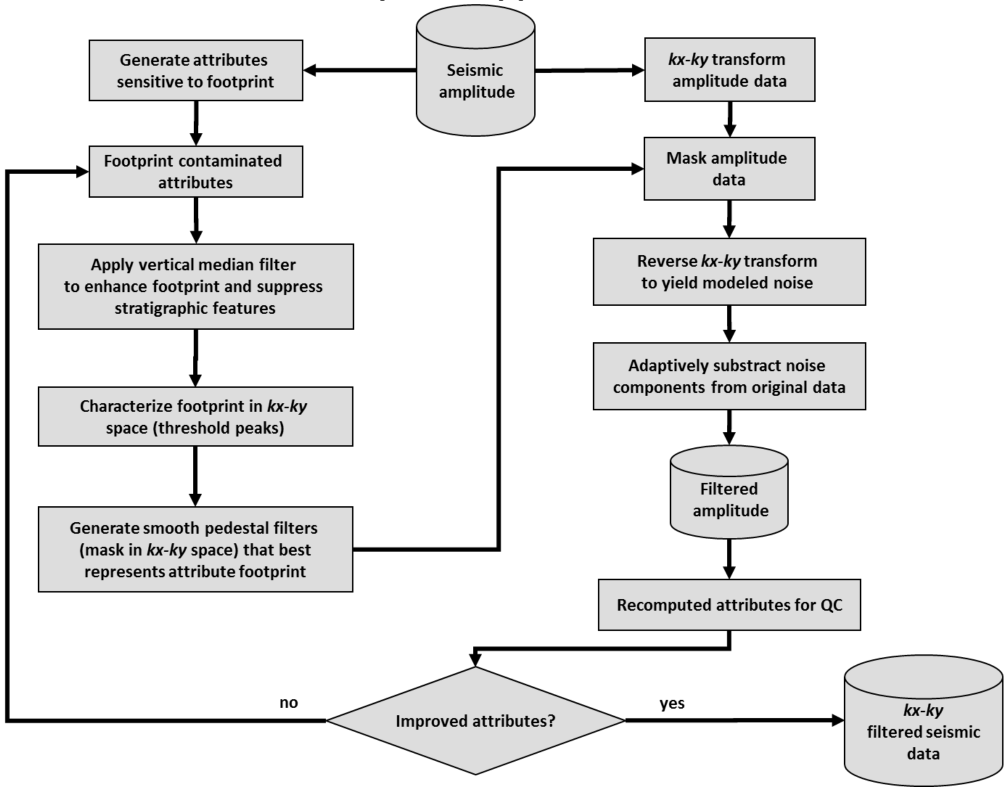
ATTRIBUTE-ASSISTED FOOTPRINT SUPPRESSION – PROGRAMS kxky_prep, kxky_forward, generate_mask, kxky_reverse, and adaptive_subtraction

Contents

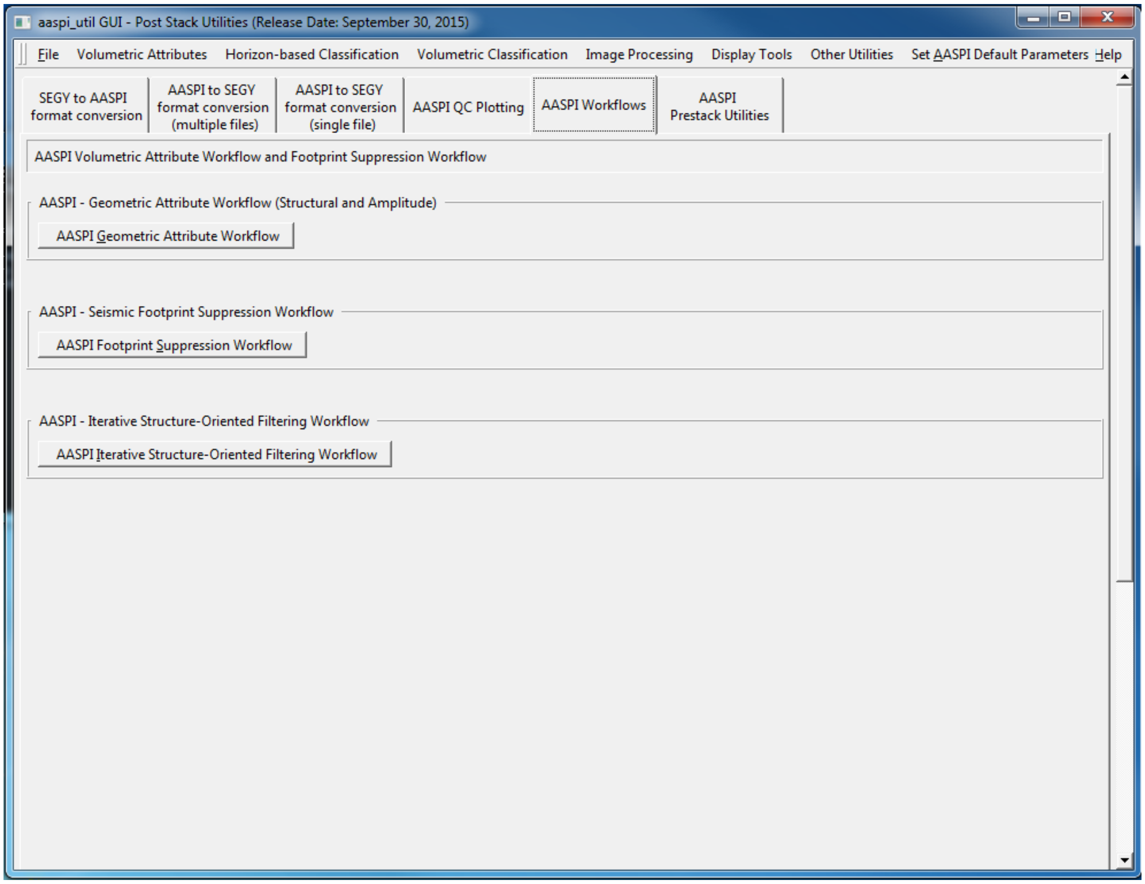
Overview

Acquisition footprint often poses a major problem for 3D seismic data interpretation. Ideally, footprint from acquisition is handled at the processing shop through more careful attention to trace balancing statics, noise reduction, and velocity analysis (Hill et al., 1999; Gülünay, 2000). Such reprocessing is not feasible on many legacy data volumes where the pre-stack data cannot be found or no longer exists. Seismic attributes often provide an effective means of delineating subtle geological features of interest such as channels, small faults and fractures, but can also enhance acquisition footprint. For this reason, attributes can be used to both design and evaluate the effectiveness of alternative footprint suppression workflows.

Computation flow chart for footprint suppression

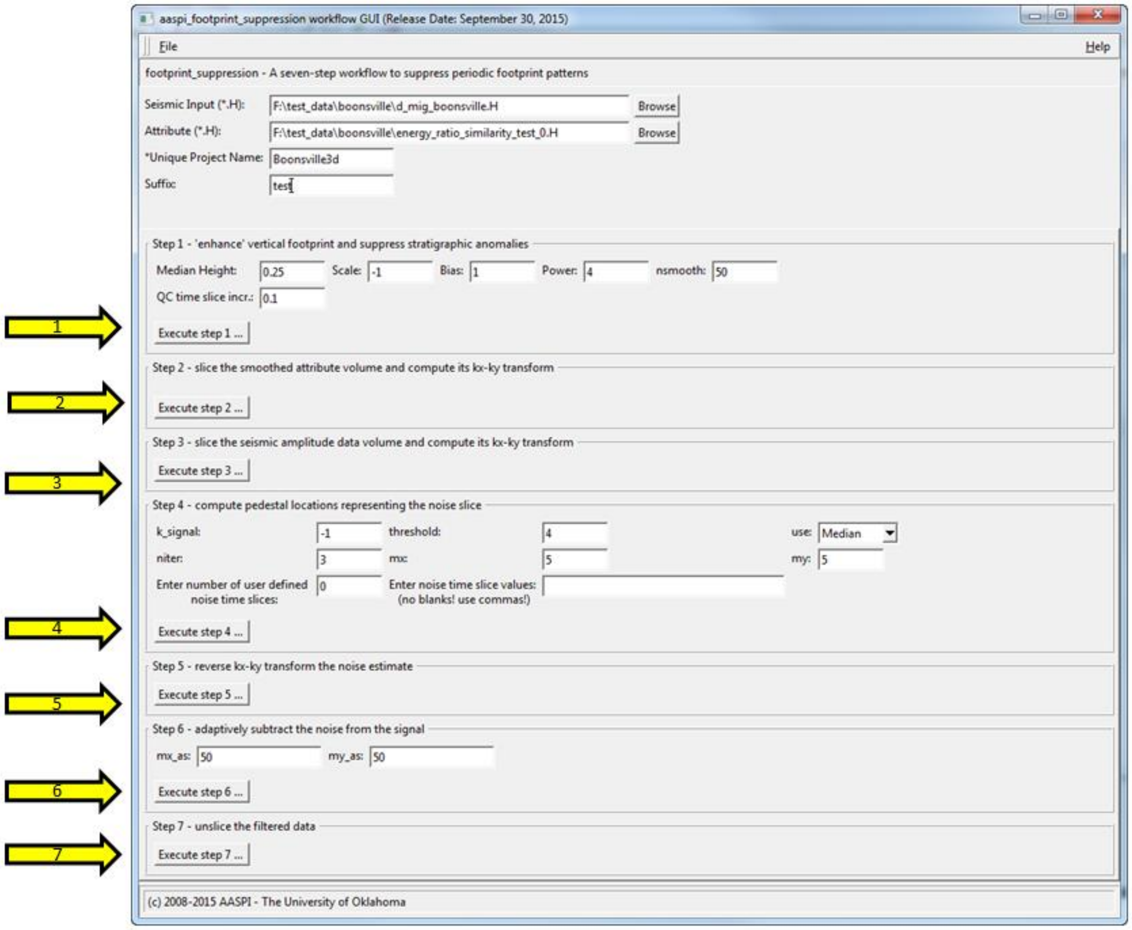


The AASPI footprint suppression GUI is found under *AASPI Workflows*.



The footprint suppression tool is actually a processing workflow using k_x-k_y filters and adaptive subtraction. k_x-k_y filters are routinely used in the image processing industry to remove periodic noise that contaminates medical images and maps. Filters can be designed as a function of the wavenumber to remove coherent, periodic or aperiodic noise (Buttkus, 2000). The figure from Falconer and Marfurt (2006) shows the detailed workflow for this process.

Since we are addressing legacy post-stack data volumes, no source or receiver geometry information is retained in the headers. Therefore, the first step is to generate footprint-contaminated attributes from the migrated seismic data. To estimate the noise, footprint is enhanced and stratigraphic signal suppressed by applying a vertical median filter that removes the stratigraphic features (1). Along with rescaling the attribute amplitudes, a constant bias may need to be added to the attribute data to force noise-free (e.g. high coherence, c=1) values to be the same as null values in muted and dead trace zones. Once the footprint is enhanced, it is transformed to k_x-k_y space and smooth pedestal filters are generated that best represent the acquisition footprint in the seismic attribute volume (2). Parallel to the footprint characterization steps described above, the seismic amplitude volume is transformed to k_x-k_y space and masked with the pedestal filters generated from the attribute data (3). The reverse transform of the masked amplitude data yields modeled noise time or horizons slices (4 and 5) that are then adaptively subtracted from the original data to produce filtered seismic data (6). Finally, we unslice the filtered seismic data (7). Footprint sensitive attributes are computed from the filtered data to QC the filtering process and decide whether the data needs more filtering or is ready for interpretation.

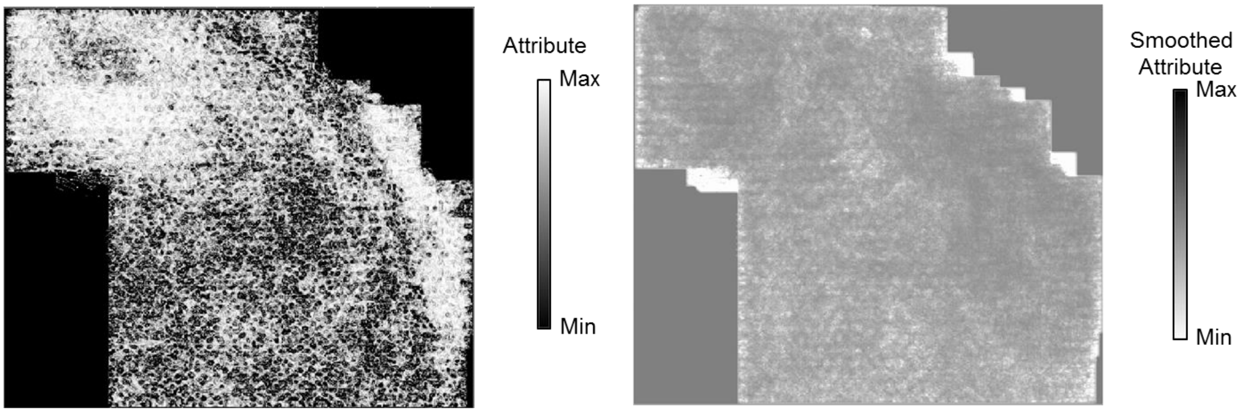


Step-by-Step Description of the Workflow

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.

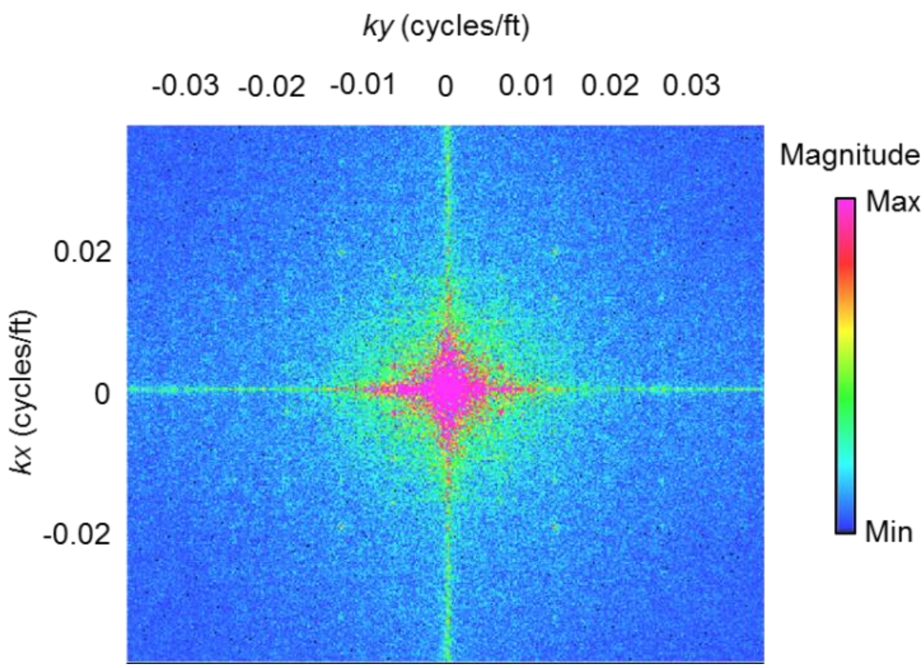
Step 1. Attributes often exacerbate the effects of acquisition footprint. The goal of step 1 is to first choose an attribute that enhances the footprint. If the footprint gives rise to anomalous amplitudes, then the total energy attribute may be a good choice. If we see changes in apparent dip due to inaccurate velocities, a curvature attribute may work well. One of the first attributes to try is the Sobel filter similarity, which is sensitive to both lateral changes in amplitude and phase.

The goal of step 1 is to further enhance the footprint. If stratigraphic features such as channels are localized vertically, or if the faults have significant dip, then a median filter applied vertically to the attribute volume will reject some of these geological components but retain, and possibly enhance the vertically-oriented acquisition footprint.



Sobel filter similarity Smoothed Sobel filter similarity

Step 2. For reasons of efficiency, almost all land acquisition is designed as a repeatable pattern that is rolled along with the source location. These patterns may be perpendicular to shot and receiver lines, a staggered brick pattern, vector tiles, or even diagonally oriented grids. This periodicity gives rise to periodic artifacts in the amplitude and phase components of the data. For this reason, step 2 first slices the smoothed attribute and then computes its k_x-k_y transform:



In order to better distinguish the structural signal and footprint noise in kx-ky domain of seismic attribute slice, we can apply a Laplacian-Gaussian filter and weight factor to Step 2.

Laplacian-Gaussian Filter (LoG)

As Laplace operator may detect edges as well as noise (isolated, out-of-range). It may be desirable to smooth the image first by a convolution with a Gaussian kernel of width σ :

$$G_\sigma(x,y) = \frac{1}{\sqrt{2\pi\sigma^2}} \cdot exp\left[-\frac{x^2\ + y^2}{2\sigma^2}\right]$$

Transforming to kx-ky domain:

$$G_\sigma(k_x,k_y) = \frac{1}{\pi\sigma^2} \cdot \left[1 - \frac{k_x^2 + k_y^2}{2\sigma^2}\right] exp\left[-\frac{k_x^2 + k_y^2}{2\sigma^2}\right]$$

Therefore, after transforming the attribute slice from *time-spatial* domain to *kx-ky* domain, we can get the magnitude slice *raw*_$AMP(k_x, k_y)$ as well as phase slice $PHI(k_x, k_y)$ (the results of step2). Then we are going to filter the magnitude slice *raw*_ $AMP(k_x, k_y)$ using the Laplacian of Gaussian Filter $G_\sigma(k_x, k_y)$, to get the filtered magnitude slice $AMP(k_x, k_y)$.

Weighted Factor

As we see the magnitude slice of step2, we found that the values far away from the center (large *kx*, *ky* values zone) is significantly small compared to the center part signal. We can multiply by the weighted factor to get a better imaging for both signal and footprint signal. The weighted factor will be calculated in follow:

$$r = \sqrt[2]{k_x^2 + k_y^2}$$

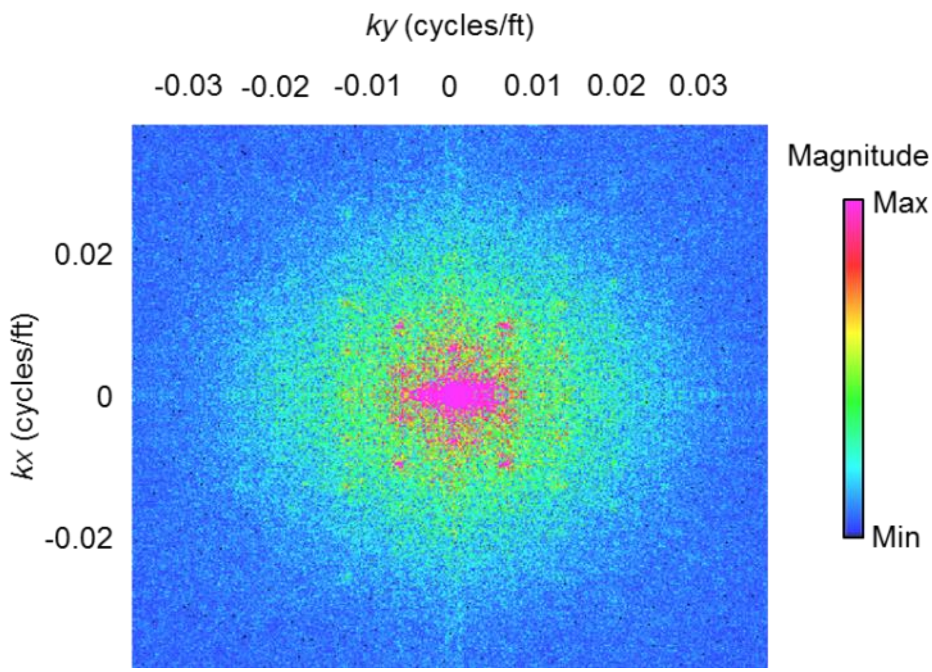
and

$$r_{max} = \sqrt[2]{k_{maxx}^2 + k_{maxy}^2}$$

$$w(k_x, k_y) = exp\left(\frac{r}{r_{max}}\right)$$

*wgt*_ $AMP(k_x, k_y)$ = *raw*_ $AMP(k_x, k_y)$ * $G_\sigma(k_x, k_y)$* $w(k_x, k_y)$

Step 3. In order to suppress these periodic artifacts, we will also need to slice and compute the k_x-k_y transform of the seismic amplitude data. Often, we have steeply-dipping migration aliasing artifacts overprinting our data. The apparent frequency of such steeply dipping events is lowered by the factor cosϑ. Ground roll also is inherently low frequency. It may therefore be useful to first low-pass filter the seismic amplitude data to reject uncontaminated high frequency signal in order to enhance footprint artifacts:



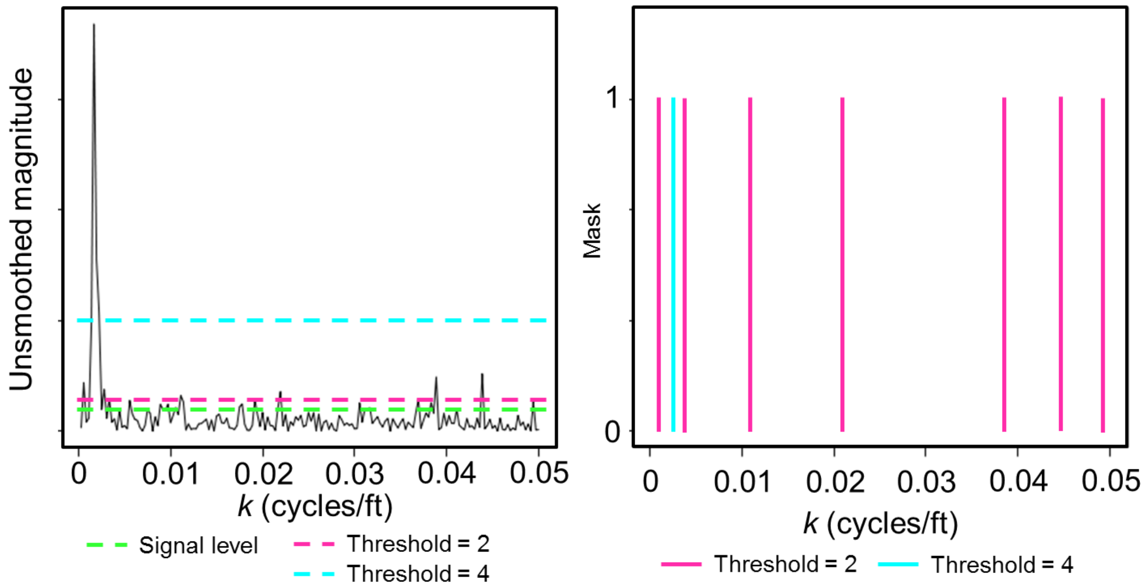
Step 4. The next step is to determine which spectral components of the k_x-k_y transformed attribute data area is anomalous, that is, that do not follow the background trend of what we would like to think of as fairly random geology.

The value of *k_signal* is easiest to understand. Perfectly flat events will map to values of k_x-k_y*=0. Smooth,* dipping events with slowly changing amplitudes will have low values of k_x and k_y. In general, channel edges and faults will have broad-band kx-ky components; however, the high wavenumber (short wavelength) will, in general, be random for a meandering channel or curvilinear suite of faults and therefore will in general not give rise to a periodic anomaly. Thus, for all spectral components ($k_x^2+k_y^2$) *k_signal,* is where most of our specular reflection data lie and will be untouched.

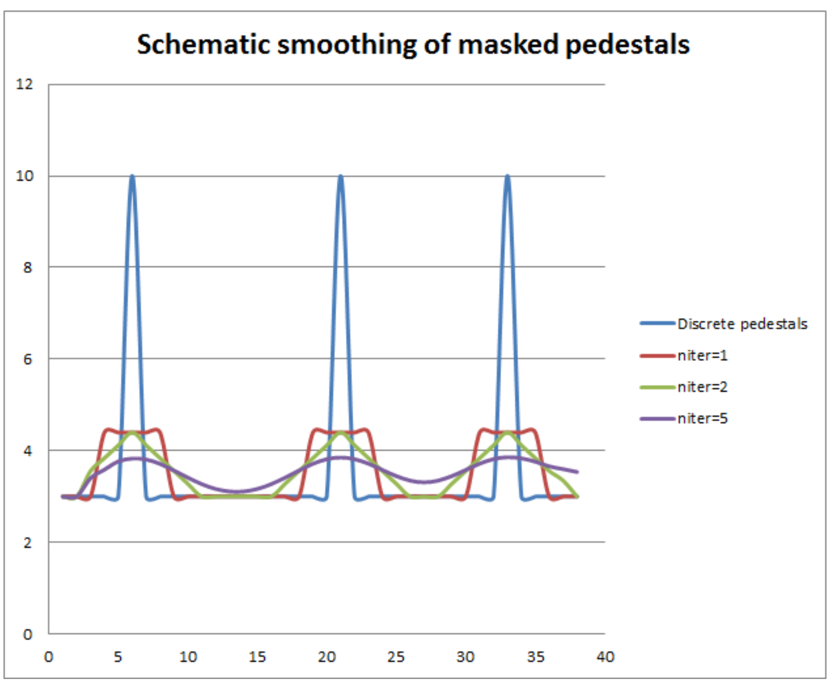
In order to estimate anomalous wavenumber components correlating to periodic footprint, program **generate_mask** needs to first estimate the background value. The values of m_x and m_y define a running rectangular window of size $(2m_x+1)(2m_y+1)$ in which we calculate either the (c) mean or median value, which we denote as $\mu(k_x,k_y)$. If the unsmoothed magnitude a(k_x,k_y) at any location falls significant above a threshold, *b*, times this average value, the mask , *M(kx,ky)=*1.

Specifically,

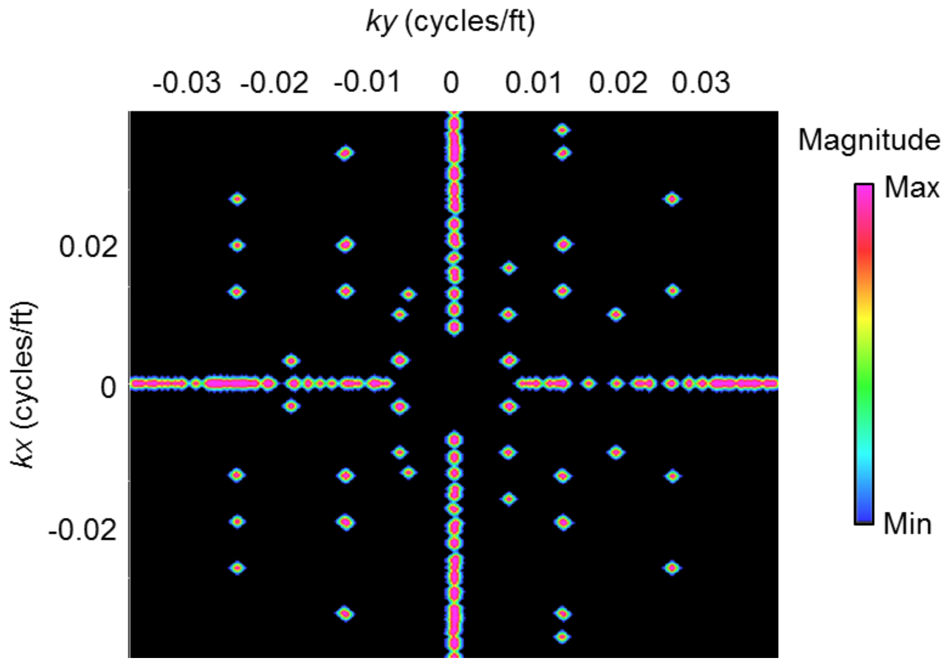
$$M(k_x,k_y)=\begin{cases}1 \text{ if } & a(k_x,k_y)\geq b\mu(k_x,k_y)\\ 0 \text{ if } & a(k_x,k_y)< b\mu(k_x,k_y)\end{cases}.$$



Such discrete pedestals would give rise to a strong Gibb's phenomenon if they were not smoothed. First, a logical fixed-variable is set to be TRUE at all values of M(k_x,k_y)=0. Then all non-fixed values of the mask will be smoothed *n-iter* times using a 5-point smoothing algorithm.



The resulting masked attribute:

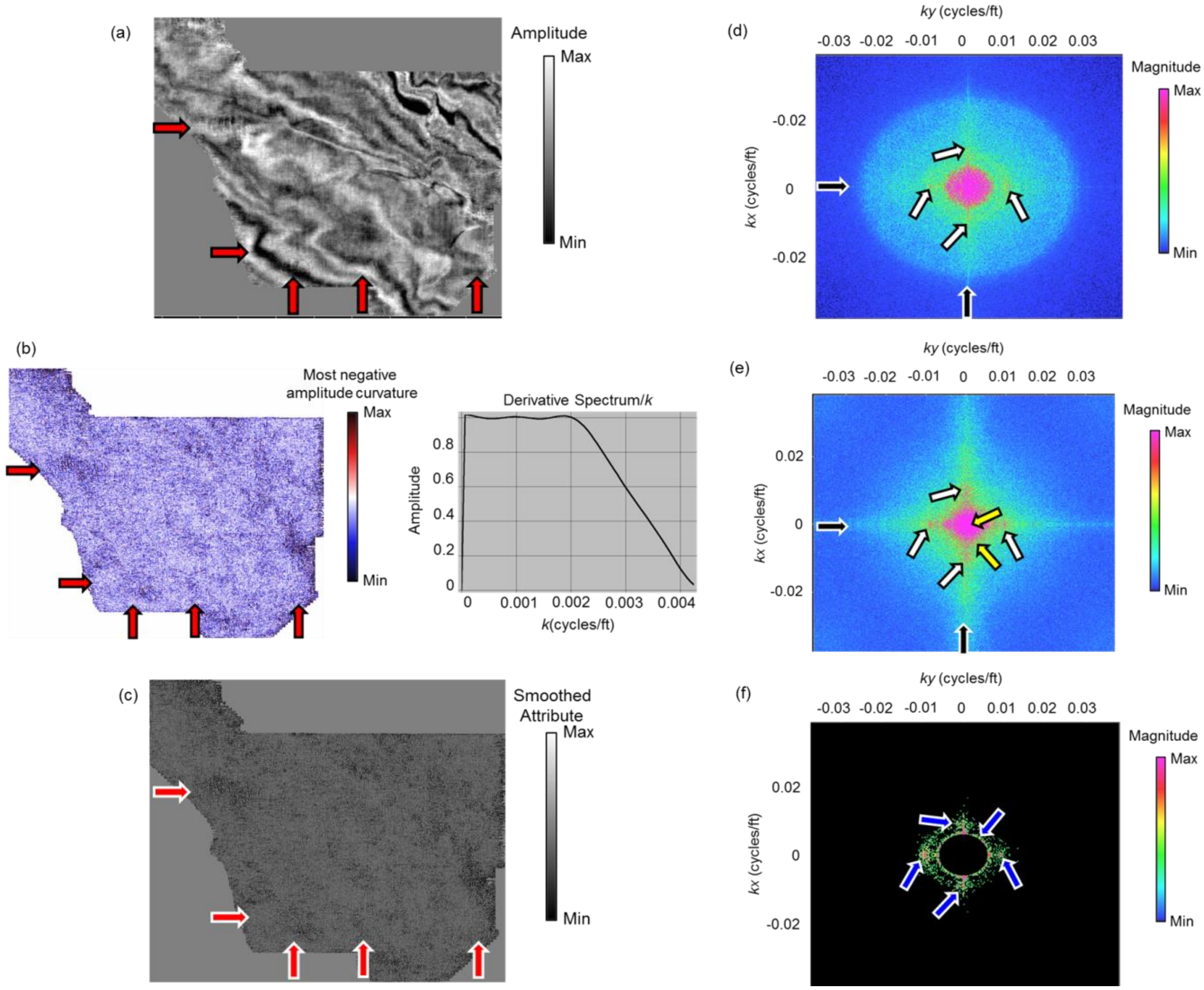


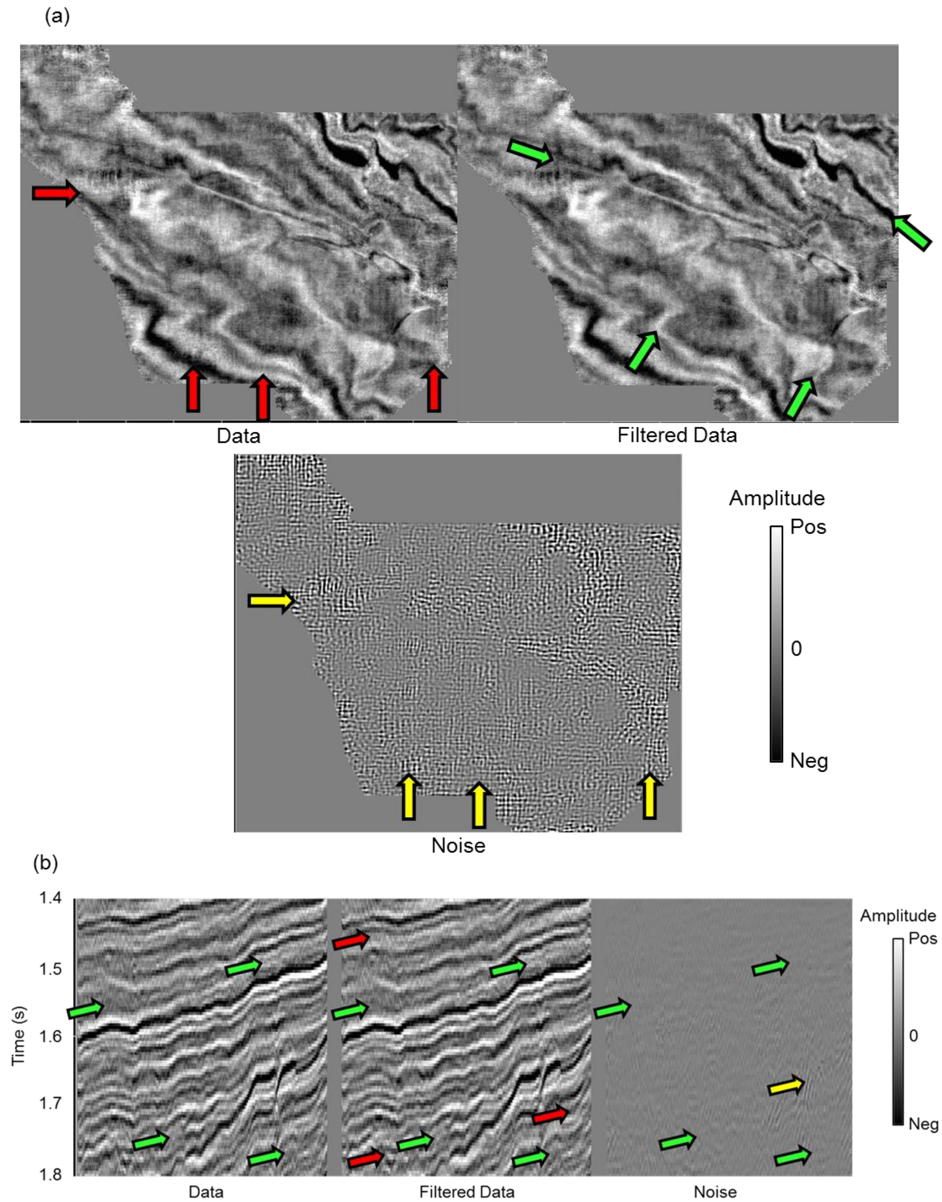
The figure below shows the footprint suppression GUI and the steps described above.

Examples

Footprint suppression of a legacy data volume: Anadarko Basin

Application of footprint suppression workflow shown above to a seismic amplitude volume acquired over the Anadarko Basin, OK. (a) Time slice through seismic amplitude at t=1.6 s horizon. Red arrows indicate footprint anomalies on the data. (b) Corresponding time slice through most negative amplitude short wavelength curvature exacerbating short wavelength footprint anomalies and its derivative spectrum. (c) Time slice through smoothed most negative amplitude curvature at t=1.6 s after median filter to suppress any remaining signal of the geologic features and enhance vertical footprint features. (d) Time slice through most negative amplitude curvature at *t*=1.6 s in the k_x-k_y domain. White arrows indicate peak amplitude anomalies due to the footprint signal in the attribute. Black arrows indicate N-S and E-W anomalies that correlated to the survey edges as well as the footprint. (e) Time slice through seismic amplitude at *t*=1.6 s in the k_x-k_y domain. Most of the smooth, relatively flat signals will cluster near the origin (yellow arrows) whereas lineaments such as faults and channels will be scattered at larger values of k_x-k_y. White arrows indicate zones where noise clusters are present. Black arrows indicate anomalies due to the survey edges. (f) Notch filter pedestals. Counter intuitively, in this step, the signal is removed from the data in order to model the noise components. Noise (blue arrows) will then be adaptively subtracted from the data for a noise reduced seismic amplitude volume.

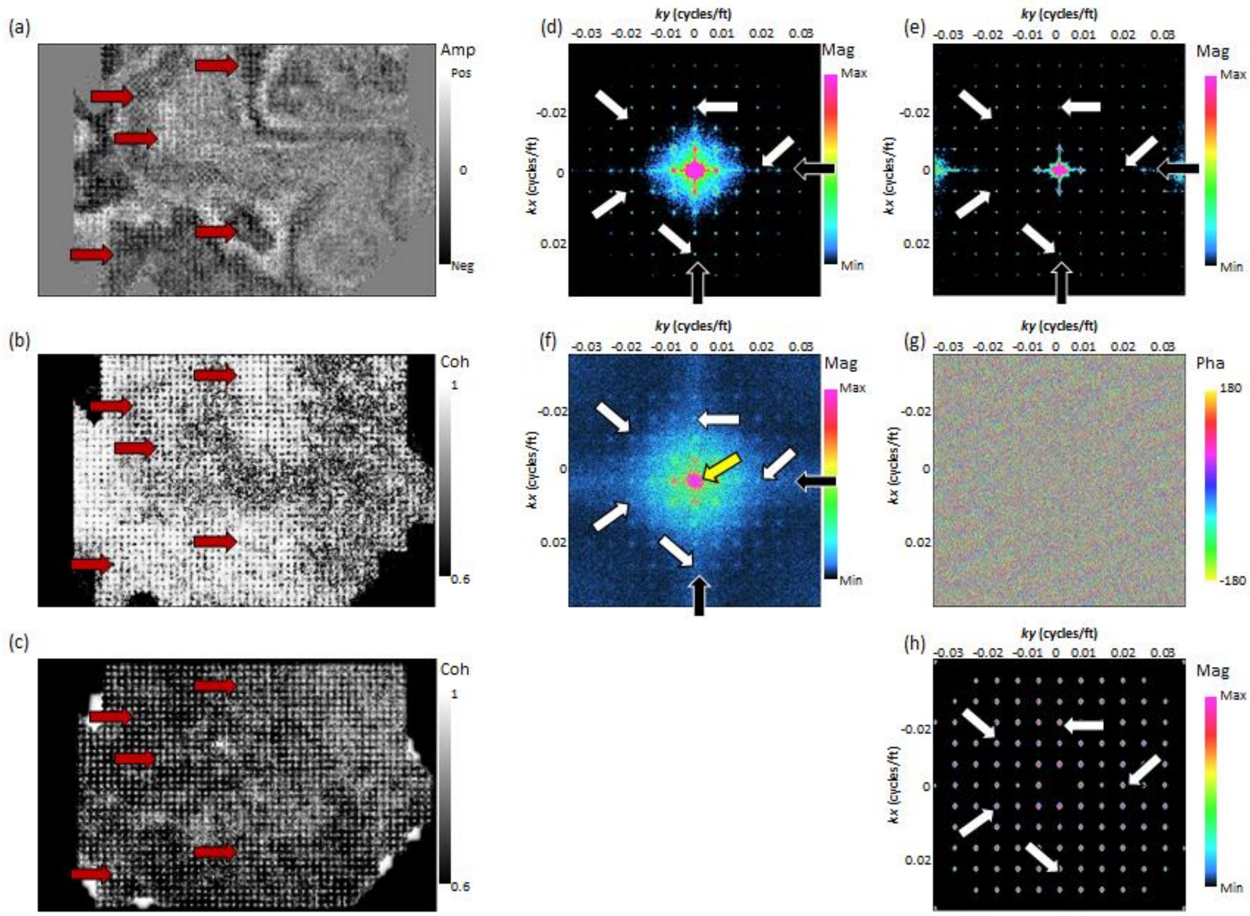


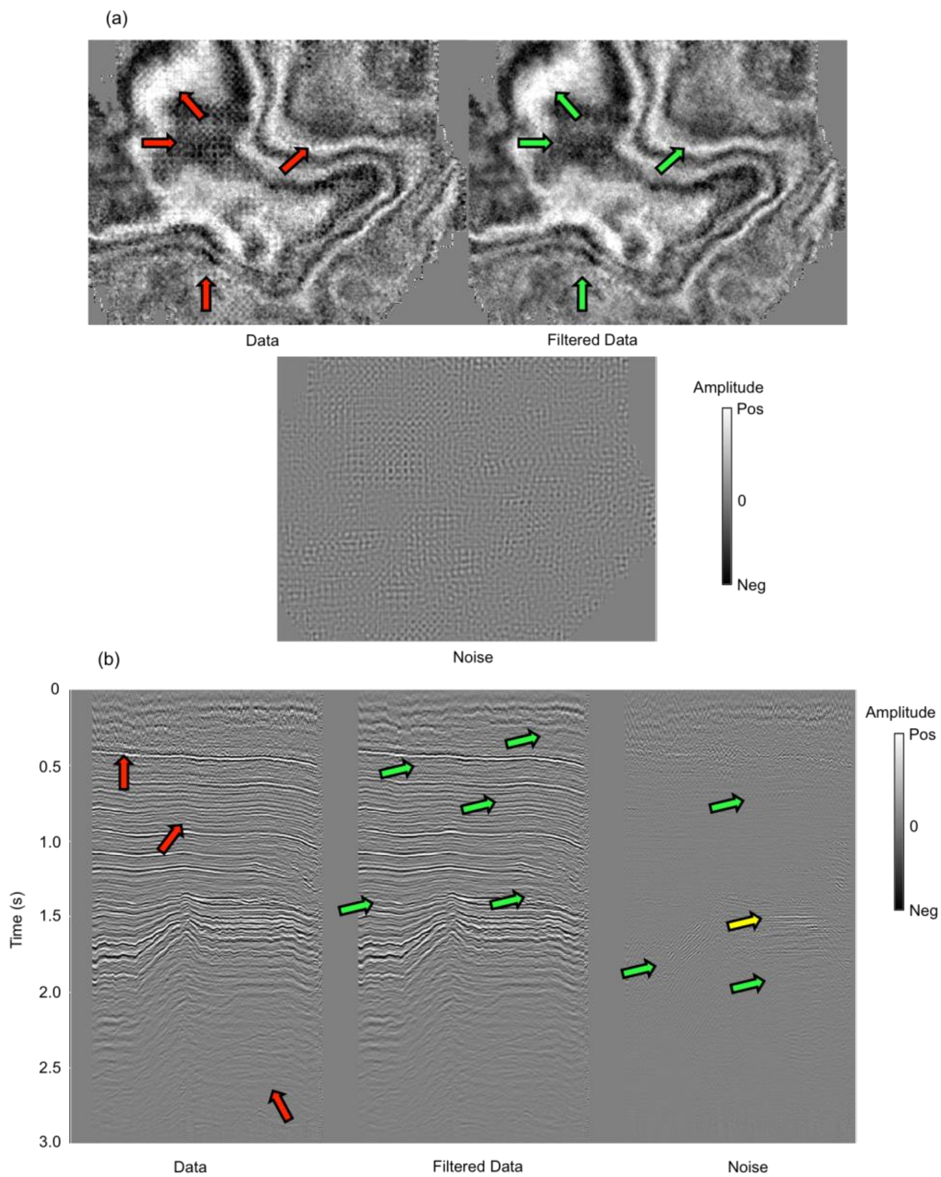


In the figure above: (a) Time slices at t=1.6 s through: original seismic amplitude data, k_x-k_y filtered seismic amplitude data and noise pattern for the dataset acquired in the Anadarko Basin, OK. Notice that most of the N-S and E-W lineaments present due to the footprint in the original data have been removed. Green arrows indicate geologic features that have been enhanced after the filtering. Yellow arrows indicate footprint pattern characterized by the k_x-k_y filter and removed from the data. (b) Representative vertical section through the original seismic amplitude data, filtered seismic amplitude data, and noise pattern for the dataset acquired in the Anadarko Basin, OK. Green arrows indicate areas where the signal-to-noise ratio has increased compared to the original data. Red arrows indicate areas where noise was removed but it is still present. Yellow arrows indicate geologic features removed by the filtering process represented by a k_x-k_y “noise” component.

Footprint suppression of a legacy data volume: Delaware Basin

Application of footprint suppression workflow shown above to a seismic amplitude volume acquired over the Delaware Basin, NM. (a) Time slice through seismic amplitude at t=0.6 s horizon. Red arrows indicate footprint anomalies on the data. (b) Corresponding time slice through energy ratio similarity exacerbating short wavelength footprint anomalies and its derivative spectrum. (c) Time slice through smoothed energy ratio similarity at t=0.6 s after median filter to suppress any remaining signal of the geologic features and enhance vertical footprint features. (d) Time slice through energy ratio similarity at t=0.6 s in the k_x-k_y domain without the application of LoG filter. White arrows indicate peak amplitude anomalies due to the footprint signal in the attribute. Black arrows indicate N-S and E-W anomalies that correlated to the survey edges as well as footprint. (e) Time slice through energy ratio similarity at t=0.6 s in the k_x-k_y domain with the application of LoG filter. The peal amplitude anomalies due to the footprint is more clear that the one in (d). Therefore, we are going to apply (e) in the following workflow. (f) Time slice through seismic magnitude at t=0.6 s in the k_x-k_y domain. Most of the smooth, relatively flat signals will cluster near the origin (yellow arrows) whereas lineaments such as faults and channels will be scattered at larger values of k_x-k_y. White arrows indicate zones where noise clusters are present. Black arrows indicate anomalies due to the survey edges. (g) Time slice through seismic phase at t=0.6 s in the k_x-k_y domain. (h) Notch filter pedestals. Counter intuitively in this step the signal is removed from the data in order to model the noise components. Noise (white arrows) will then be adaptively subtracted from the data for a noise reduced seismic amplitude volume.


(a)
Amp
Pos
0
Neg
(b)
Coh
1
0.6
(c)
Coh
1
0.6
(d)
(e)
(f)
(g)
(h)
ky (cycles/ft)
-0.03 -0.02 -0.01 0 0.01 0.02 0.03
kx (cycles/ft)
-0.02
0
0.02
Mag
Max
Min
Pha
180
-180



In the figure above: (a) Time slices at t=0.6 s through: original seismic amplitude data, k_x-k_y filtered seismic amplitude data and noise pattern for the dataset acquired in the Delaware Basin, NM. Notice that most of the N-S and E-W lineaments and localized low amplitude "spots" present due to the footprint in the original data have been removed. Green arrows indicate geologic features that have been enhanced after the filtering. (b) Representative vertical section through the original seismic amplitude data, filtered seismic amplitude data and noise pattern for the dataset acquired in the Delaware Basin, NM. Red arrows indicate areas where footprint is strongest. Green arrows indicate areas where the signal-to-noise ratio has increased compared to the original data. Yellow arrow indicate geologic features removed by the filtering process represented by a k_x-k_y "noise" component.

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