is not stable. For these reasons, in this paper the TFR obtained via adaptive SST are filtered in the time-frequency domain.

We benefited the SST method proposed by Sattari (2017) to calculate the analytic part of a signal to have higher resolution compare to the other known methods. The windowed HT can be defined in the time-frequency domain as:

$$Z(\omega.\tau) = X(\omega.\tau)[1 + iH(\omega)] = \begin{cases} 2X(\omega.\tau) & \omega > 0 \\ X(\omega.\tau) & \omega = 0 \\ 0 & \omega < 0 \end{cases} \tag{1}$$

Improved Hilbert transform

To cope with the problems of seismic attribute analysis due to noisy signals, we employ a time-frequency adaptive filter to the TFR obtained via adaptive SST. This filter is based on the assumption that the higher amplitude spectrum has more signal content and is formed as:

$$g(\omega.\tau) = \frac{|X(\omega.\tau)|^{N-1}}{\underset{\omega}{argmax}(|X(\omega.\tau)|^{N-1})}, \tag{2}$$

where N is a weighting factor and $N \geq 1$, $|X(\omega.\tau)|$ is the amplitude spectrum of $X(\omega.\tau)$.
The analytic signal can be constructed as:

$$z(t) = \int_{-\infty}^{\infty} F^{-1}(\tilde{Z}(\omega.\tau))\, d\tau, \tag{3}$$

where

$$\tilde{Z}(\omega.\tau) = X(\omega.\tau)g(\omega.\tau)[1 + iH(\omega)], \tag{4}$$

and $F^{-1}(\tilde{Z}(\omega.\tau))$ is the inverse Fourier transform of $Z(\omega.\tau)$.

Increases in the value of N, result in amplification of the frequencies with the maximum amplitude. The value of N depends on the signal to noise ratio (SNR); the higher the SNR, the lower N. By applying N greater than one, the SST develops into the RSST with enhanced higher amplitude frequency components and suppressed lower ones. Although the SST is supposed to render less noisy results, it fails to suppress the noise when the SNR is low. On the other hand, the adaptive filter proposed by Lu and Zhang (2013) cannot distinguish the discrepancy between the desired signal and undesired noise, if applied directly to the TFR.

Results

We assess the performance of the proposed approach against RWHT and SST through some synthetic examples. In Figure (1), the performance of different approaches for a double-liner chirp signal with sampling rate of 2 *ms* and length of 2*s* is studied. This figure, includes two panels. The left panel shows the TFR results of three methods. In the right panel we added Gaussian random noise to the signal, in which the signal to noise ratio is set to be 1 dB. The weighting factor *N* was taken 7 in the example. For both cases, the proposed RSST outperforms the RWHT and SST methods. The RWHT is less accurate than the others. In other words, some information has lost in the TFR panel given by the RWHT method as indicated by ellipse and arrows in the left panel. For noisy signal, the RSST method clearly demonstrates its robustness.

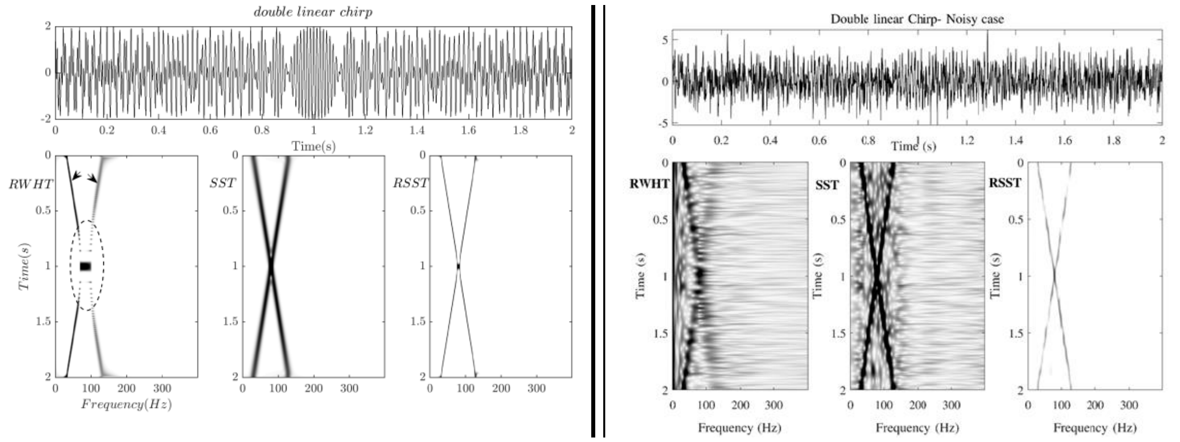

Figure 1. Double linear chirp example. (Left panel): The results of RWHT, SST and RSST for noise-free signal. (Right panel): The results for noisy signal.

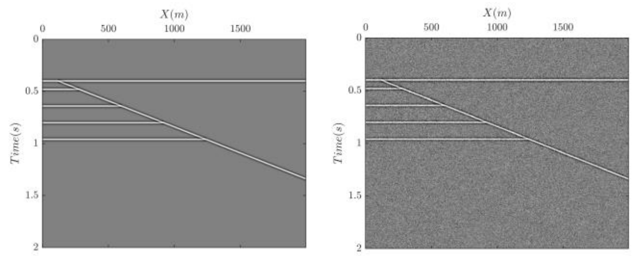

Figure 2. Wedge model example. (Left): noise free section. (Right): noise contaminated data.

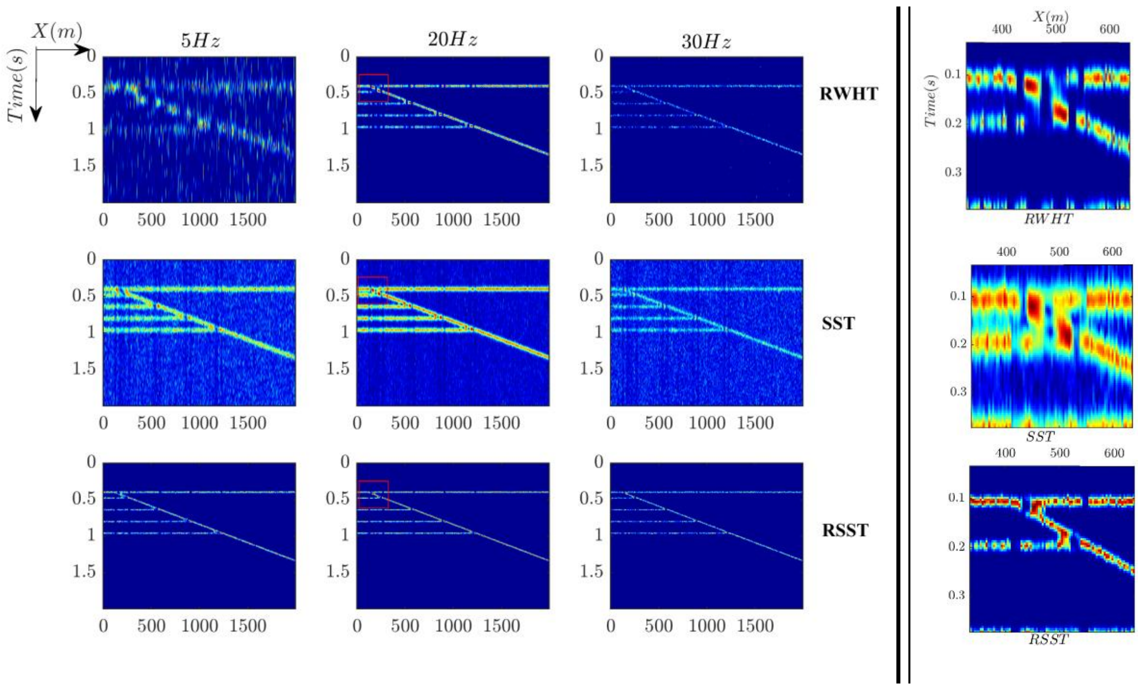

Figure 3. Wedge model example. (Left panel): The results of the RWHT, SST, and WSST for the mono-frequency components of 5, 20 and 30 Hz. (Right panel): The zoomed view of the red boxes for frequency of 20 Hz.

In the next example, we deal with a synthetic wedge model. For this case, we set the SNR value to be 2 dB. The comparison between noise-free and noisy sections is given in Figure (2). We used this data as the inputs of three methods and set the parameter N equal to 5. The results of TFR for three mono-frequency components (5, 20, and 30 Hz) are shown in the left panel of Figure (3). It can be seen that the RSST method outperforms other methods. For low-frequency components (i.e. 5 Hz), it can be observed that the RWHT has failed to maintain the valuable information, while for higher frequency components, the resulting TFRs are satisfactory. On the other hand, the SST method still suffers from noise. For a better comparison, a part of the TFR (the red box) is selected for the frequency of 20 Hz from all three methods and demonstrated in the right panel, which clearly shows that the RSST method has dealt with the tuning effect successfully.

CONCLUSION(S)

In this paper, estimation of a stable, high-resolution complex trace analysis was addressed within the framework of sparsity-based optimization and time-frequency spectrum weighting orders. The proposed method employs a zero-phase adaptive filter to suppress the residual noise by enhancing the frequency components with larger amplitudes.

The results of the 1D signal and 2D wedge model proved the advantage of the proposed method in obtaining high resolution and robust instantaneous attributes, compared to the conventional methods. Indeed, the proposed method regularized the entire frequency content of the signal by setting only one window parameter and suppressed the noise spread in both the time and frequency domains by adjusting the weighting order *N*. The proposed method has vast implications for interpreting complex trace analyses.

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