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Detecting buried channels using linear least square RGB color stacking method based on deconvolutive short time Fourier transform

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Abstract

Buried channels are one of the stratigraphic hydrocarbon traps. They are often filled with a variety of porous and permeable sediments so they are important in the exploration of oil and gas reservoirs. In reflection seismic data, high-frequency components are sensitive to the channel thickness, whereas, low-frequency components are sensitive to the channel infill materials. Therefore, decomposition of seismic data to its spectral components provides useful information about both thickness and infill materials of buried channels. A 4D spectral data is produced by applying spectral decomposition to a 3D seismic data cube which is decomposed into several single frequency 3D cubes. Since different frequencies carry different types of information, each single frequency cube cannot show all subsurface information simultaneously. Therefore, we used color stacking method and constructed RGB plots, which represent more information than single frequency volumes. In this paper, we applied three methods of Deconvolutive Short Time Fourier Transform (DSTFT), S Transform (ST) and Short Time Fourier Transform (STFT) to a land seismic data from an oil field in the south-west of Iran. We used the resulting spectral volumes to create RGB color stacking plots for tracing buried channels. According to the results, the RGB plots based on the DSTFT method revealed more details than the ST and STFT methods.

Key words: buried channels, spectral decomposition, deconvolutive short time Fourier transform, color stacking method

1 Introduction

Ancient stream channels are usually involved with hydrocarbon accumulation. Channels due to different sedimentation may have different velocity in comparison with surrounding layers. So it is important for an interpreter to detect channels and determine their lateral continuation. In reflection seismic data, high-frequency components are sensitive to channel thickness and low-frequency components are sensitive to the channel

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infill materials. Therefore, decomposition of seismic data to its spectral components can provide good information about both thickness and infill materials of buried channels (Guo et al., 2006, 2009; Liu and Marfurt, 2007b; Nikoo et al., 2012; Sadeghi et al., 2014). Due to the non-stationarity property of seismic signals, time-frequency transforms have widely been used in seismic data interpretation. The time-frequency transforms can reveal the characteristics of the signal that are not easily observed at the time or the frequency representation. There are various methods for spectral decomposition of signals such as short time Fourier transform (STFT) (Gabor, 1946; Sattari et al., 2013), wavelet transform (Mallat, 1999, 2008), Wigner–Ville distribution (WVD) (Wigner, 1932; Ville, 1948; Roshandel Kahoo and Nejati kalatah, 2011), and S transform (Stockwell et al., 1996). In spite of the wide applications of the conventional time-frequency transforms, they have some disadvantages. The resolution of the STFT strongly depends on the length of the window function and the applications of the WVD are limited by cross-terms (Boashash, 2003; Boashash, 2015). Auger et al. (1996) introduced smoothed pseudo WVD (SPWVD) to eliminate the cross-terms. Smoothing the WVD leads to a trade-off between the time-frequency resolution and cross-terms elimination. When the smoothing function is replaced by the WVD of window function used in STFT, the SPWVD will become the STFT spectrogram (Zhang and Lu, 2010; Lu and Li, 2013; Zarei et al., 2012). There are no cross-terms in STFT spectrogram, but it has low resolution in time and frequency. Therefore, a 2D deconvolution operator can be used instead to generate a high time-frequency representation of a signal with no cross-terms. The resulting spectrogram after 2D deconvolution is called deconvolutive STFT or DSTFT.

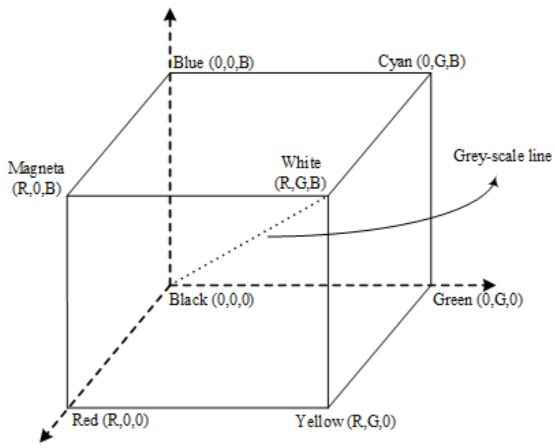


Figure 1. Schematic view of primary colors and their intensities in RGB color model (after Plataniotis and Venetsanopoulos, 2000).

Each 3D seismic volume is decomposed into a group of single frequency 3D volumes (or, alternatively, a 4D volume). An interpreter investigates the single frequency 3D volumes individually by producing the frequency slices from them at the target horizon time (Fahmy et al., 2005). The most common means of investigating these components is simply by scrolling through them to determine manually which single frequency best delineates an anomaly of interest. The simultaneous interpretation of all single frequency 3D volumes and their slices is very difficult even for a professional interpreter. Since different frequencies contain different types of information (low frequencies are sensible to channel content and high frequencies are sensible to channel boundaries), these single frequency 3D volumes can be combined to create a new 3D volume, which has all of the information simultaneously. One of the best methods of combining the single frequency 3D volumes is the Red-Green-

Blue (RGB) plot (Onstott et al., 1984; Theophanis and Queen, 2000; Stark, 2005; Liu and Marfurt, 2007a; Sadeghi et al., 2012). Although RGB images achieved from this method have more acceptable quality in comparison with single frequency scanning method, but they ignore a big part of frequency bandwidth. In this workflow, we constructed RGB plot using three predetermined cosine raised basis functions (Liu and Marfurt, 2007b). We used the linear least square method to approximate the spectrum by these basis functions and plotted the coefficients against red, green and blue. This method is less time consuming and displays moderate details of full amplitude spectrum (Liu and Marfurt, 2007b). Our results showed that RGB color stacking method produces more detailed images than single frequency representation method. We also showed that DSTFT due to better time and frequency resolution, produces more precise RGB images in comparison with ST and STFT results.

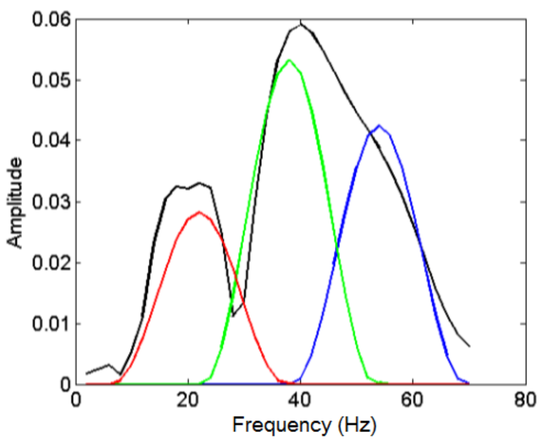


Figure 2. schematic view of least square coefficients of fitted basis functions to instantaneous frequency versus amplitude (black line).

2 Deconvolutive Short Time Fourier Transform (DSTFT)

There are different methods which perform spectral decomposition on signals. Short time Fourier transform (STFT) is a technique which is carried out by multiplying a time window to the signal. The STFT of signal $x(t)$ is given by (Zhang and Lu, 2010):

$$STFT\left(t,f\right)=\int_{-\infty}^{+\infty}x(u)h^{*}(u-t)e^{-(2\pi ifu)}du \tag{1}$$

where, $h(u-t)$ is the window function and * means conjugate transpose. The STFT spectrogram, which is the squared modulus of the STFT, is given by (Lu and Li, 2013):

$$SPEC(t,f)=\left|STFT\left(t,f\right)\right|^{2}. \tag{2}$$

But the resolution of its spectrogram may be affected by the length of the window. A good time resolution requires a short time window and a good frequency resolution requires a narrow-band filter, i.e. a long time window, but unfortunately, these two cannot be simultaneously granted. The Wigner–Ville distribution (WVD) is an alternative technique which solves the problem of time and frequency localization but its application is limited due to the presence of the cross-terms. In order to suppress the cross-terms, a 2D smoothing function is applied to the WVD of the signal but this may reduce the time-frequency resolution too. Several methods such as Pseudo WVD or PWVD and Smoothed Pseudo WVD or SPWVD have been introduced to eliminate the cross-terms (Auger et al., 1996). The WVD of signal $x(t)$ is given by (Boashash, 2015):

$$WVD(t,f)=\int_{-\infty}^{+\infty}x(t+\frac{\tau}{2})x^{*}(t-\frac{\tau}{2})e^{-j2\pi f\tau}d\tau, \tag{3}$$

where * denotes conjugate transpose. The SPWVD of the signal $x(t)$ is defined as Eq. (4) (Boashash, 2015):

$$SPWVD_x(t, f) = \int_{-\infty}^{+\infty}\int_{-\infty}^{+\infty} \varphi(u, \tau) \times WVD(t-u, f-\tau)\,du\,d\tau. \quad (4)$$

If we choose the kernel function $\varphi(u,\tau)$ as the WVD of the window function, the result will be the STFT of the signal $x(t)$ and can be expressed as 2-D convolution form Eq. (5) (Zhang and Lu, 2010):

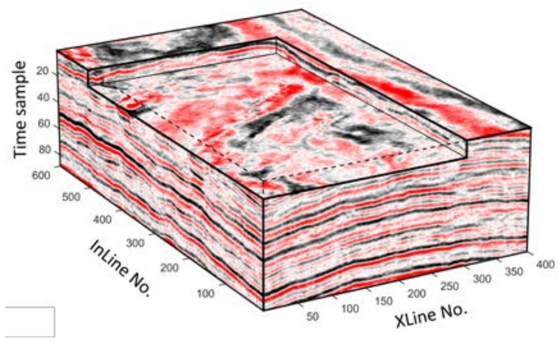
$$SPEC_x(t, f) = WVD_h(t, f) ** WVD_x(t, f), \quad (5)$$

where $WVD_h(t, f)$ and $WVD_x(t, f)$ are the WVDs of the window function $h(t)$ and the signal $x(t)$, respectively.

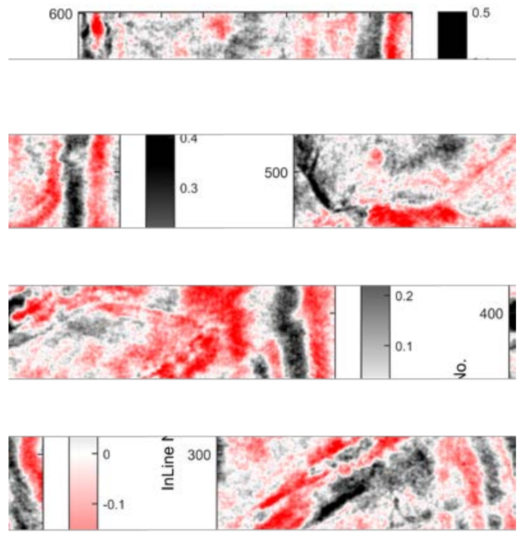
$SPEC_x(t, f)$ has poor time and frequency resolution, but the problem of cross-term interferences is almost obviated. By applying 2-D deconvolution to the STFT spectrogram by Lucy–Richardson algorithm a good estimate of WVD_x can be achieved which has an acceptable time and frequency resolution and no cross-term interferences as (Lu and Zhang, 2009):

$$WVD_x^{k+1} = WVD_x^k \left(WVD_h ** \frac{SPEC_x}{WVD_h ** WVD_x^k} \right), \quad (6)$$

where $k+1$ is the iteration number and $WVD_x^0 = SPEC_x$. The obtained spectrogram is called deconvolutive short time Fourier transform (DSTFT) which has a suitable resolution as WVD and no cross-term interference.



(a)



(b)

Figure 3: (a) 3D view of reasl seismic data and (b) horizontal slice from real seismic data at time sample 12.

3 S Transform

S transform (Stockwell et al., 1996) is one of time–frequency transforms combining elements of short time Fourier transform (STFT) and wavelet transform (WT). It uses analyzing window having a width inversely and a height linearly scaled with the frequency. Scaling will improve frequency resolution for both high and low frequencies like WT but in addition it maintains the absolute phase of frequency components. The S transform of signal $x(t)$ can be given by (Stockwell et al., 1996):

$$ST(t,f)=\int_{-\infty}^{+\infty}x(\tau)\frac{|f|}{\sqrt{2\pi}}e^{-\frac{(t-\tau)^2 f^2}{2}}e^{-2\pi i f\tau}d\tau. \qquad (7)$$

4 RGB color stacking method

RGB images, also known as true color images, are $M\times N\times 3$ arrays which R denotes the red, G the green and B the blue component of each pixel. The intensity of each component varies between 0 and 1. So (0, 0, 0) defines the black color and (1, 1, 1) defines the white color. As can be seen in Figure 1, when the intensity of one component is higher than the others, the final color of the pixel tends to that component and when two components have the same intensity, the final color tends to secondary colors.

One of the first multi-attribute displays was introduced by Onstott et al. (1984). They plotted near-, middle- and far- angle stacks to red, green and blue components to obtain a color stack model for investigating amplitude variation with offset (AVO). Bahorich et al. (2002) applied this method to spectral components (i.e. single frequency slices) to construct simple RGB images. This will lose a big part of information existing in the unused spectral components. Stark (2005) computed average frequencies and mapped them against red, green and blue (low frequency average against red, middle frequency average against green, and high frequency average against blue). Sadeghi et al. (2012) used the ST and STFT transforms for decomposition of seismic data. They constructed RGB plots by basis functions. By using basis functions and defining windows, they introduced some frequency intervals and plotted them versus primary components. Three simple raised cosine functions with different frequency centers and different periods were chosen. Although it improved the images quality, but it was time consuming. An alternative method is carried out by approximating the spectrum with cosine raised basis functions (Liu and Marfurt, 2007b) and finally by mapping the coefficients against red, green and blue. In this workflow, we used the DSTFT method (rather than the STFT and ST) for spectral decomposition and linear least square method to reduce timing and improve the results. Figure 2 shows a schematic view of the least square coefficients of the fitted basis functions to instantaneous frequency versus amplitude (black line).

The equation we have used for basis function is given by (Liu and Marfurt, 2007b):

$$\text{Basis function}=\frac{1}{2}\left(1+\cos\left(\frac{\pi\left(f-f_{RGB}\right)}{k\times f_{bandwidth}}\right)\right), \qquad (8)$$

where f_{RGB} is the frequency center of different intervals, $f_{bandwidth}$ is frequency bandwidth of seismic data and k is an arbitrary constant. It is obvious that the magnitude of k, directly affects the length of basis function window. So a larger value of k will lead to including a bigger part of spectral components and consequently, it affects RGB images quality. That is, the bigger magnitude of k will result to closer coefficients and consequently to a grey scale image.

5 Results for real seismic data

The RGB plots can reveal events with sharp frequency response such as features with varying trends and varying lithology and buried channels have these kinds of properties.

Figure 3a demonstrates the of the real seismic data of an oil field in SW of Iran

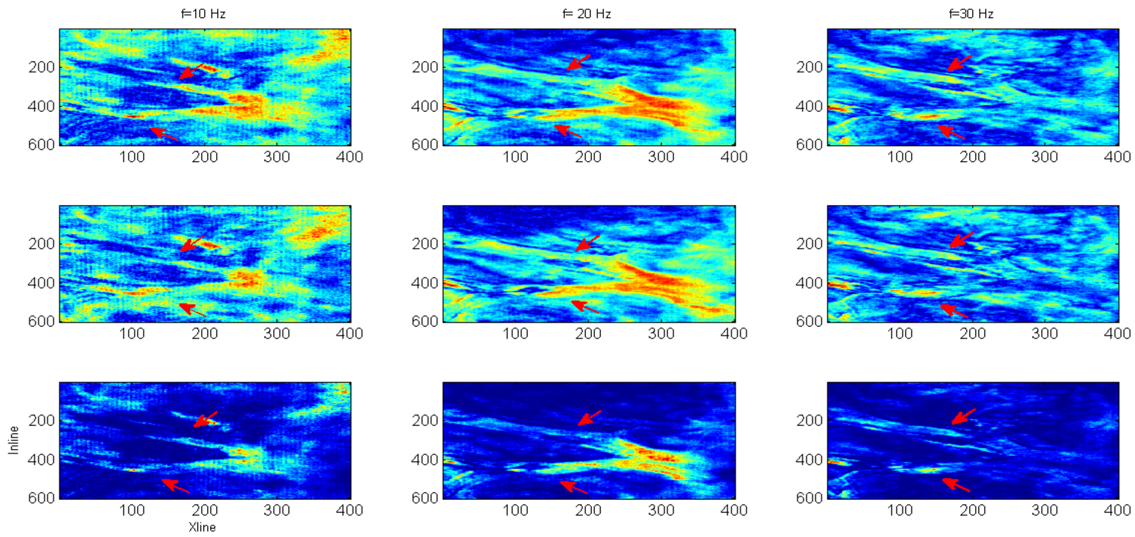


Figure 4. Single frequency slices corresponding to the frequencies 10, 20, 30 Hz (left, middle and right columns, respectively) for the STFT, ST and DSTFT (upper-, middle- and lower-row, respectively).

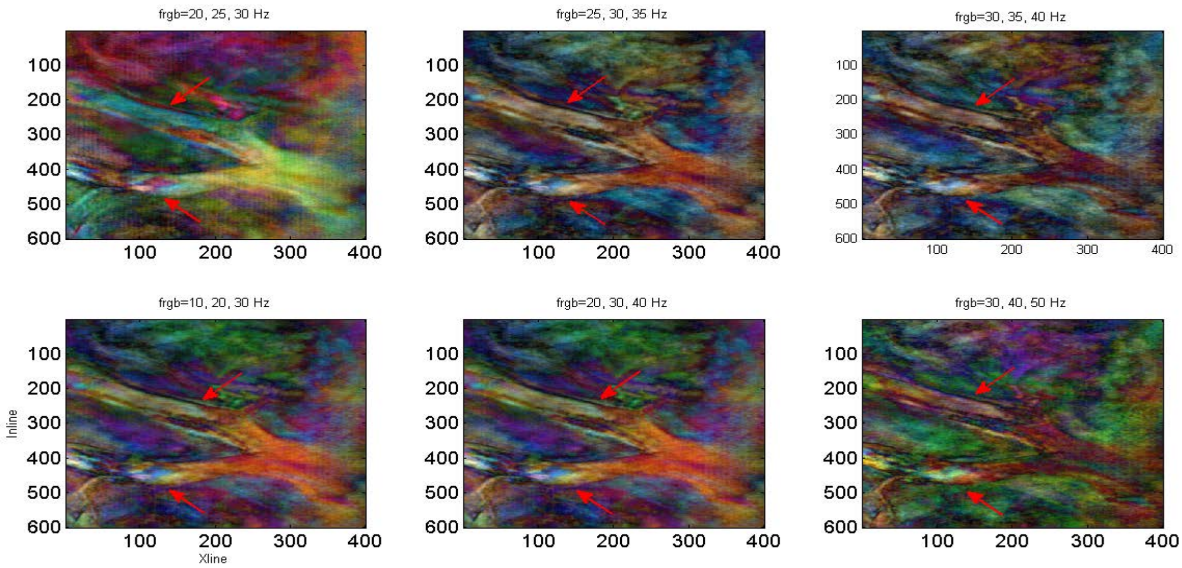


Figure 5. The RGB plot exhibition of spectral frequencies for the STFT ($k = 0.075$).

having 601 inline number and 400 xline number. Frequency band width of data is 70 Hz.

According to the unpublished reports, we expect a buried channel at the time sample 12. Figure 3b shows a horizontal slice view at the same time sample extracted from the seismic volume. The anticipated channel is not much clear in this time slice.

Figure 4 (up-, middle- and bottom-row) shows single frequency slices of 10, 20, 30 Hz for STFT, ST and DSTFT respectively. We can see that infill material of the channel has a higher amplitude in low frequency slices but boundary resolution is not sharp. Conversely, the amplitude of infill material is lower in high frequency slices but boundary resolution grows up. An expert interpreter may achieve some information by observing variations in these spectral components. Figures 5 through 7 show least-square based RGB images of the Figure 4, for the STFT, ST and DSTFT, respectively. As one can see, the STFT and ST images do not have considerable differences but the DSTFT because of better time and frequency resolution, has generated images with more color contrast and less color interference. So it delineates channel boundaries precisely.

Also we can see that different centers reveal different details. The low frequency centers show channel content properties, and the high frequency centers show channel boundaries better.

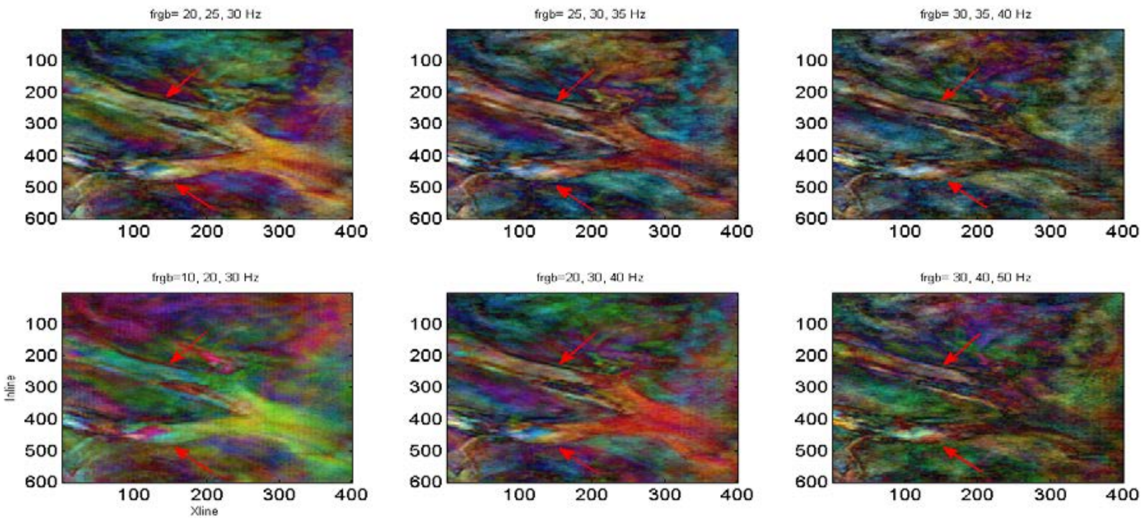


Figure 6. The RGB plot exhibition of spectral frequencies for the ST ($k = 0.075$).

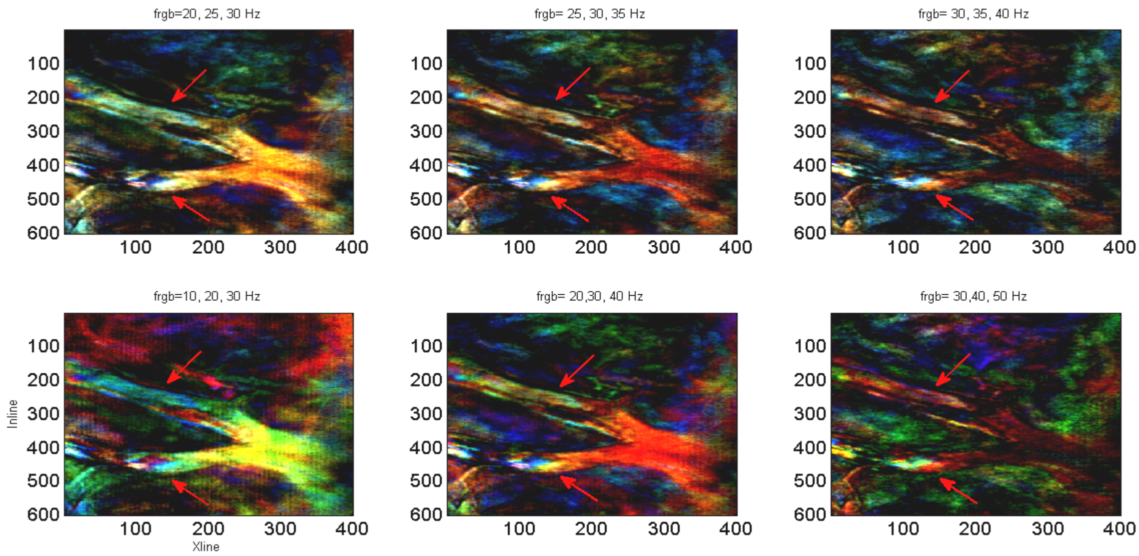


Figure 7. The RGB plot of spectral frequencies for the DSTFT ($k = 0.075$).

6 Conclusions

In this paper, we investigated the potential of the RGB images in representing subsurface details contained in 3-D seismic data cubes. The RBG generated images were compared to those obtained from horizontal slices of constant frequency cubes. Comparing the results showed that the single frequency slices did not reveal the fine quality image and did not show all the features existing in the data. However, the RGB images exposed channel and its fine branches without requiring the generation of 3-D single frequency volumes. We showed that due to the better time and frequency localization of the DSTFT, its images had better color contrast in comparison with the ST and STFT, and channel boundaries were precisely identified.

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