ATTRIBUTE-ASSISTED FOOTPRINT SUPPRESSION USING A 2D CONTINUOUS WAVELET TRANSFORM
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SUMMARY

Acquisition footprint manifests itself on 3D seismic data as linear grid pattern of noise on time or horizon slices. Ideally, footprint suppression should be handled in the processing workshop. Unfortunately this is not an option for vintage poststack volumes where no pre-stack data exist. In this work we explore the use of a modified Continuous Wavelet Transform in a bid to suppress the footprint. The method involves decomposing the time slices of the seismic data and attributes into voices and magnitudes using raised-cosine filters. We rely on seismic attribute ability to highlight acquisition footprint to design a mask to suppress it.

INTRODUCTION

The interpretation of 3D land and marine seismic data and attribute analysis can be quite challenging in the presence of severe acquisition footprint. To avoid these artifacts a dense acquisition survey should be implemented. Alternatively, one should treat footprint in the processing workshop through the use of 5D interpolation for instance. Understanding the causes behind these artifacts is key to suppressing them. Hill et al. (1999) provide a detailed analysis on the origin of acquisition footprint. Marfurt et al. (1998) classified footprint into two types, first, is correlated to the source-receiver geometry pattern. Spars 3D acquisition, bin to bin fold spacing and offset azimuth variation fall under this category. The second is due to seismic data processing. Inaccurate velocities, imaging aperture and inaccurate statics fall under this category.

A notable feature of footprint noise is that there is an appearance of periodicity to it regardless of the directivity and pattern of noise in a time slice. Therefore, it may be possible to reduce its effect on the interpretation of seismic data. Sahhui et al. (2006) proposed the use of simple 2D pass filter in the \( kx - ky \) domain to suppress the footprint. Chen et al. (2012) used an adaptive Stationary wavelet transform to suppress footprint and other random noise. Al-Bannagi et al. (2004) used truncated singular value decomposition for the same purpose. Drummond et al. (2000) used adaptive noise estimation to filter footprint.

In this paper we present a straight forward modified Continuous Wavelet Transform (CWT) to suppress noise. In recent years the CWT has been implemented into the field of geophysics most notably with the advent of the spectral decomposition algorithm. Chakraborty and Okaya (1995) showed the benefits of applying a CWT based spectral decomposition in order to delimit different seismic events, such as reflections and different types of noise. Other usage include seismic bandwidth extension (Smith, et al., 2008). In this work we propose to use 2D CWT to suppress footprint on poststack data.

DATA

A seismic volume from Vacuum field, New Mexico, is used in this project. This is a vintage data acquired in the 1970s and shows strong acquisition footprint in the first 500 ms. Figure 1 show a time slice at 450 ms through the seismic amplitude and coherency.

THEORY

Fourier Transform:
Following Liner (2010), we define the 2D Fourier transform \( f(k_x,k_y) \), as:

\[
\hat{f}(k_x,k_y) = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} f(x,y) e^{-2\pi i (k_x x + k_y y)} dx dy
\]  

(1)

where \( f(x,y) \) is the seismic data/attribute time slice and \( i = \sqrt{-1} \). Figure 2 shows the \( k_x - k_y \) domain of the time slice and attribute slice through the Vacuum field data set shown in Figure 1. The Fourier Transform provides information about the frequency content of a given signal, but sacrifices time resolution in the process. For this reason, several approaches have been proposed in order to extract the best frequency content while preserving the original time resolution of the signal. One such approach is the Continuous Wavelet Transform.

Continuous Wavelet Transform:
We define the 2D wavelet transform following as Liner (2010):

\[
\mathcal{F}(a,b,\kappa,\nu) = (ab)^p \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} f(x,y) \psi(\frac{x-k}{a}) \psi(\frac{y-v}{b}) dxdy
\]  

(2)

where \( \mathcal{F}(a,b,\kappa,\nu) \) refers to the transformed function, \( f(x,y) \) is the original function in the space domain and \( \psi \) is the wavelet applied to the function. \( a \) and \( b \) are the scaling parameters, while \( \kappa \) and \( \nu \) are shifting values. Note that the wavelet applied may differ for each dimension.

Filter Banks:
A filter bank is a system that divides an input signal into a set of analysis signals, each of which correspond to a different region in the spectrum of the original signal (Cassidy and Smith, 2008). We design the filter bank by dividing the wavenumber domain of the data into a grid of \( n_{k_x} \times n_{k_y} \) components. Then we use a 2D raised-cosine to represent the wavelets’ spectrum in the wavenumber domain. Figure 3 shows the 9 components (center and 8 outer components) of filter bank in the wavenumber domain generated using \( 11 \times 11 \) components. Further, Figure 4 shows 2D wavelets of the spectrums shown in Figure 3. Based on the number of components used to design the filter
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bank, the corresponding 2D wavelet will change. Hence we can consider the number of components as the variable controlling the scale $a$ and $b$ in equation 2. We transform the data to the space domain after applying the filter bank and obtain a 4D matrix $\mathcal{F}(n_{kx}, n_{ky}, x, y)$, where $n_{kx}$ and $n_{ky}$ are the number of components defined along $k_x$ and $k_y$ and $x$ and $y$ are the 2D spatial dimensions. We define the voices and magnitudes for the component $(i, j)^{th}$ to be

$$mag(i, j) = |\mathcal{F}(i, j, x, y)|$$

$$voc(i, j) = \Re[\mathcal{F}(i, j, x, y)]$$

where $mag$ are the magnitudes, $voc$ are the voices and $\Re$ is the real part. Ultimately, one can consider the voices and magnitude as the data decomposed into different wave number content using the 2D wavelets.

**Mask:**

The mask, $m(i, j)$, applied to the $(i, j)^{th}$ component is generated using the magnitudes, $mag(i, j)$, of an attribute sensitive to footprint (such as coherence or curvature) and is defined as

$$m(i, j) = 1 - \frac{\epsilon \cdot mag(0, 0)}{voc(0, 0) + mag(i, j)}$$

where $mag(0, 0)$ is the zero wavenumber (or constant background magnitude component) and $\epsilon$ is a fractional value. Equation 4 allows us to reject CWT components that are significantly greater than a user-defined percentage of the background value. Thus, if $mag(i, j) < \epsilon \cdot mag(0, 0)$, the mask, $m(i, j) \approx 0$, and the $(i, j)^{th}$ component is rejected. In contrast, if $mag(i, j) \approx \epsilon \cdot mag(0, 0)$, the mask, $m(i, j) \approx 1$ and the $(i, j)^{th}$ component is kept.

The value of ranges between 0 and 1, with higher values rejecting more magnitudes. We apply the mask to the voices and reconstruct the footprint component of the data. We then adaptively subtract the noise estimated from the original data. The reconstructed data, lacking the voice(s) representing the footprint, is a more interpretable data set with better signal. Since we use single “wavelet characteristics” for each slice we prefer to call this method a modified CWT.

To put things in perspective, we show the workflow of the code we implemented in Figure 5.

**RESULTS**

To illustrate how the technique works, we apply the code to the Vacuum field data using $11 \times 11$ components and $\epsilon = 0.12$. We display the 9 center components for the magnitude and voices of the amplitude and coherence. Figure 6 shows the magnitudes of the amplitude data. The center $(0,0)$ component $6.e$ shows a similar pattern to that seen of the amplitude data in Figure 1. The magnitude in Figure 6b and 6h show a weak vertical trend. While Figure 6d and 6f show a weak horizontal trend. Next, we consider the voices of the amplitude data shown in Figure 7. The trends on the voices are more apparent than on the magnitudes. Figure 7b and 7h show a vertical trend, while Figure 7d and 7f show a horizontal trend and four corner magnitude show a diagonal trend. These patterns are a consequence of the 2D wavelet in the space domain. Notice how the central part of the seismic amplitude is differentiated by a strong amplitude contrast, possibly generated from dipping layers. The rest of the time slice is more heavily affected by a footprint due to the generally low values of the attribute. The 9 center magnitudes of the coherence attribute are shown in Figure 8. We do not observed a preferred orientation/trend in all magnitudes. This leads us to think that the magnitude of the coherence is sensitive to the noise but not to the geology. Thus, the magnitudes of the coherence become the best candidate to compute the mask to filter out the noise For this purpose, we use the magnitude generated from the coherence to compute the mask.

Figure 9 shows the voices of the amplitude data. We observe the vertical trend on Figure 9b and 9h. While Figure 9d and 9f show a horizontal trend. Finally, the four corners show a diagonal trend. All the trends seen on the different components have preserved the geology.

Figure 10 shows the result after applying the mask and reconstructing the filtered data. We notice that most of the noise is removed while preserving the geology. Calculating attribute on this data is more desirable for interpreters over the previous one. Finally, Figure 11 shows the $k_x$ and $k_y$ transform of the filtered data. Compared with Figure 2a, we see that a lot of periodic noise is suppressed and the geology representation remained unaltered.

**CONCLUSION**

For reasons of cost and site access, many 3D vintage surveys can not be reshott. Old data are often contaminated by footprint. Ideally, footprint should be dealt with in the acquisition / processing workshop. We present in this work an effective method using a modified CWT to suppress footprint and random noise on time slice. As demonstrated by the real data example, the user needs to ensure the balance between the number of components in the filter bank and threshold ($\epsilon$) to filter the footprint. Results from the vacuum 3D data are promising. The code can significantly impact structural and stratigraphic interpretation as well as the performance of subsequent coherence algorithms.

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Figure 1: Time slice at 450 ms through (a) amplitude and (b).

Figure 2: Time slices $k_x k_y$ transforms of (a) amplitude (b) coherence shown in Figure 1.

Figure 3: The 9 center wavelets in the space domain from $11 \times 11$ components filter bank.

Figure 4: The center trace of the wavelets in the space domain from $11 \times 11$ components filter bank.

Figure 5: $K_x K_y$ CWT code work flow.
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Figure 6: The 9 center CWT magnitudes corresponding to the time slice shown in Figure 1a.

Figure 7: The 9 center voices for the amplitude data shown in Figure 1a. Note the geology leaks into (b), (h) and (d), (f).

Figure 8: The 9 center magnitude for the coherence attribute shown in Figure 1.

Figure 9: The 9 center voices for the coherence attribute shown in Figure 1b. Note the lack of geology but strong the footprint in (b), (h) and (d), (f).

Figure 9: Filter data after CWT processing.

Figure 10: $k_xk_y$ transform of the filtered data.
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