Applications of Adapted Waveform Analysis for Spectral Feature Extraction and Denoising

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Summary

While tackling tough problems in processing and analysis of seismic data we exploit the rich resources of Adapted Waveform Analysis, AWA. Wavelets, wavelet packets, and local trigonometric waveforms are among the many tools made available by AWA to augment the yield of information from seismic data. In this paper we illustrate AWA utilization with two examples, pertaining to spectral feature extraction and application to difficult noise scenarios.

Adapted Waveform Analysis, Background

Adapted Waveform Analysis, AWA, provides a canon of methods and tools for analyzing and modeling signals and other data, in terms of libraries of waveform templates, such as wavelets, wavelet packets, and local trigonometric waveforms. Over the last 15 years, application of AWA brought about many useful methods of signal analysis, with applications in domains such as medical and radar image processing, audio signal compression and restoration, and general signal feature extraction for classification. In mainstream seismic data analysis and processing AWA methods retain a specialty reputation, although recent years have seen an increase in interest, research, and applications. We describe two such applications in seismic data processing and interpretation practice. In one application, intended to complement and extend current approaches to spectral decomposition, we use AWA for spectral feature extraction. In another application, we have implemented tools for denoising in order to tackle noise problems that are difficult or even impossible to solve with other attenuation techniques.

AWA utilizes libraries of localized waveforms to analyze signals in terms of their local correlations with scaled and shifted versions of those waveforms. One method in particular, Wavelet Packets Analysis, WPA, yields a redundant signal transcription that can be searched algorithmically for sparse subsets optimally adapted for a given application, such as denoising, compression, or feature extraction [Coifman 1997], where each subset can be a basis for the signal allowing its perfect reconstruction. There are many advantages to a signal basis representation that is obtained adaptively. In particular, WPA can capture non-stationary signal energy that is localized in time, space, and frequency and do so adaptively, without a pre-established resolution grid in those domains. In comparison, analysis based on the short-time Fourier transform, STFT, provides only a fixed-resolution view of the analyzed signal, thus preventing exact modeling of strongly localized features.

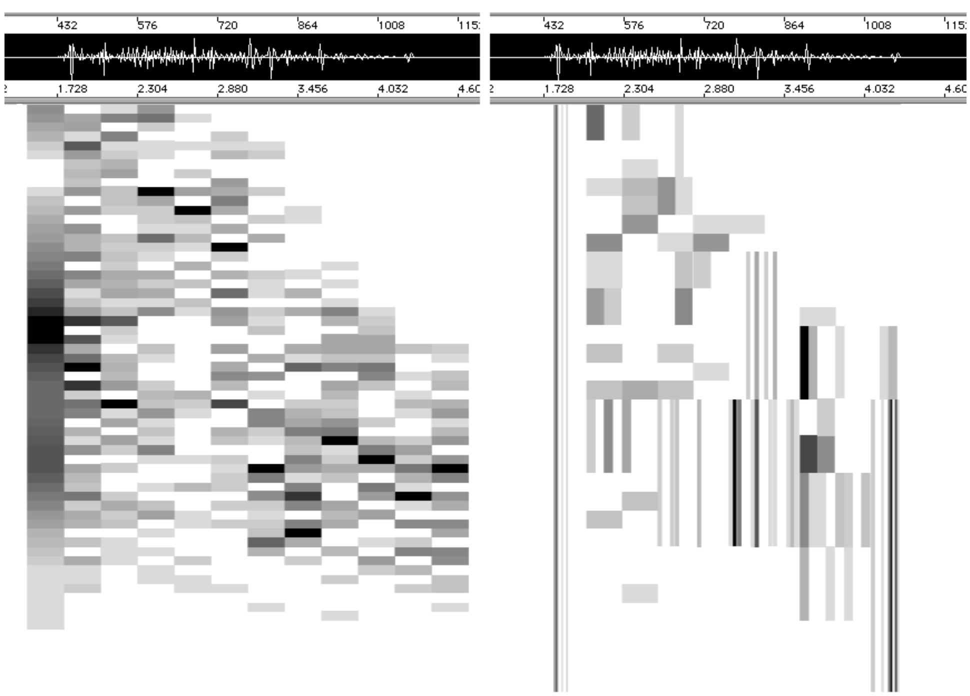

Figure 1: STFT and WPA time-frequency decompositions of a seismic trace. Vertical dimension represents frequency up to the Nyquist rate. Boxes represent transform coefficients, with darker shade corresponding to higher amplitude.

Figure 1 illustrates this by comparing, schematically, plots of time-frequency decompositions obtained by means of STFT and WPA for the 1-dimensional case of a single seismic trace. The STFT results in tiling the phase plane by a single time-frequency window, with a fixed resolution in time and frequency. The tiling obtained from WPA with so-called best-basis extraction [Coifman, Wickerhauser 1992] allows for a great variety of time-frequency windows that are adapted to the signal's actual energy distribution. Narrow and wide windows can occur over the same time interval, thus allowing for simultaneous optimal representation of both rapid transients and extended signal components, and even various superimpositions of these.

Adaptive Spectral Feature Extraction

In seismic data processing practice we extend WPA to 2 and 3 dimensions, to analyze lines and volumes. Here we illustrate one application of such analyses, developed to offer a complement to current spectral decomposition techniques in some scenarios. In particular, we address the data proliferation problem of spectral decomposition [Partyka 1999] for 3-D volumes, which initially generates numerous narrow-band versions of a data set. The integration of such a potentially unwieldy result into the work flow is rendered practical by focusing on limited zones of interest, however, it may pose a problem for exploring large data sets as a whole. Instead of generating numerous frequency volumes, one for each frequency within a desired range, and then combining them into animated frequency slice stacks, we extract a small series of spectrally contiguous sparse volumes by applying WPA iteratively. At each iteration we compute adaptively the best-analyzing set of wavelet packets. Those packets' spectrum then represents the spectrum of a feature subset and it is used to extract that subset. By iterating this process on the residual the original data is decomposed into a sequence of such feature subsets. Instead of scanning an entire volume for the next best-adapted spectrum we can also obtain a feature set at a location of interest, such as a well, and use it to scan the entire volume. For example, in one application, we have computed local feature sets at producing and non-producing wells and used these to discriminate between one or the other well class throughout a large data volume.

WPA-based spectral feature extraction produces seismic data, hence the result is readily visualized or brought into a work flow as another attribute volume. Figure 2 below illustrates a single extracted feature volume, rendered along with several producing wells. The feature predicts the wells and invites further interpretation of a larger potential zone of interest. Figure 3 shows the spectra of features 1 through 4 extracted from the data where feature 2 predicted the four given producing wells. As shown, an individual feature's spectrum has a characteristic bandwidth and envelope and may well overlap with one or more other feature spectra, just as structural features of interest may overlap in the actual data. WPA enables strong separation of such features, unlike methods that are not adaptive, and, as implemented in the spectral feature extraction used here, provides a robust measure of cohesiveness and continuity across the time, space, and frequency domains.

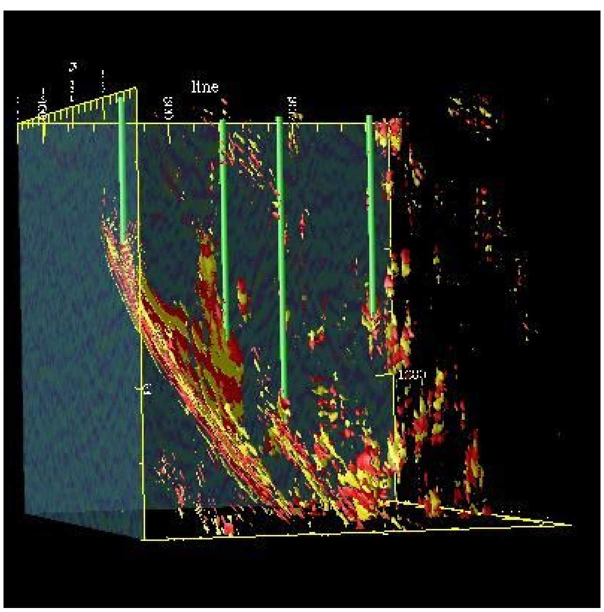

Figure 2: Feature 2 with four producing wells.

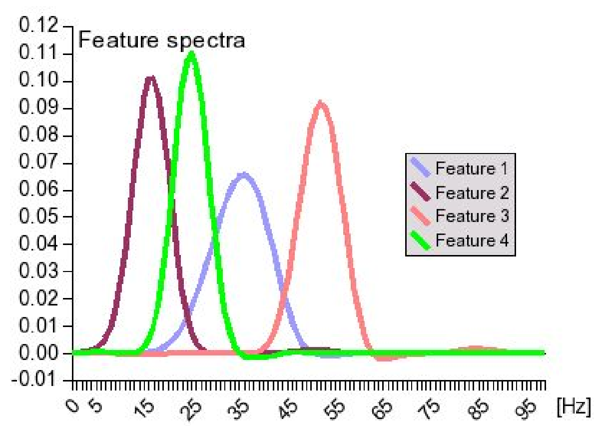

Figure 3: Spectra of features 1-4 from a WPA-based feature extraction (feature 2 spectrum peaks at ca 14 Hz).

Applications of Adapted Waveform Analysis

Adaptive Noise Attenuation

Strong presence of any one of many possible types of noise in seismic data constitutes a serious impediment to proper processing and interpretation, especially when the noise is highly energetic and highly coherent. In such scenarios available denoising techniques may often fail to do a good job or they may even seriously damage the data proper.

The classical approach to denoising with adapted waveforms assumes a transform and resulting representation that map desired signal energy onto a small set of large coefficients and the noise to be attenuated onto a long “tail” of low-amplitude coefficients. A thresholding strategy is then applied to the tail prior to signal reconstruction [Donoho 1992]. For this to work, the chosen basis must capture the data proper well and the noise poorly. Noise in seismic data resulting from ocean surface swell, cable jerk, acquisition footprint, but also various migration artifacts is not trivially modeled in this fashion, especially when noise and data align and overlap and the search for a transform domain where they might “magically” separate is hopeless.

To attack hard noise problems, we have developed and implemented software tools to apply AWA-based feature analysis for denoising. Noise and signal are understood as feature sets, one desired and the other undesirable, and models are built adaptively for each. To further improve the process, both models are built gradually over a series of iterations. At each iteration both models are used to discriminate against each other and, gradually, to extract and accumulate more of their respective energy from each other, by steering the WPA algorithm to choose a basis that best represents energy that is sought and worst that is to be removed.

Figure 4 illustrates selected stages of the process for the case of swell noise. We start with initial signal and noise models obtained by brutally over-denoising the input data. In this first step we try to separate out as much of the noise structure as possible even at the cost of losing signal energy in the process. Over a series of iterations we then use the basic structure remaining in the initial data model to “pull” more of the signal energy back from the emerging noise model and, conversely, to migrate any still lingering noise energy into the noise model. The final feature separation is nearly perfect, with even the fine signal structures “behind” the separated out noise feature set preserved.

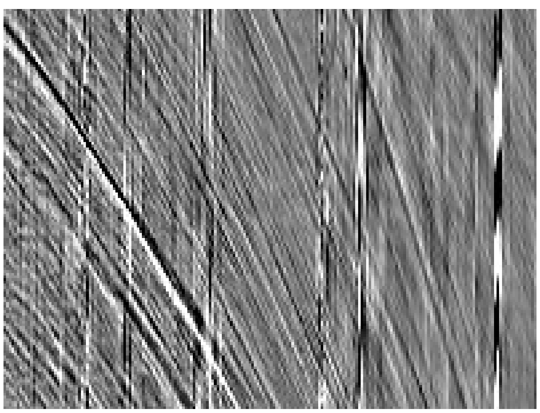

Figure 4-1: Original data

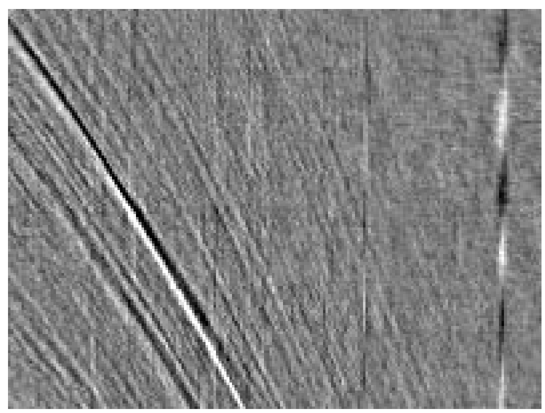

Figure 4-2: Initial data model

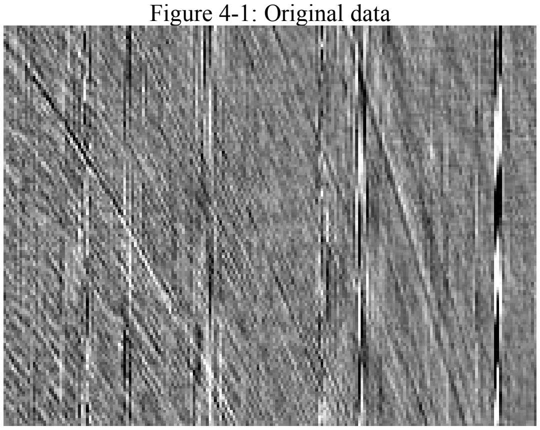

Figure 4-3: Initial noise model

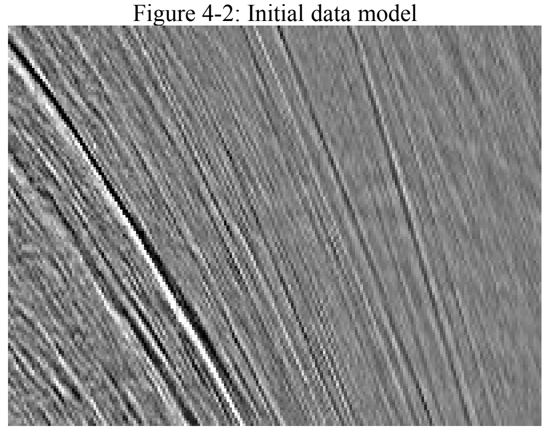

Figure 4-4: Final data model after 7 iterations

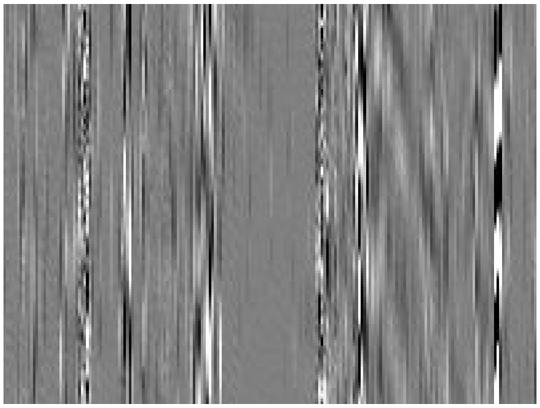

Figure 4-5: Final noise model after 7 iterations

The basic analysis algorithm is parametrized to allow steering the algorithm with a small number of parametric tuning “knobs”, with the goal of achieving an observable improvement at each iteration. As with our spectral feature extraction, intermediate results obtained by reconstruction from a best-basis, are seismic data so that the denoising progress is easily monitored. In complex scenarios, where different types of noise interfere with each other and with the data proper, the process may be applied in succession, removing one class of noise at a time.

Conclusion

Data analysis and processing tools incorporating Adapted Waveform Analysis, AWA, can provide assistance with routine and specialized tasks and complement existing methods to promote the never-ending quest for a better image of the subsurface. No single tool or method will fulfill all needs. However, AWA provides a flexible and expandable collection of building blocks that awaits further development and utilization in many more applications than we were able to show here.

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