Seismic attributes via robust and high-resolution seismic complex trace analysis

Mohsen Kazemnia Kakhki1,4 · Kamal Aghazade3 · Webe João Mansur1,2 · Franciane Conceição Peters1,2

Abstract
Seismic attribute analysis has been a useful tool for interpretation objectives; therefore, high-resolution images of them are of particular concern. The calculation of these attributes by conventional methods is susceptible to noise, and the conventional filtering supposed to lessen the noise causes the loss of the 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 stabilised for random noise. The procedure initiates by using sparsity-based, adaptive S-transform to regularise abrupt variations in the frequency content of the non-stationary signals. An adaptive filter is then applied 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 and real data sets. Seismic attributes estimated by the proposed method are superior to the conventional ones, in terms of robustness and high-resolution imaging. The proposed approach has a detailed application in the interpretation and classification of geological structures.

Keywords Time–frequency decomposition · Sparsity-based adaptive S-transform · Zero adaptive filter · Robust window Hilbert transform

Introduction
Data interpretation in signal analysis can be better accomplished if a distinct aspect of the data is accessible. This aim can be achieved by transforming the data from one domain to another. The Fourier transform is one of the common transformations which empower us to survey the average properties of a remarkably vast portion of a trace, although it does not represent local variations. The complex trace was first introduced to seismology by Taner et al. (1979); it resolved this problem by maintaining the local significance and providing a new perspective.

Traditional seismic interpretation methods are incapable of deciphering subtle geological features; this fact has been investigated by researchers, who have explored various techniques to resolve this challenge. Instantaneous seismic attributes take advantage of the complex trace in order to elongate 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; Verma et al. 2018); 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)). Yuan et al. 2019 benefited the instantaneous phase and proposed a 3D geosteering phase attribute to recognise the geometry of subsurface features, such as discontinuities related to structural anomalies. Thin-bed tuning is the other challenging structure which is detectable by instantaneous frequency (Chopra and Marfurt 2005). The reservoir characterisation and limestone formations were delineated via seismic instantaneous amplitude,
frequency and phase by imaging various target units (Farfour et al. 2015). Ali et al. (2019) used the dominant frequency attribute to define the characterisation of a hydrocarbon-bearing reservoir. Verma et al. (2018) inferred the dunal and interdunal deposits in 3D seismic data volume by combining coherence attributes and inverted P-impedance. Texture and edge attributes were used by Asjad and Mohamed (2015) to extract a salt dome.

Another significant stratigraphic exploration issue is when porous rocks are bound in a non-porous matrix. Bedi and Toshniwal (2019) estimated the porosity of a reservoir from the seismic attributes that have a reasonable correlation with the porosity properties of a rock (energy, mean, instantaneous amplitude, homogeneity, autocorrelation, cosine phase, contrast, dissimilarity and instantaneous frequency). Takam Takougang et al. (2019) applied coherence and similarity attributes when delineating fault and fractures from reverse time-migrated seismic sections. Liu et al. (2014) used a large variety of seismic attributes to characterise the turbidity channel. The channel boundaries are also detectable using seismic coherence and other edge-sensitive attributes, although their thickness cannot be defined via these attributes. Hence, spectral decomposition, which is sensitive to channel thickness, is used to complement the coherence and edge-sensitive attributes (Anees et al. 2019). Obiadi et al. (2019) applied spectral decomposition, integrated with seismic attributes, to identify the geometry and structural discontinuities of hydrocarbon reservoirs within complex tectonic settings. Cichostępski et al. 2019 have also benefited the spectral analysis in detection of bright spots in the presence of thin beds. Recently, Qi and Wang (2020) have employed local polynomial Fourier transform to tackle the nonlinear variation of the signal properties and obtain instantaneous frequency.

Although complex seismic attributes are applicable when defining complex structures, they are problematic in noisy data due to their sensitivity to noise. To alleviate this defect, Luo et al. (2003) presented a generalised version of the Hilbert transform (HT). Liu and Marfurt (2007) outlined the efficiency of time–frequency representation (TFR) in achieving cleaner instantaneous frequency in thin-bed and channel detection. Lu and Zhang (2013) introduced the windowed Hilbert transform (WHT), a TFR form of HT accompanied by a zero-phase adaptive filter to enhance instantaneous complex attributes. Despite the efficiency of filtering in order to remove the undesired frequency components in complex trace analysis, loss of the original data is the primary concern. Concerning 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, in order to achieve stable and high-resolution instantaneous spectral attributes, the SST is improved by the robust adaptive WHT (RAWHT) to achieve robust sparse S-transform (RSST), which concerns the abrupt changes in the frequency content of the signal and is less sensitive to the noise. The role of the adaptive filter is to suppress the lower-amplitude frequency components and improve the higher amplitudes.

In this study, 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. The main aim of the proposed method is to use sparsity-based window-parameter optimisation to improve the resolution of the seismic attributes while taking advantage of a zero-phase adaptive filter to stabilise the contaminated data when calculating the analytic signal in the time–frequency domain. We begin with the explanation of complex trace analysis followed by the calculation of instantaneous attributes. The analytic signal is then improved by using SST and a zero-phase adaptive filter and ending with synthetic and real examples to compare the performance of the proposed method to the SST and the RWHT.

Methodology

Calculation of the complex trace

If we assume that the real signal \( x(t) \) is \( x(t) = A(t) \cos \theta(t) \) and the imaginary part is \( y(t) = A(t) \sin \theta(t) \), the complex trace \( z(t) \), or the analytic signal, is computed as:

\[
z(t) = x(t) + iy(t) = Ae^{i\theta(t)}
\]

where \( y(t) \) is the HT of the input signal \( x(t) \) derived from the convolution of \( x(t) \) with the function \((-1/\pi t))\). Hilbert transform is considered as a linear, time-invariant system with impulse response,

\[
h(t) = -\left(\frac{1}{\pi t}\right)
\]

Signal \( x(t) \) can be analysed by applying the HT in the frequency domain. Considering \( X(\omega) \) as the Fourier spectrum of \( x(t) \) then \( Z(w) \), the spectrum of the analytic signal, is calculated as follows:

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

where \( H(\omega) \) is the filter as:
\[ H(\omega) = \begin{cases} 
-i & \omega > 0 \\
0 & \omega = 0 \\
i & \omega < 0 
\end{cases} \]  \hspace{1cm} (4)

The amplitude spectrum of the complex trace \( z(t) \) is double for positive frequencies, while it is zero for negative ones. Therefore, the complex trace can be formed by taking the Fourier transform of the real trace, making the amplitude of negative frequencies zero and doubling the amplitude of positive frequencies, then applying the inverse Fourier transform. After this, the instantaneous frequency and phase are easily achievable via the analytic signal.

Seismic instantaneous attributes (Taner et al. 1979) can be derived from the analytic signal. \( A(t) \) and \( \theta(t) \) denote the instantaneous amplitude and the instantaneous phase in Eq. (1), respectively. The instantaneous frequency can be obtained by taking the derivative of the instantaneous phase

\[ \varphi(t) = \frac{d\theta(t)}{dt} \]  \hspace{1cm} (5)

The real seismic signal can have abrupt changes and interference (both in terms of time and frequency) because it carries information about the heterogeneous subsurface. Therefore, it can affect the obtained analytic signal, especially in terms of resolution. Sattari (2017) attempted to address this problem via optimised windows and proposed sparse ST.

**Analytic signal using sparse ST**

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 uses 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 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. Sattari (2017) applied this strategy by exploiting the matrix formula of ST as

\[ TFR_{ST}^{[l]}[l,k] = IFT\left\{ A_{st}[l,m] \odot \hat{X}[l,m] \right\}, \]  \hspace{1cm} (6)

in which \( A_{st}[l,m] \in \mathbb{R}^{N \times N} \) is the desired adaptive windows matrix. The columns of this matrix are constructed by the shifted random windows and the rows via the standard Gaussians window function, moved alongside the frequency axis employing \( m = 0, \ldots, N-1 \). Moreover, \( 1 \leq k \leq N \) and \( 1 \leq l \leq N \) are the time and frequency indices, respectively, and \( s[l] \) denotes the standard deviation of the window function. \( \hat{X}[l,m] \in \mathbb{C}^{N \times N} \) stands for the frequency domain of the input signal \( \hat{x}[l] \) with \( N \) elements repeated \( m \) times. Furthermore, operators \( \odot \) and IFT represent the Hadamard product of the 2 matrices and the inverse Fourier transformation, respectively.

Taking advantage of the valuable information included in the input signal amplitude spectrum to distinguish between high- and low-amplitude frequency components according to their known positions (and by changing the optimisation direction from frequency to frequency shift) enabled us to use the amplitude spectrum to create the above-mentioned sparsity under the matrix formulation. According to the linear program provided by Sattari (2017), the change in the optimisation direction is performed by a simple transpose in the algorithm of the ST. This modification results in the optimised standard voice Gaussians along frequency shift (rows of \( A_{st}[l,m] \)) where smooth and differentiable random windows are automatically attained along frequency (columns of \( A_{st}[l,m] \)). The Gaussians’ window-length \( s[l] \) is supposed to be a curve reversely proportional to the smoothed amplitude spectrum \( \hat{x}_{sa}[l] \) with the scale between zero and one (Eq. 7).

\[ s[l] = \frac{L}{2} \left\{ \frac{1}{r \cdot \left| \hat{x}_{sa}[l] \right| + 1} \right\} \]  \hspace{1cm} (7)

where \( L \) is the length of the input signal and \( \left| \hat{x}_{sa}[l] \right| \) is its smoothed and scaled spectrum amplitude. The range of the curve is varied from 1 to \( r+1 \) using \( \left\{ \frac{1}{r \cdot \left| \hat{x}_{sa}[l] \right| + 1} \right\} + 1 \); thus, the reciprocal term is in the range 1/(\( r+1 \)) and 1. The range of \( s[l] \) is controlled by the parameter \( r \), which is readily adjustable owing to its linear behaviour. For example, according to their bandwidth and spectral diversity, we can select the \( r \) equals to 1 or 2 for band-limited signals, 3 or 4 for seismic signals and 5–10 for wide-band signals.

The arbitrary windows of SST follow the criteria of the partition of unity (Lamoureux et al. 2003), which means that the superposition of them on the columns of \( A_{st}[l,m] \) onto the frequency axis adds up to 1. This characteristic makes the adaptive SST invertible similar to the conventional ST by a simple projection of the SST map onto the frequency (Eq. 8).

\[ x[k] = \sum_{l=1}^{N} TFR_{ST}^{[l]}[l,k] \]  \hspace{1cm} (8)

Figure 1 compares the performance of the adaptive SST and the ST as well as the adaptive arbitrary windows applied to a non-stationary signal.
As a result, 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. This means it even performs better than the alternative energy concentration (ECM) methods used for adaptivity enhancement of Fourier-based spectral decomposition (Sattari et al. 2013). These methods are computationally heavy as they require computation of several time–frequency decompositions with different window-lengths, among which the sparsest result is searched for, while in the adaptive SST, the window parameters are optimally set to create sparsity. This makes the ECM methods impractical for real-world applications. In addition to the complexity, Sattari (2017) also showed the superiority of the adaptive SST over the standard ST and STFT optimised by ECM methods, in terms of robustness to noise, temporal and spectral interference resolution and the fact that it has only one free parameter to set (which is linear and well-behaved). However, under the low SNR, the SST is not stable. For these reasons, in this paper the TFR obtained via adaptive SST is filtered in the time–frequency domain.

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

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

(9)

**Improved Hilbert transform**

To resolve the problem of noise in the signal, 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

\[
g(\omega, \tau) = \frac{|X(\omega, \tau)|^{N-1}}{\arg \max_{\omega} (|X(\omega, \tau)|^{N-1})},
\]  

(10)
where $N$ is a weighting factor and $N \geq 1$, $|X(\omega, \tau)|$ is the amplitude spectrum of $X(\omega, \tau)$. The dominator in Eq. 10 is actually an optimisation subproblem to find the maximum value of $|X(\omega, \tau)|^{N-1}$ for each frequency, $\omega$. The term argmax denotes this process.

The analytic signal can be constructed as:

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

where

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

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. The weight factor proposed by Lu and Zhang (2013) reduces the noise at the cost of losing the signal and conclusively losing the subsurface information. Therefore, applying a weighting order to the obtained TFR in SST can not only result in high-resolution TFR as SST but can also suppress the noise, as well as RWHT with the difference that the signal maintained. The main purpose of the applied adaptive filter is the enhancement of instantaneous attributes estimation in noisy data, although it has an application in improving the other seismic attributes.

**Results**

The performance of the proposed method is validated by applying the synthetic and real data set. We compare the RSST in obtaining seismic attributes with the SST and RWHT method to observe the discrepancies in their performance.

**Numerical examples**

The choice of adaptive Fourier-based time–frequency decomposition is user-dependent, which is relevant to whether the type of analysis focuses on the time or frequency domain and, more important than that, the characteristics of the signal (Radad et al. 2015). Seismic data are narrow in frequency and wide in time; therefore, adaptive SST can be the best analytical choice, owing to the higher sparsity of the input frequency domain signal. Moreover, decomposition of the sparser version of the input signal can suppress the scattered random noise more efficiently in both the time and frequency domains, although not completely. The aforementioned facts are the reasons for applying SST in the first step to obtain high-resolution spectral attributes. In the following steps, a weight factor is added to the sparse TFR to suppress almost all of the noise available in the TFR; according to our scope of analysis, this results in a robust, high-resolution spectral amplitude.

To diagnose the superiority of the RSST over the SST and RWHT for decomposing narrowband signals, we compare the TFR of 5 non-stationary signals in Fig. 2. The signal, taken from Andrade et al. (2018), is a sum of 5 signals generated by a sampling interval of 0.003 s:

$$\begin{align*}
x_1(t) &= 0.8 \cos(30\pi t) & 0 \leq t \leq 6s \\
x_2(t) &= 0.6 \cos(70\pi t) & 0 \leq t \leq 6s \\
x_3(t) &= 0.7 \cos(130\pi t + 5\sin(2\pi t)) & 4s \leq t \leq 8s \\
x_4(t) &= \sin\left(\frac{8\pi 100^3}{\log(100)}\right) & 6s < t \leq 10s \\
x_5(t) &= 3e^{-1250(t-2)^2}\cos(710(t-2)) & 0 \leq t \leq 10s
\end{align*}$$

where $x_1$ is a harmonic component of 15 Hz, $x_2$ is another harmonic with 35 Hz, $x_3$ is a frequency-modulated harmonic of about 65 Hz, $x_4$ is a sliding harmonic from 35 to 158 Hz, and $x_5$ is a Morlet wavelet with a central frequency of 113 Hz. The signal is shown in Fig. 2, along with its corresponding TFR obtained by SST, RWHT and RSST.

As can be seen, the TFRs obtained by RSST give spectra with higher resolution and more stability, in terms of time or frequency or both. In this example, the values of the input parameters are the same. We set the value of $N$ and $r$ to be 2 and 10, respectively. The filtering effect of the RWHT method can be observed in the time–frequency panel, as indicated by arrows. In these regions, the energy of the signal is attenuated, while the result of RSST proves its capability in deriving a high-resolution time–frequency spectrum without losing the effective energy of the signal. This is the result of employing the sparsity properties of SST in the RWHT algorithm. Furthermore, in comparison with SST, the RSST method generates higher resolution.

In Fig. 3, we examined the performance of different approaches for a double-linear chirp signal. In this example, the time–frequency panels of the signal are estimated via 3 methods with a sampling interval of 2 ms and the maximum time of 2 s. For RWHT, the central part of the panel, in which the spectra of 2 chirp signals cross each other, has lost its information (the ellipse in Fig. 3). The amplitude of the 2 signals is distinct due to the filtering effect of the RWHT method (the arrows in Fig. 3). Of the 3 methods we
compared, the resolution of TFR obtained by the RSST is noticeably higher.

The adaptive filter \( g(\omega, \tau) \) defined in Eq. (10) tries to maintain signal information and avoid noise leakage into time–frequency panel. In Fig. 4, we added random noise to the chirp signal (Fig. 3) to demonstrate the role of the \( g(\omega, \tau) \). It can be seen that unlike the TFR obtained via the SST method, \( g(\omega, \tau) \) is similar to the desired TFR of the chirp signal (Fig. 4b). Meanwhile, multiplying the TFR(\( \omega, \tau \)) by \( g(\omega, \tau) \) causes that the random noise filtering carries out automatically, which results in higher resolution of the final TFR.

Although the SST reversely scales the global trend of the amplitude spectrum to be indifferent to the added noise, it is still susceptible to the random noise since the weight that the windows are applying to the signal is the same for the noise. Contrary to this, the RWHT method is robust in detecting the noise but at the cost of losing the signal. This point is depicted in Fig. 5 for a double-linear chirp signal with additive random noise of 1 dB SNR. The parameters taken in the example are the same as for the three TFRs for smoothing (\( r = 10 \)) in SST and RSST and de-noising (\( N = 7 \)) in RSST and RWHT. As can be seen, the RWHT method tries to de-noise the TFR panel, while most of the signal’s information has been lost in this domain. The resolution of the SST method suffers from the presence of noise which is not the case in the RSST method.

The value of the weighting factor (i.e. \( N \) in Eq. 10) is a crucial parameter in either RWHT or RSST. There is a trade-off between resolution resulted from applying the proposed filter and the SNR value. This trade-off is controlled by the value of \( N \). In the case of noise-free signals (or signals with high SNR), our goal is to increase the resolution of the time–frequency panel. Overall, \( 5 \leq N \leq 10 \) works well for high SNR values. However, in the presence of noise (i.e. low SNR), the noise filtering requires a high value of \( N \) at the cost of losing the resolution. In this regard, selecting the proper value of \( N \) is essential and requires setting a balance between resolution and de-noising criteria. Therefore, Fig. 6 shows the effects of this parameter on the results of the RSST method obtained for the noisy signal in Fig. 3. Based on the results, using high values of \( N \) results in losing some of the useful information in the signal (in the case of RWHT), while low values of \( N \) are incapable of dealing with noise (similar to SST).

The numerical examples show that the RSST outlines a higher resolution and is more robust to the noise when compared to the SST and RWHT. The input signal in this
Fig. 3  a Double chirp signal and b–d its time–frequency panel for methods RWHT, SST, RSST, respectively. The RWHT method has failed in the central part of the panel indicated by an ellipse. Also, 2 arrows demonstrate the effect of filtering the higher frequencies of the signal.

Fig. 4  The role of adaptive filter a TFR panel, b the adaptive filter, c final TFR panel after applying adaptive filter.
method can be regularised in time–frequency, while estimating the analytic signal owing to its low susceptibility to random noise. It is worth mentioning that regularising the true positions and amplitudes of different components in the time–frequency domain results in more accurate instantaneous attributes because the scattered energy in the time–frequency domain can cause fake complex indices.

**Wedge model**

To evaluate the performance of different methods, a synthetic wedge model is used in the next example (Fig. 7). For this case, we initiated the SNR value at 2 dB. After running the algorithms, the results of TFR for 3 single-frequency components are shown in Fig. 8. It can be seen that the RSST method outperforms the other methods. For low-frequency components (i.e. 5 Hz), 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 panel (the red box) is selected for a frequency of 20 Hz from all 3 methods, and this shows that the RSST method has dealt with the tuning effect successfully (Fig. 9).

In Fig. 10, the results of instantaneous amplitude and the cosine of phase attributes for the noisy wedge model are shown. As can be seen, the SST method gives higher-resolution results compared to the RWHT method. However, with respect to accuracy, it can be observed that the layers of the noisy model achieved by the RSST are of higher resolution and of lower noise. As can be seen in the instantaneous amplitude, the non-filtered SST ignores the presence of noise, while filtering via RSST smoothens them. The filtering applied in RWHT enhances the peak frequency contribution to the reconstructed analytic signal while causes the loss of the initial spectral bandwidth. Of the 3 methods compared, the instantaneous attribute obtained by the RSST is more robust and efficient in resolving interfered wavelets under the random noise while maintaining the preliminary bandwidth. The cosine of instantaneous phase achieved by the RSST proves the power of proposed method in resolving interfered wavelets with details although the SST represents almost the same result. The resolution in RSST has improved via
optimising window parameters and rendering the weight order to the signal in each selected window.

**Real data**

In this section, we consider the performance of 3 methods on both a 1D trace and 2D data set. In the first example, a real trace is chosen with a sampling interval of 2 ms and a recording time of 7 s (Fig. 11a). The related TFRs for different methods are also calculated with the same input parameters ($N = 10$ and $r = 15$).

Although an apparent trend is detectable in the time–frequency spectrum of the RWHT method, it is stretching along the frequency coordinate. On the other hand, the resolution of TFR obtained by the SST is not satisfactory. The RSST method successfully derived a meaningful trend with a sparse nature in the time–frequency panel.

The next example is an excerpted part of a 2D section with a sampling interval of 4 ms from the F3 block of the North Sea (Fig. 12). A bright spot, which is an anomaly caused by biogenic gas pockets, and gas chimneys in the deeper parts are shown in the data.

For these data, both the SST and RSST methods were run and the resulting instantaneous frequency is shown in Fig. 12. In the deeper parts of the data, which are related to the presence of gas chimneys, the low frequencies are...
visible due to the seismic energy absorption. This abrupt reduction in the instantaneous frequency is more obvious in the results obtained by RSST than the SST counterpart. Furthermore, the bright spot is successfully detectable from instantaneous frequency information derived by the RSST method than the SST.

**Conclusion**

In this paper, we have looked at the problem of estimating a stable, high-resolution complex trace analysis within the framework of sparsity-based optimisation and time–frequency spectrum weighting orders. Poor-resolution and noise problems in the time–frequency domain illustrate the necessity for a stronger method to deal with these shortcomings. Therefore, the sparsity-based, adaptive S-transform was proposed as a spectral decomposition tool to enhance the resolution of the time–frequency WHT. The optimised windows satisfied the requirements for regularisation of abrupt frequency changes and were superior to the previous methods, in terms of computational cost and interference removal without leading to fake indices, although they were vulnerable to random noise. Therefore, the proposed spectral decomposition is improved via a zero-phase adaptive filter.
to suppress the residual noise by enhancing the frequency components with larger amplitudes. As for the computational cost, the proposed method was slightly slower than SST because of extra de-noising in TFR; however, it was faster than RWHT due to an additional inverse Fourier transform.

The proposed robust spectral decomposition approach was conclusively used to implement complex trace

Fig. 10 Complex trace analysis for the noisy wedge model. Cosine of phase attribute (a–c) and instantaneous amplitude (d–f).

Fig. 11 Time–Frequency analysis of a single trace obtained via b the RWHT, c the SST and d the RSST.
analysis of synthetic and real data sets. The results proved that the power of robust, adaptive ST in regularising the abrupt frequency changes and suppression of random noise resulted in high-resolution and robust instantaneous attributes, compared to the conventional methods that ignore these changes. Indeed, the proposed method regularised 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 is an adaptive, high-resolution, invertible and frequency-dependent time–frequency decomposition approach that has vast implications for interpreting complex trace analyses. It should be mentioned that the reason for using ST in this procedure (as a spectral decomposition) was relevant to the input data and corresponding applications and other transforms (like STFT) could also be used.

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