Random and coherent noise attenuation by empirical mode decomposition

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SUMMARY

This paper proposes a new filtering technique for random and coherent noise attenuation by means of empirical mode decomposition (EMD) in the f-x domain. The motivation behind this development is to overcome the potential low performance of f-x deconvolution for signal-to-noise enhancement when processing highly complex geologic sections, data acquired using irregular trace spacing, and/or data contaminated with steeply dipping coherent noise.

The resulting f-x EMD method is shown to be equivalent to an auto-adaptive f-k filter with a frequency-dependent, high-cut wavenumber filtering property. It is useful in removing both random and dipping noise in either pre-stack or stacked/migrated sections and compares well with other noise-reduction methods such as f-x deconvolution, median filtering and local singular value decomposition. In its simplest implementation, f-x EMD is parameter free and can be applied to entire datasets in an automatic way.

INTRODUCTION

Spatial prediction filtering in the f-x domain is an effective method for random noise attenuation. The idea, originally proposed by Canales (1984), exploits signal predictability in the spatial direction. Noise-free events that are linear in the t-x domain, manifest themselves as a superposition of harmonics in f-x domain. These harmonics are perfectly predictable using an autoregressive (AR) filter. When the data are corrupted by random noise, the "signal" is considered to be the part of the data which can be predicted by the AR filter and the "noise" is the rest.

However, in reality seismic events do not follow exactly Canales' assumptions and display nonlinear and nonstationary spatial behaviour. Examples include a hyperbolic moveout or a linear event with an amplitude that varies with offset. The "signal" is no longer mapped to a superposition of simple harmonics, but rather a superposition of *nonlinear* and *nonstationary* ones. More distortion is added to Canales's model, when the seismic data are irregularly sampled in the spatial direction. The use of a recursion-type filter (e.g. an AR filter), which assumes regular spacing, is not necessarily optimal in this case.

Standard spatial filtering techniques like f-x deconvolution or a k-filter cope with nonlinearity and nonstationarity by filtering the data over a short spatial window. This leaves the choice of finding optimal parameters for the window and the filter to the processing specialist. The selection of these parameters depends strongly on the smoothness of the data and varies with the frequency f. Filtering should be ideally data-adaptive to achieve best performance. This is however difficult to implement manually and is rarely done in practice.

In this paper we propose a new data-driven technique for noise attenuation in the f-x domain. Empirical mode decomposition (EMD) was developed by researchers at NASA with the specific aim of analysing nonlinear and nonstationary data (Huang et al., 1998). It constitutes therefore an interesting novel domain to design data-adaptive filters for the reduction of seismic noise.

THE EMPIRICAL MODE DECOMPOSITION (EMD)

General background

EMD decomposes a data series into a finite set of signals, called intrinsic mode functions (IMFs). The IMFs represent the different oscillations embedded in the data. They are constructed to satisfy two conditions: (1) the number of extrema and the number of zero-crossing must be equal or differ at most by one; and (2) at any point the mean value of the envelope defined by the local maxima and the envelope defined by the local minima must be zero. These conditions are necessary to ensure that each IMF has a localised frequency content by preventing frequency spreading due to asymmetric waveforms. Unlike the Fourier transform, which decomposes the signal into a sum of single-frequency constant-amplitude harmonics, the IMFs are elementary amplitude/frequency modulated harmonics, that can model the nonstationarity and the nonlinearity in the data (Huang et al., 1998).

The IMFs are computed recursively, starting with the most oscillatory one. The decomposition method uses the envelopes defined by the local maxima and the local minima of the data series. Once the extrema are identified, all the local maxima are interpolated by a cubic spline to construct the upper envelope. The procedure is repeated for local minima to produce the lower envelope. The mean of the upper and lower envelopes is subtracted from the initial data, and the same interpolation scheme is reiterated on the remainder. This sifting process terminates when the mean envelope is reasonably zero everywhere, and the resultant signal is designated as the most oscillatory or the first IMF. The first IMF is subtracted from the data and the difference is treated as a new signal on which the same sifting procedure is applied to obtain the next IMF. The decomposition is stopped when the last IMF has a small amplitude or becomes monotonic.

An example of applying EMD on a real signal is shown in Figure 1. The original signal (Figure 1a) is non-stationary and has a clear nonlinear oscillatory behaviour. The IMFs are iteratively derived starting with the fastest component, IMF1, to the slowest one, IMF7 (Figures 1b–1h). IMF1 captures the high frequency oscillations in the data and the IMFs become subsequently smoother. The last IMF represents in general the trend in the data.

F-x domain EMD

How can EMD be used to remove seismic noise? It is arguably true that random noise corresponds mostly to high-wavenumber energy in the f-x domain. IMF1 represents the fastest oscillations in the data, i.e., it contains the largest wavenum-

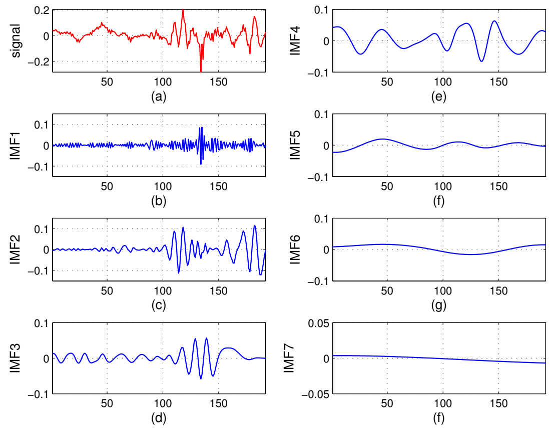

Figure 1: Example of using EMD to decompose a signal into IMFs. The signal (a) exhibits a clear nonstationary behaviour. The decomposition performed by EMD yields here 7 IMFs (b)-(h). The number of oscillations decreases with increasing IMF number. IMF7 (h) represents the trend in the data. EMD is different from simple bandpass filtering in that different IMFs can have a partly overlapping frequency content (e.g., IMFs 2 and 3).

ber components for the real and imaginary parts of a spatial sequence in the f-x domain. Therefore, signal enhancement can be achieved by subtracting IMF1 from the data.

To process a whole seismic section, f-x EMD filtering is implemented in a similar way to f-x deconvolution.

1. Select a time window and transform the data to the f-x domain;
2. Then for every frequency:
   (a) Separate real and imaginary parts in the spacial sequence;
   (b) Compute IMF 1 for the real signal and subtract to obtain the filtered real signal;
   (c) Repeat for the imaginary part;
   (d) Combine to create the filtered complex signal;
3. Transform data back to the t-x domain;
4. Repeat for the next time window.

Unlike f-x deconvolution, which uses a fixed filter order for all frequencies, EMD adaptively matches its decomposition to the smoothness of the data offering the ability to implement a different filtering scheme for each frequency. It is worth emphasising that removing IMF1 solely at each frequency is a single possibility among many. This scheme is the simplest one and has led to good performance on all datasets we have tested.

REAL DATA APPLICATIONS

The performance of f-x deconvolution and f-x EMD for signal enhancement is compared on two real datasets. The f-x analysis is implemented by a short-time Fourier transform with a sliding temporal window of length 512 ms and an overlap of 50% to remove edge effects. Frequencies beyond 60% of the Nyquist frequency are not processed and are damped to zero.

Shot gather

A single shot gather that contains 192 traces of 2.5 s length sampled at 2 ms is shown in Figure 2a. The data contains some interesting features such as: shallow back-scattered energy, a linear right dipping event, ground roll, linear left dipping events and weak amplitude zones, probably due to bad geophone coupling. The primary objective in processing this gather is to enhance the target reflections (the nearly flat events) and to attenuate all others. F-x deconvolution is implemented using an AR filter of order 4, and 20 spatial samples are used to estimate the filter coefficients.

$F-x$ deconvolution boosts all coherent events, including the unwanted ones such as the left dipping events and the ground roll (Figure 2b). It also interpolates events across the weak zones. The latter property can be an advantage or a disadvantage depending on the event considered. It is a clear advantage if we consider the target events, but a disadvantage if we consider the left dipping events. The difference section for f-x deconvolution (Figure 2c) demonstrates that the back-scattered energy and the right dipping event are partly removed, yet other events are emphasised (e.g., the ground roll). The interpolation property of f-x deconvolution is also clearly visible in the weak amplitude zone (around trace number 80).

F-x EMD emphasises the target reflections and filters out the back-scattered energy and the ground roll very effectively (Figure 2d). It also removes the right dipping events (Figure 2e). F-x EMD has less interpolation power compared to f-x deconvolution. The weak amplitude zone between trace number 70-80 has not been reduced. This is due to the fact that EMD is not a recursive spatial filtering method, so no signal energy is passed to the next sample.

Inspection of the difference sections (new minus old) shows that f-x EMD performs much better than f-x deconvolution on this shot gather. F-x deconvolution will boost any coherent energy and is therefore less appropriate for this dataset. Changing its parameter settings does not lead to significantly better results in this case.

To understand better the filtering behaviour of f-x EMD, we consider the f-k spectra of the original and filtered data (Figure 3). The wavenumber axis is normalised by the Nyquist value. Standard f-k transforms assume implicitly that the data are regularly sampled both in time and space. This is not the case here. The trace spacing of this shot gather is highly irregular and alternates between 5 and 7 m, leading to several aliasing artifacts visible in Figure 3a. For instance, the upside-down half cones centred at normalised wavenumber of $\pm$ 1 are artifacts caused by the irregularity in the spatial sampling. They disappear if only regular spaced traces are extracted. Despite these artifacts, the f-k spectra reveal many interesting features of f-x EMD versus f-x deconvolution and gives a physical interpretation of its filtering behaviour.

The ground roll (B) is spatially aliased and mirrored in (B1). The refraction (C) dominates the signal energy, while the background noise (D) is spread out over the high-frequency area of

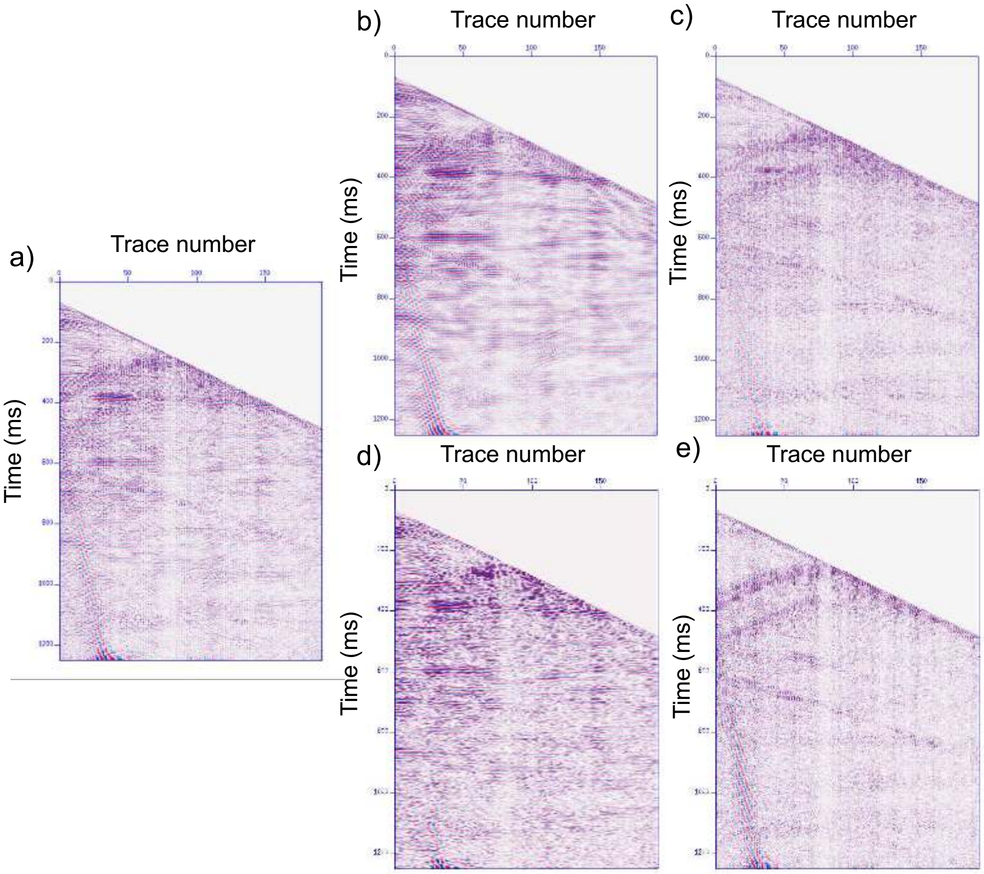

Figure 2: A land shot gather. (a) Original data, (b) filtering result of f-x deconvolution, (c) residual of f-x deconvolution, (d) filtering result of f-x EMD, (e) residual of f-x EMD. F-x deconvolution reduces the background noise but it enhances all coherent energy, whereas f-x EMD removes most background noise, the backscattered energy, most remnant ground roll and the linear dipping events. Data courtesy of BP.

the spectrum. The target reflections (E) are located around zero wavenumber (they are predominantly horizontal in Figure 2).

F-x deconvolution removes some of the background noise (D), enhances the reflections (E), but leaves the ground roll (B, B1) unaffected (Figure 3b). F-x EMD on the other hand, enhances the reflections (E), while largely attenuating the ground roll (B, B1), its aliased energy (B1) and the high frequency components (typically above 60Hz) of the refractions (C).

F-x EMD acts as an adaptive high-cut wavenumber filter in the f-k domain (Figure 3c). At the lower frequency end, the ground roll has been removed. At the middle-to-high frequency spectrum, all energy outside the normalised wavenumber [-$\frac{1}{3}$, $\frac{1}{3}$] has been dampened, leading to the automatic suppression of background noise and much of the aliased energy. The algorithm determines, from the data, what wavenumbers are to be suppressed as a function of frequency. This is very different from the behaviour of f-x deconvolution which emphasises any coherent energy and is mostly appropriate only for suppression of random noise.

Stacked section

Next, we consider a stacked section containing shallow horizontal and marginally dipping reflectors in the middle (Figure 4). Some crossing artifacts are present in the bottom of the section, which are probably due to previous processing applied to the data. We apply f-x EMD and f-x deconvolution with the same parameter values as for the first example. The results are displayed in Figure 4.

F-x deconvolution attenuates some of the background noise. However it leaves the crossing artifacts untouched (Figures 4b and 4c). It also causes amplitude distortion by partially removing useful reflector energy (particularly those at 600 ms), as shown in the difference section (Figure 4c). F-x EMD (Figure 4d) attenuates also some of the background noise but very little amplitude distortion occurs, as little reflector energy is visible in the difference section (Figure 4e). More importantly f-x EMD is able to remove the crossing artifacts, leading to an overall performance improvement over f-x deconvolution.

We have also compared f-x EMD with other techniques to reduce noise contamination in seismic data such as median filtering and local singular value decomposition (Bekara and Van der Baan, 2007). It proves to be a very interesting processing alternative to such local methods for signal-to-noise enhancement.

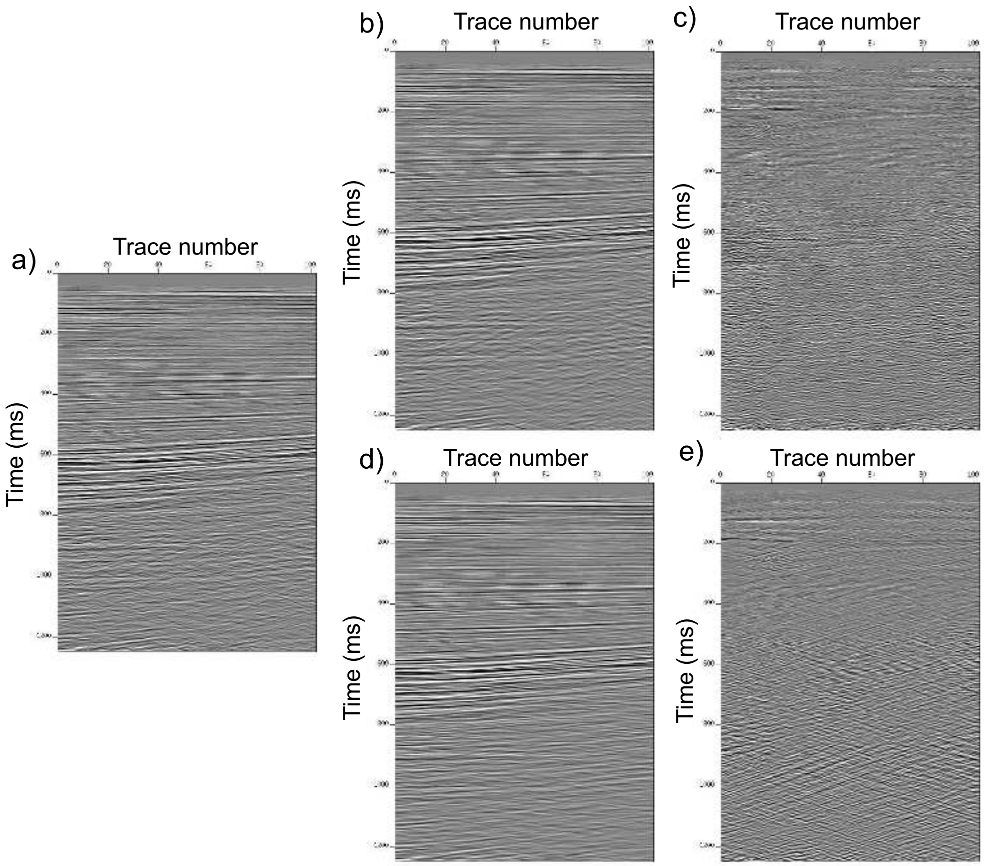

Figure 4: A marine stacked section. (a) Original data, (b) filtering result of f-x deconvolution, (c) residual of f-x deconvolution, (d) filtering result of f-x EMD, (e) residual of f-x EMD. Both f-x deconvolution and f-x EMD reduce the background noise but only f-x EMD removes the criss-crossing artifacts. Data courtesy of Shell.

CONCLUSION

F-x EMD is equivalent to an auto-adaptive f-k filter, with a high-cut wavenumber property. It can attenuate both dipping and random noise and does not require regular spatial sampling. It is expected to work most effectively when the target events are relatively horizontal, compared with the noise. Typical examples include NMO corrected and stacked sections.

We recommend routine inspection of difference sections to determine if any useful other signal has been removed, and for comparison with other noise-reduction tools such as f-x deconvolution. One of the most interesting aspects of f-x EMD is the fact that it is a parameter-free filtering tool in its simplest implementation which removes the first intrinsic mode function only. Other schemes are possible gaining more flexibility in the type of noise removed at the expense of introducing more user interaction.

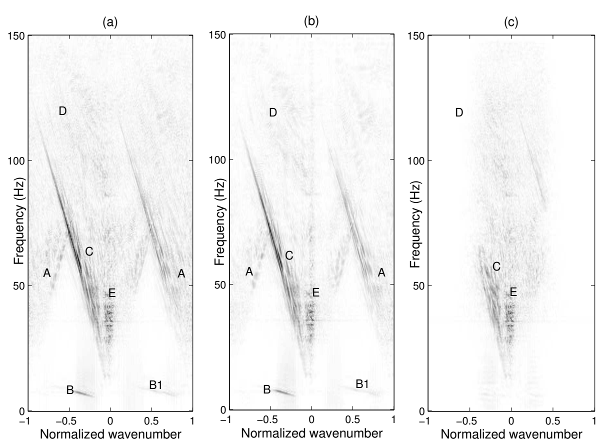

Figure 3: F-k spectra related to data sections in Figure 2. (a) Data and results of (b) f-x deconvolution and (c) f-x EMD filtering. F-x EMD corresponds to an auto-adaptive filter in the f-k domain that reduces random and coherent noise and can handle irregularly spaced data.

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EDITED REFERENCES

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