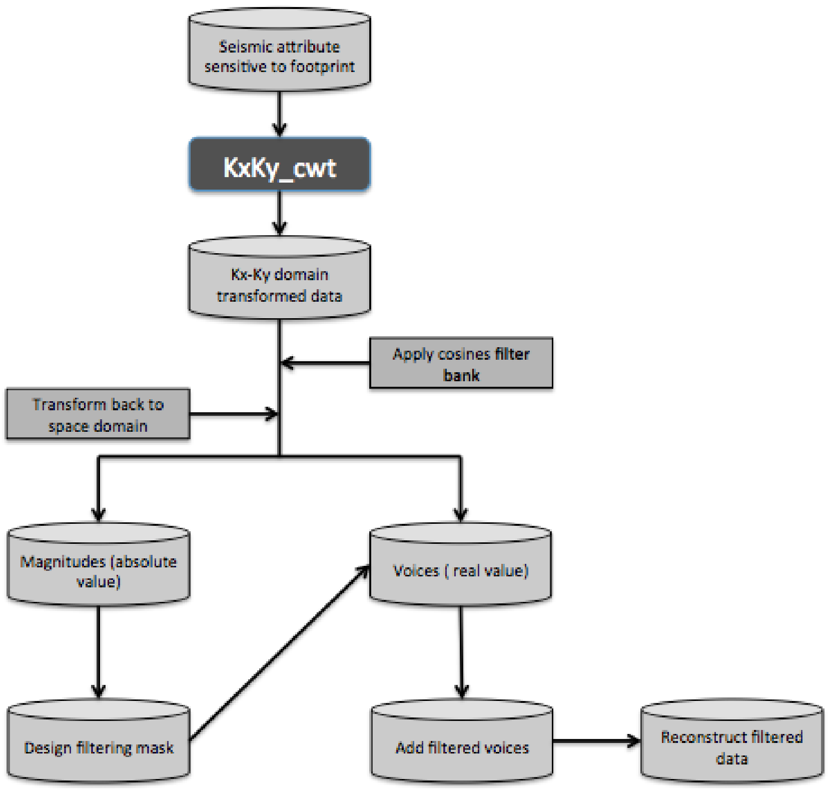
ATTRIBUTE-ASSISTED FOOTPRINT SUPPRESSION USING A 2D CONTINOUS WAVELET TRANSFORM: PROGRAM kxky_cwt

Contents

Overview

Acquisition footprint manifests itself on 3D seismic data as linear grid pattern noise on time slice or horizon amplitude. Ideally, acquisition footprint should be handled in the processing workshop with careful attention (Hill et al. 2009). Unfortunately, this is not an option for vintage poststack volumes where no prestack seismic data exits. In this work we explore the use of a modified Continues Wavelet Technique in a bid to suppress the footprint. The method involves decomposing the data slices into voices and magnitudes using filter bank operators. We rely on seismic attribute ability to highlight acquisition footprint to design a mask to suppress it on seismic and attribute volumes.

Computation flow chart



The AASPI footprint suppression GUI is found under *AASPI Workflows*.

Theory: Fourier Transforms, the CWT, and Filter Banks

- Fourier Transform:

The foundation for our work is the Fourier Transform and its corresponding analysis. Following C. Liner (2010), we can define a function $f(x,y)$ in the space domain and it's Fourier Transform $\hat{f}(k_x,k_y)$ as:

$$\hat{f}(k_x,k_y) = \iint_{-\infty}^{\infty} e^{-2\pi i(xk_x,yk_y)} f(x,y)dxdy \qquad (1)$$

where the scaling constant have been omitted and $\mathrm{i} = \sqrt{-1}$. The Fourier Transform provides information about the frequency content of a given signal, but scarifies time resolution in the process. For this reason, several approaches have been taken in order to get the best frequency content while preserving the original time resolution of the signal. One of such approaches is the Continuous Wavelet Transform.

- Continues Wavelet Transform:

We will define the wavelet transform in a similar fashion as C. Liner (2010), applying the concept in the space domain. Thus:

$$F(a,b,\kappa,\upsilon) = (ab) \iint_{-\infty}^{\infty} \psi \frac{(x-\kappa)}{a} \psi \frac{(y-\upsilon)}{b} f(x,y)dxdy \qquad (2)$$

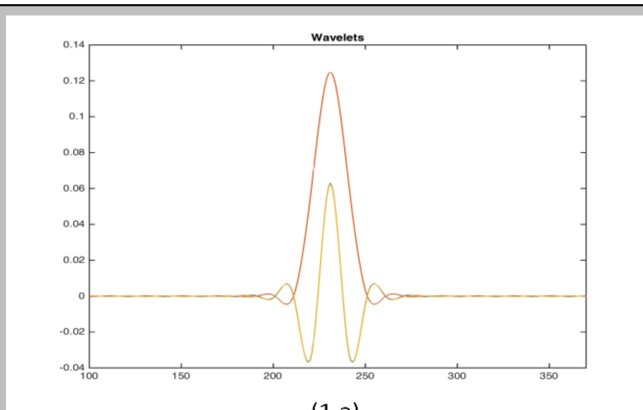
where $F(a,b,\kappa,\upsilon)$ refers to the spatial function in the wavelet domain, $f(x,y)$ is the original function in the space domain and ψ is the wavelet applied to the function. "a" and "b" are the scaling parameters, while "κ" and "υ"are the shifting values. The wavelet applied may or may not differ for each dimension.

- Filter Banks

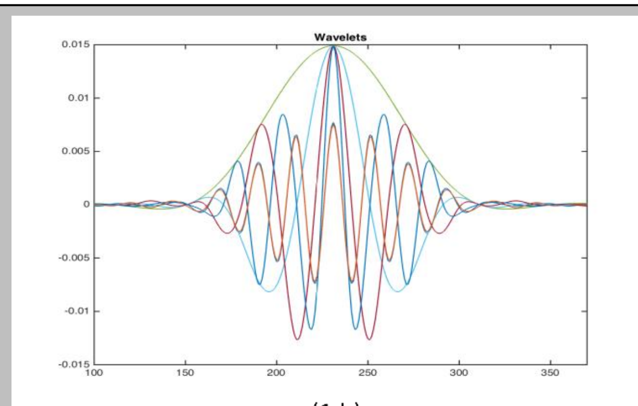
A filter bank is a system that divides an input signal into a set of analysis signals, each of which correspond to a different region in the spectrum of the original signal (Cassidy and Smith, 2008). The design of the filter bank was very simple: Raised-cosine based wavelets were created with an argument that is modified depending on the region of the wavenumber domain that is being analyzed. The general form of such cosines will be:

$$\mathrm{FB2D}(\mathrm{k_{cx}}) = \left(\cos\frac{\mathrm{k_{cx}}\pi}{2}\right)^2 \qquad (3)$$

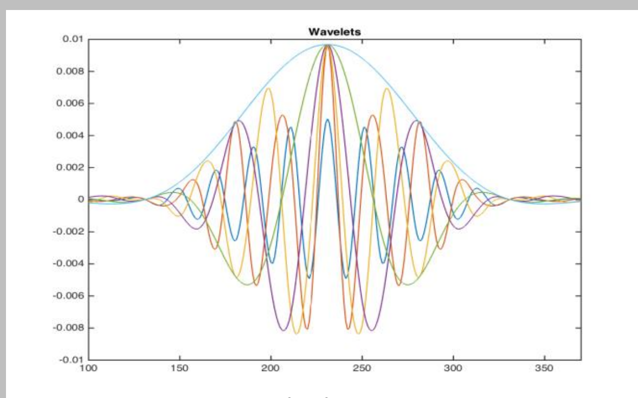
where $\mathrm{FB2D}(\mathrm{k_{cx}})$ is the filter bank being applied and $\mathrm{k_{cx}}$ is the central wavenumber component analyzed. To appreciate how the filter bank changes with different parameters, let's consider figure (1.a). It shows the central trace from the filter bank in the space domain generated using 3 x 3 components in the wavenumber domain. Based on the number of components used to design the filter 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) above. Figures (1.b) and (1.c) show the central trace in the space domain for a filter bank generated using 9 x 9 and 11 x 11 components. Finally, figure 2 shows in 2D the 9 center components of the 11 x 11 in the space domain. Essentially, the filter bank enables us to generate voices (real value) and magnitude (absolute value). The voices and magnitude are the result of breaking the data using 2D wavelets into different frequency content.



(1.a)



(1.b)



(1.c)

Figure 1: (a) Center trace from a filter bank generated using 3 x3 components, (b) center trace from a filter bank generated using 9 x 9 components and (c) center trace from a filter bank generated using 11 x 11 components. Notice how the number of component in the wavenumber domain changes the behavior of the wavelet in the time domain.

Theory: Defining a filter mask

The mask, *m(i,j)*, applied to the *(i,j)th* component is generated using the magnitudes, *a(i,j)*, of an attribute sensitive to footprint (such as coherence or curvature) defined as

$$m(i,j) = 1 - \left(\frac{\varepsilon a(0,0)}{\varepsilon a(0,0) + a(i,j)}\right) \quad , \tag{4}$$

where *a(0,0)*, is the zero wavenumber (or constant background magnitude component) and ε 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 $a(i,j) \ll \varepsilon\, a(0,0)$, the mask, $m(i,j) \approx 0$, and the *(i,j)th* component is rejected. In contrast, if $a(i,j) \gg \varepsilon\, a(0,0)$, the mask, $m(i,j) \approx 1$ and and the *(i,j)th* component is kept.

The value of ε ranges between 0 and 1, with higher values rejecting more magnitudes. We apply the mask to the voices and reconstruct the filtered data. After reconstructing the data, that is now absent of the voice representing the footprint, we are capable of producing a more interpretable data set with suppressed of acquisition footprint. Since we use one scale “wavelet characteristics” for each slice we prefer to call this method a modified CWT.

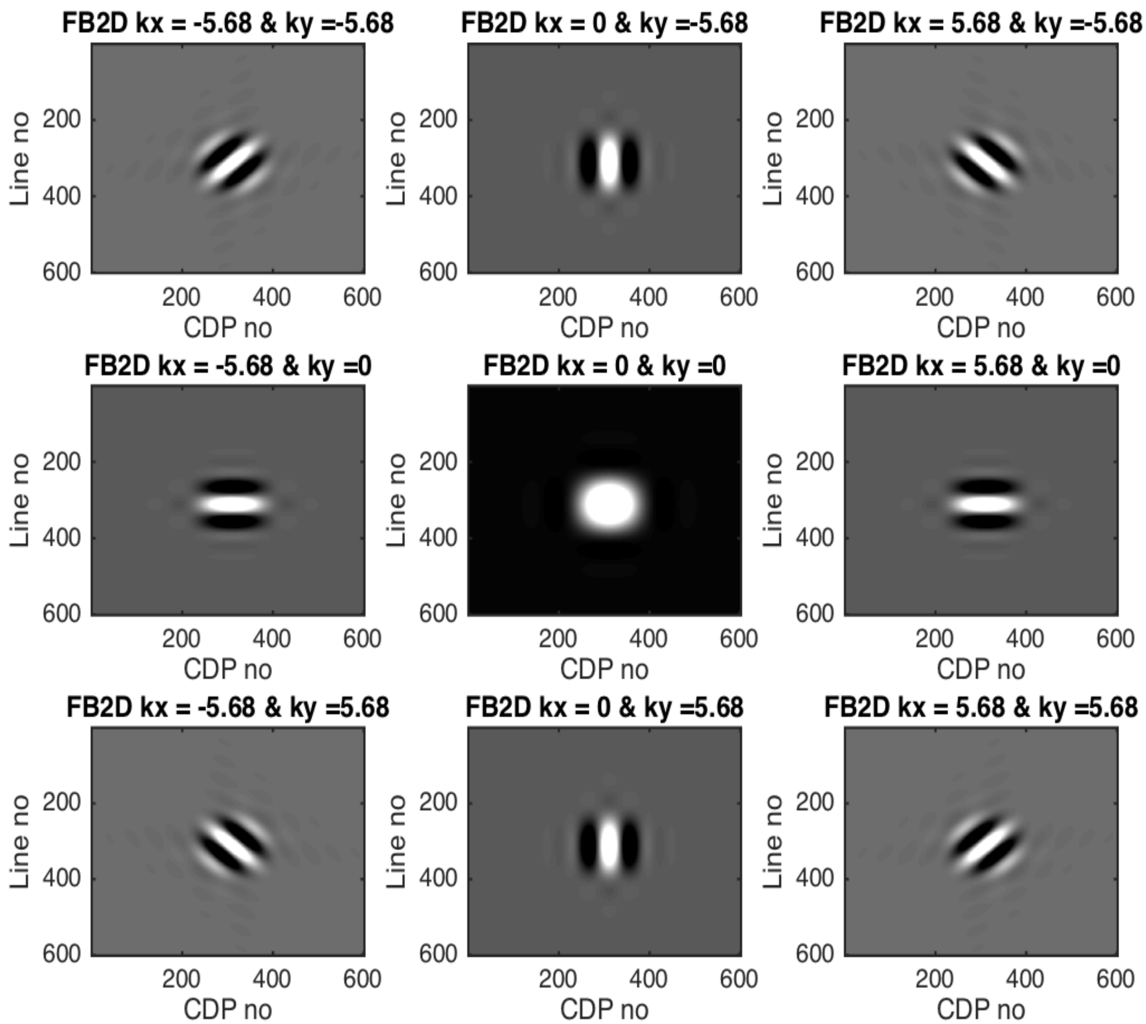
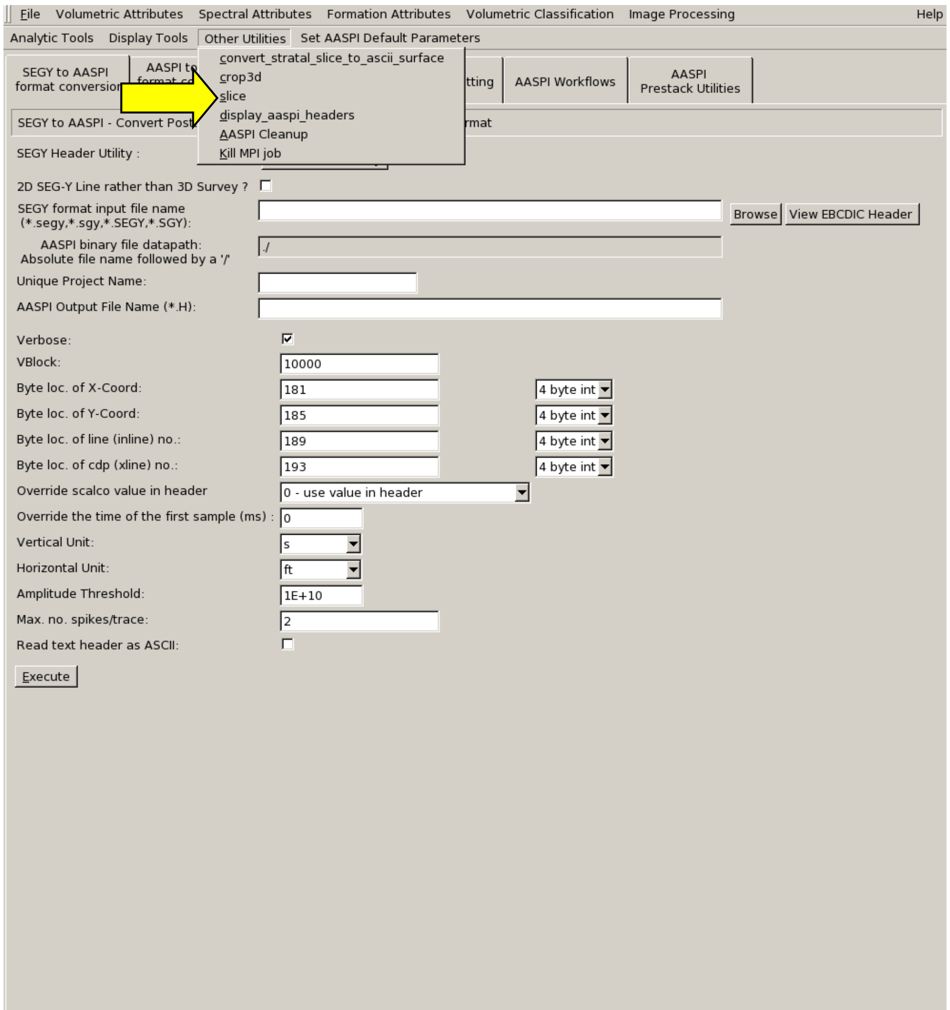


Figure 2. 2D CWT wavelets (filter banks) that will be convolved with time slice seismic amplitude or attribute volumes. Wavenumbers k_x and k_y are in cycles/km.

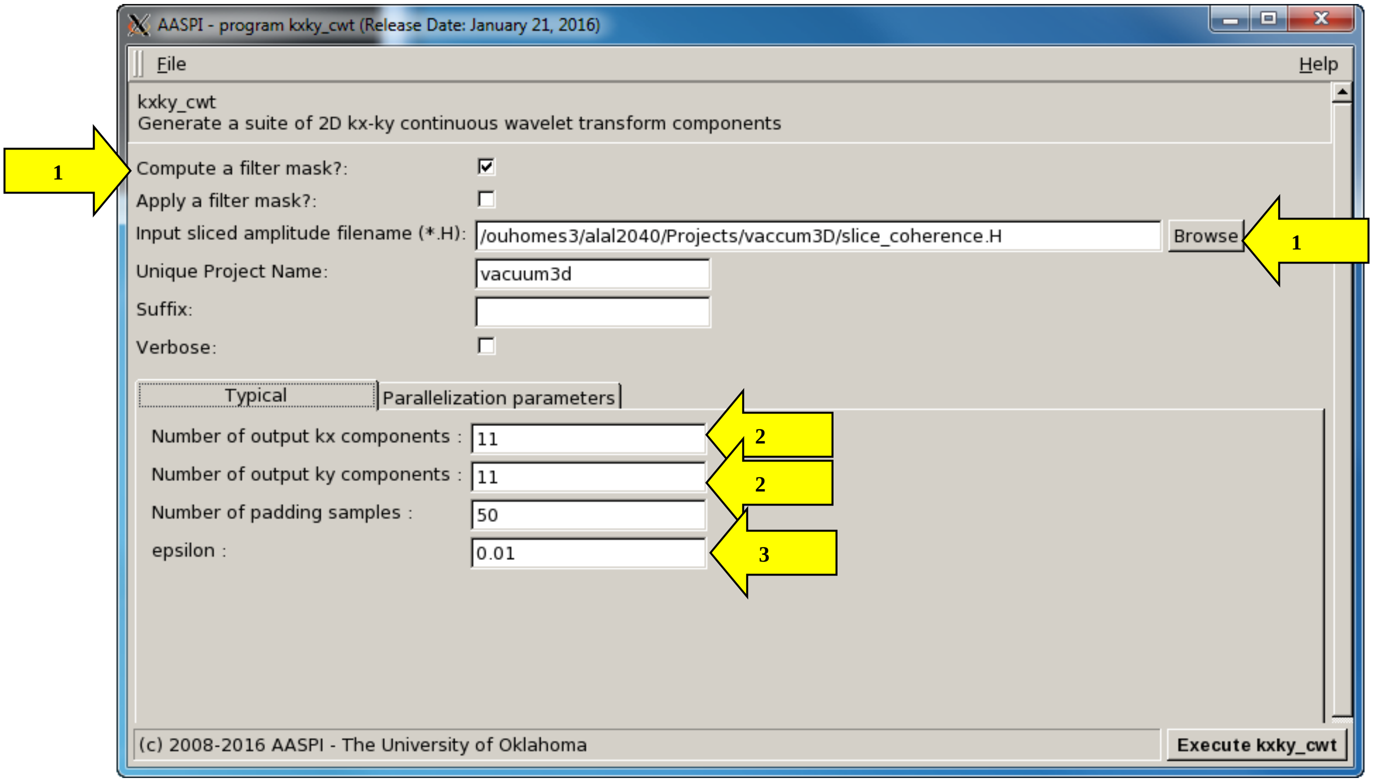
Step-by-Step Description of the kx_ky_cwt code

The goal of the footprint suppression workflow is to generate an estimate of the footprint noise component, which will be subsequently subtracted from the original unfiltered data using a least-squares adaptive subtraction technique.

Step 1. Convert the data volume/ Horizons to a slice using AASPI module (**slice**) under *Other utilities*.

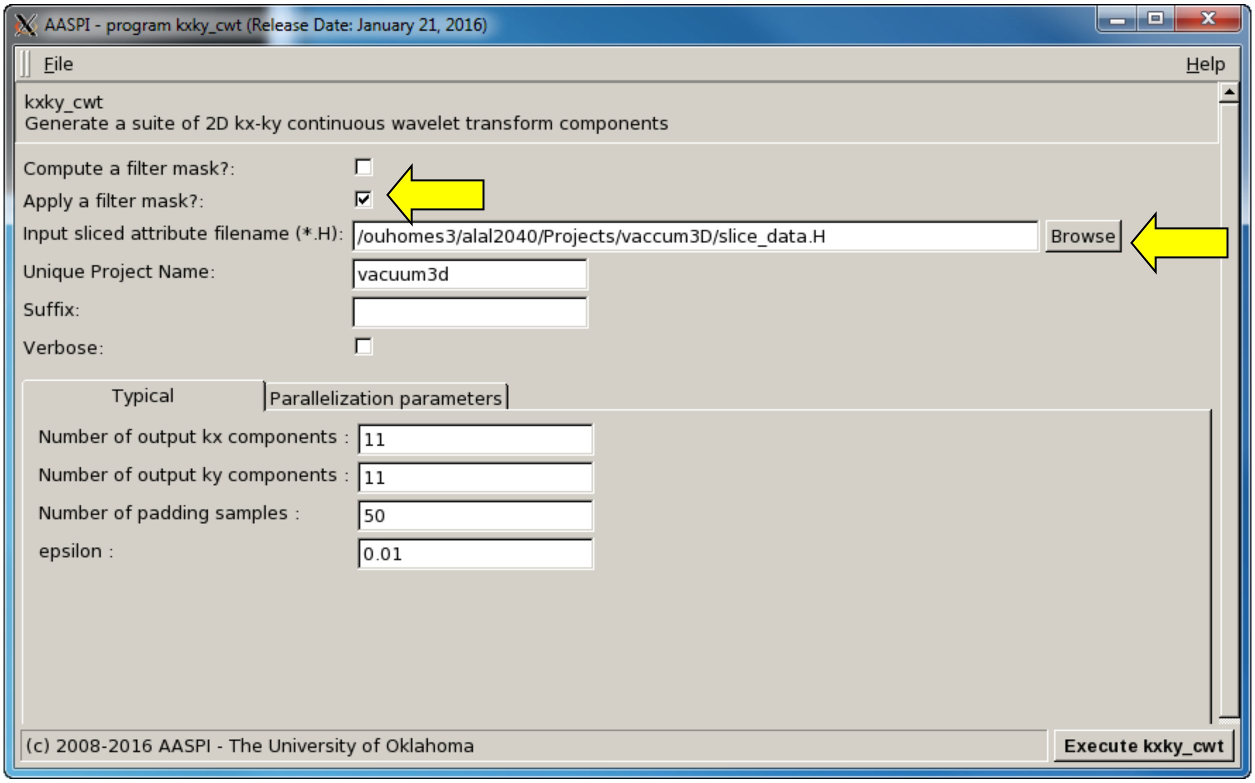


Step 2. Compute the filter mask the using the edge detection attribute using the module **aaspi_kxky_cwt**.



First: we choose the slice of the edge detection attribute and make sure the option (Compute a filter mask) is clicked. *Second*: we choose the number of output kx and ky components. The periodicity of the footprint in the *kx-ky* domain should guide us on the number of components of choice. This can be easily calculated if we the prestack gathers. Alternatively, one could look at the *kx-ky* transform of the data and make an educated guess. *Finally,* the *ε* is to threshold our solution. A high value would indicate we are over-smoothing. A small value, on the other hand, would indicate we are rejecting more of the non-zero components.

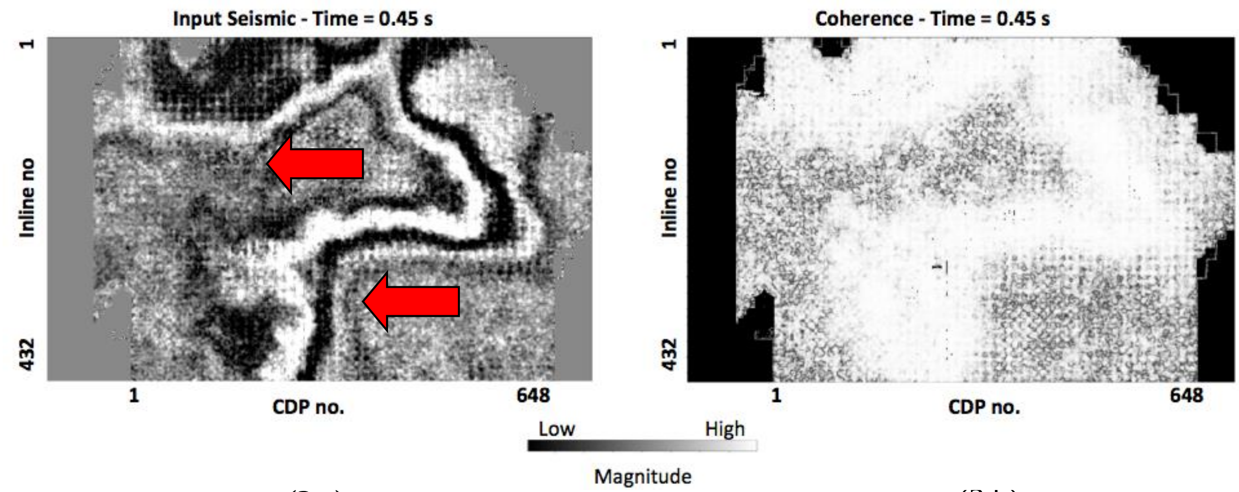
Step 3. Apply the calculated filter mask on the amplitude slice.



Example

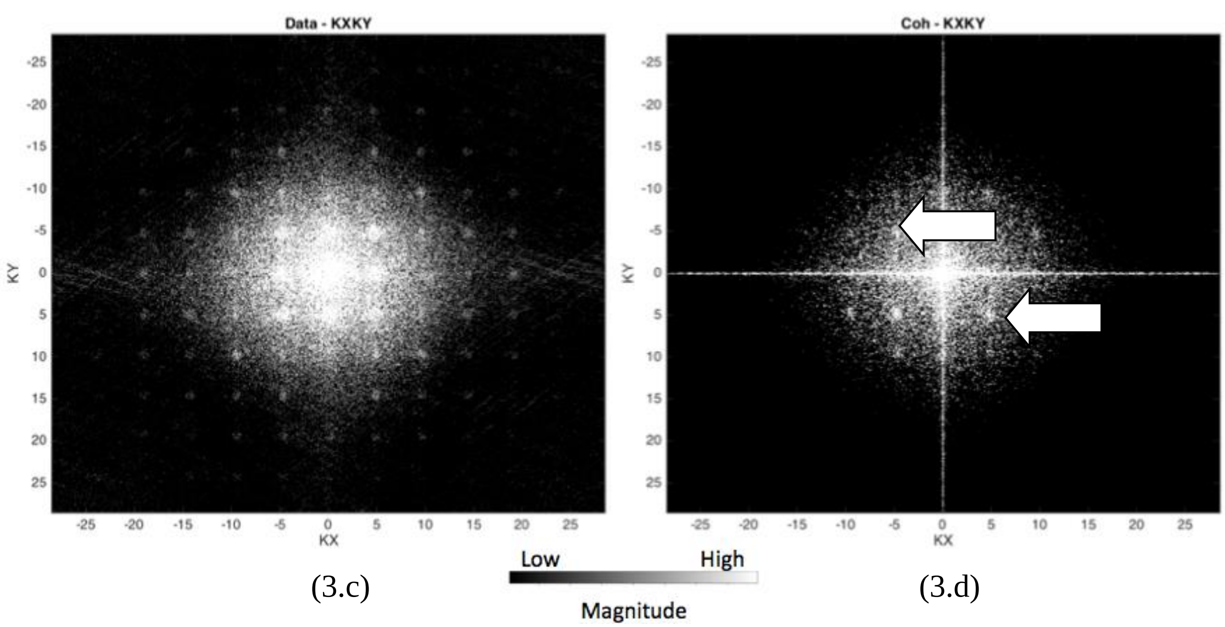
Footprint Suppression of a Legacy Data Volume: Delaware Basin, NM, US

We demonstrate how the code suppresses footprint on an amplitude volume acquired over the Delaware Basin, NM. Figure (3.a) shows the time slice through seismic amplitude at the t=0.45 s horizon. The red arrows indicate some of footprint anomalies in the data. (3.b) shows the corresponding time slice through energy ratio similarity. (3.c) Time slice at t=0.45 s in the *kx-ky* domain. The white arrows indicate peak amplitude anomalies due to the footprint signal in the attribute. (d) Time slice through energy ratio similarity at t=0.45 s in the *kx-ky* domain. Figures (e -f) show the 9 center wavenumber components magnitudes and voices from an 11 x 11 filter bank for the time slice and coherence respectively. A number of observations can be made on the trend seen on the voices: a vertical trend in the top and bottom voices, a 45-degree trend for the four corners and a horizontal trend for the rest. Both the magnitude and voices from the time slice and coherence highlight different patterns as well. We use the magnitudes in Figure (3.e) to generate the mask. The *(0,0)* wavenumber component contains most of the data and least noise. The mask is basically constructed by comparing every magnitude with the center one with a threshold epsilon. A high value of epsilon means we are rejecting more voices components in the process. Hence good care should be given in this analysis. The mask is then applied to the voices of the amplitude data to suppress the footprint. Figure (4) shows the result using 11 x 11 wavenumber components. The result shows an overall improvement and the footprint is certainly less pronounced. The compromise between suppressing the noise or over smoothing the data is what a keen interpreter would have to do in this case. Knowledge of the receiver and source line spacing could help predict the most contaminated wavenumber and we can design our filter bank accordingly.



(3.a) (3.b)

Figure 3: (a) Time slice at 0.45 s, red arrows indicates acquisition footprint. (b) Coherence slice at 0.45 s.



(3.c) (3.d)

Figure 3: (c) *kx-ky* transform of the input data. (d) *kx-ky* transform of the coherence. White arrows indicate acquisition footprint in the transform domain.

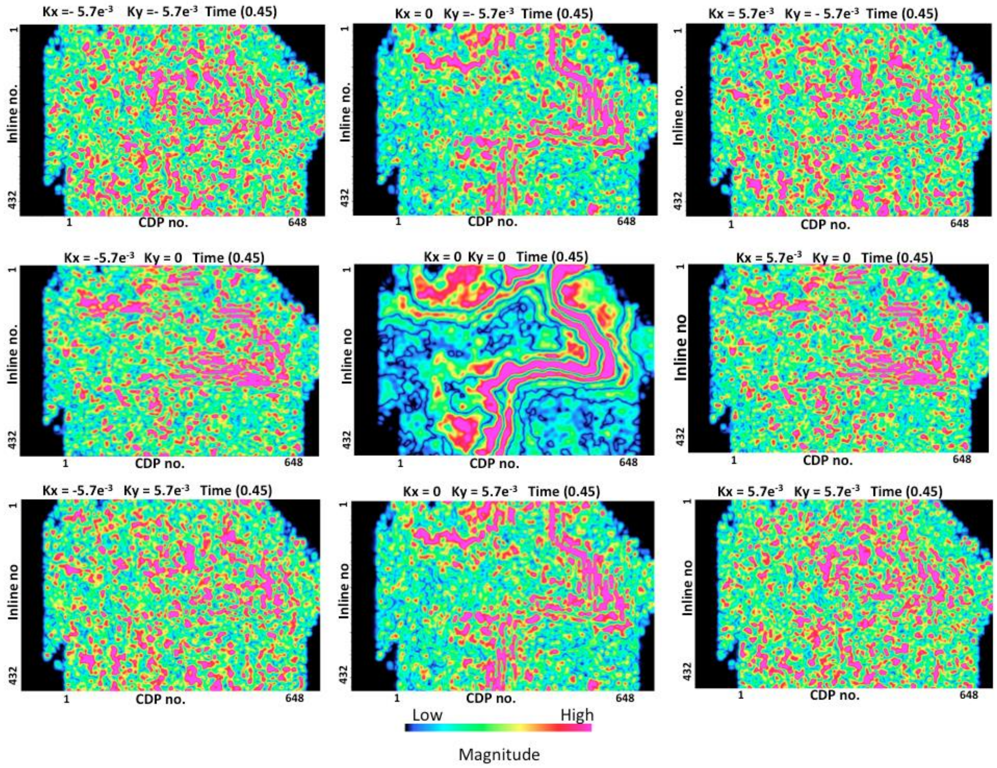


Figure 3: (e) 9 center wavenumber components of the coherence magnitudes.

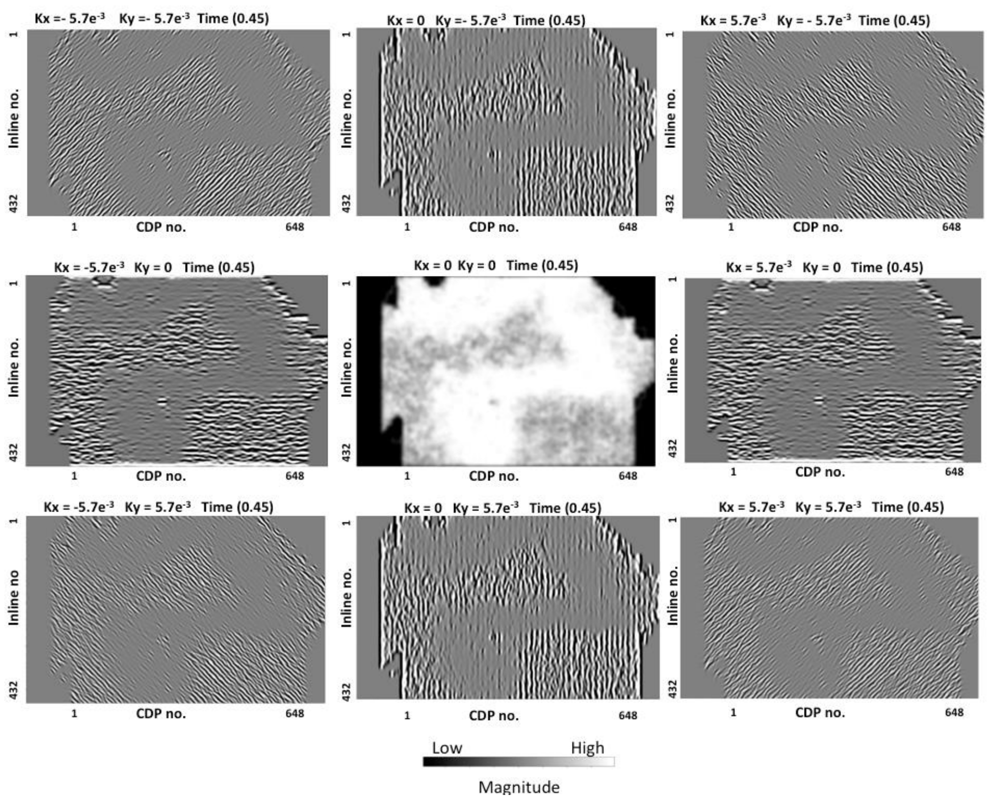


Figure 3: (f) 9 center wavenumber components of the coherence voices.

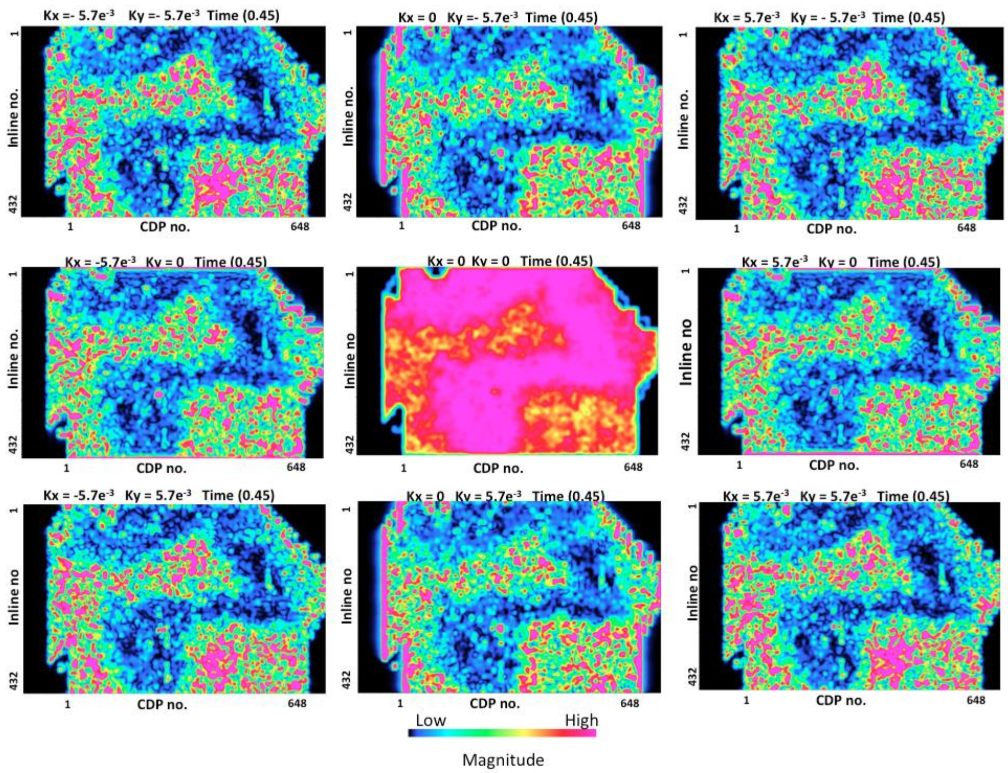


Figure 3: (g) 9 center wavenumber components of the amplitude magnitudes.

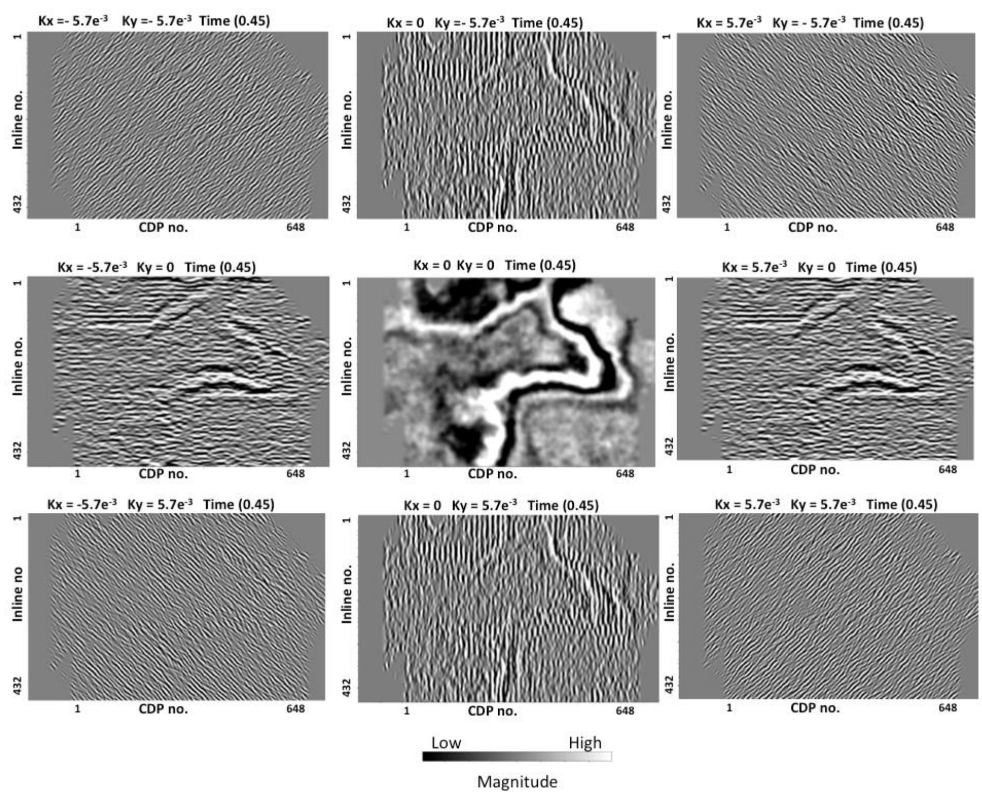


Figure 3: (h) 9 center wavenumber components of the amplitude voices.

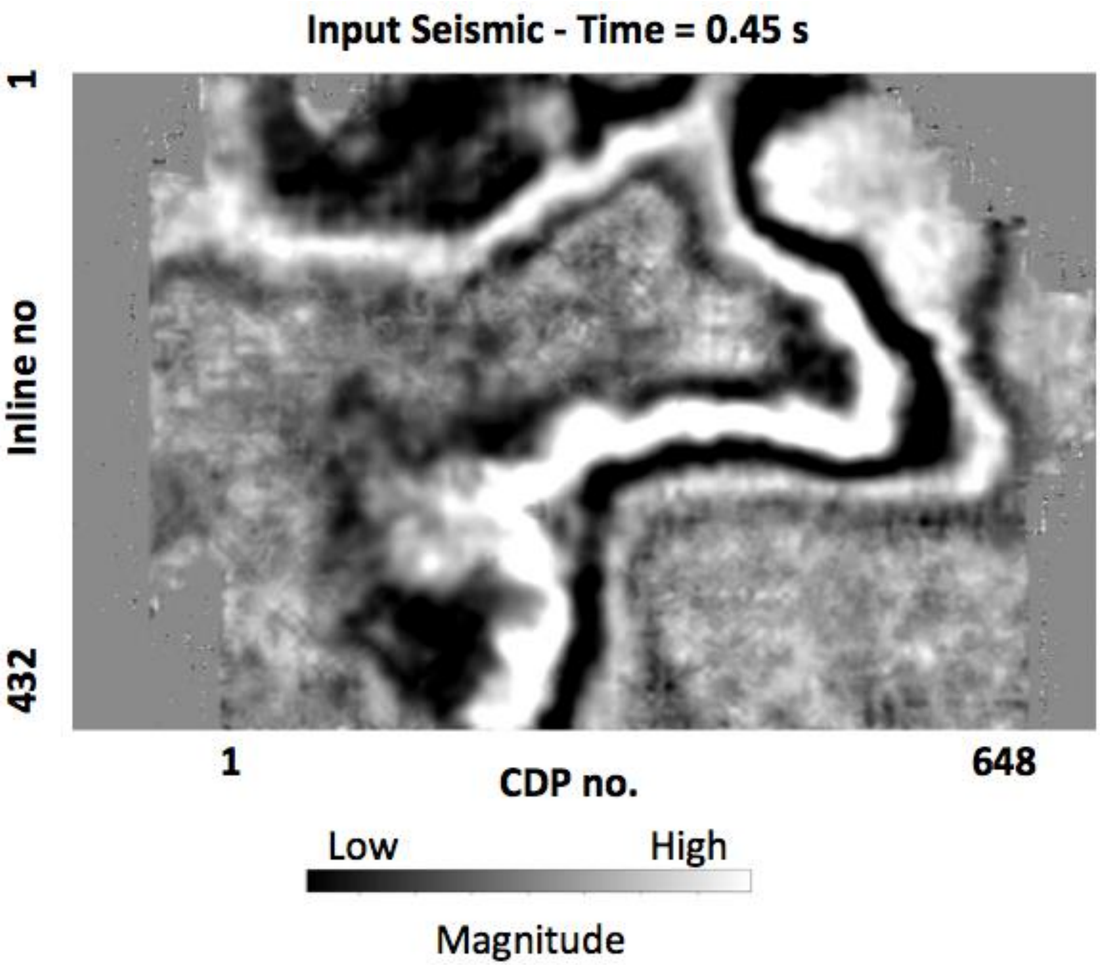


Figure 4. Time slice 0.45 s with acquisition footprint suppressed.

References

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