

The Borga Transform and some applications in seismic data analysis

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ABSTRACT

Signal transforms form the bases for many seismic data processing and analysis algorithms. We present the adjoint of the Gabor transform, which we call the Borga transform. The Gabor transform uses the operations of first windowing and then Fourier transform while the Borga transform reverses the order so that the window is applied in the frequency domain. The result is a real-valued time-frequency decomposition that is essentially a complete set of filter slices. When summed, the frequency slices exactly recreate the original signal.

The Borga transform can be used in a various processing steps. Since surface noise is predominantly low-frequency and high-amplitude, one can separate it from the signal in a raw shot gather. Other types of noise can have a band-limited nature and anomalous amplitudes as well. By assuming local linear behavior of the amplitudes in a CMP NMO-corrected gather, we can design a noise attenuation algorithm, based on Borga frequency slices. The process can lead to better results in AVO analysis and inversion. The transform can be a natural choice for time-variant spectral whitening as well. By applying an amplitude gain function to frequency slices, one can compensate for time and frequency dependant amplitude attenuation.

INTRODUCTION

Signal transforms form the bases for many seismic data processing and analysis algorithms. Examples include the Fourier transform, the Radon transform, the Gabor transform and so on. The basic idea is that in a different domain, various physical events (primaries, multiples, surface waves) and noise a better separable.

In this publication we present a new type of transform, the Borga transform, which can be viewed as adjoin of the Gabor transform. We believe that it can be implemented in various seismic processing and analysis algorithms. Three examples are presented: CMP NMO-corrected gather noise attenuation, high-amplitude data separation and time-variant spectral whitening.

THE BORGA TRANSFORM

In recent years the Gabor transform (short-time Fourier transform) has seen an increase usage in seismic data processing, analysis, and interpretation. Examples include the Gabor deconvolution (Margrave and Lamoureux, 2001) and spectral decomposition. In this publication we present the adjoint of the Gabor transform, which we call the Borga transform. The Gabor transform uses the operations of first windowing and then Fourier transform while the Borga transform reverses the order so that the window is applied in the frequency domain. The result is a real-valued time-frequency decomposition that is essentially a complete set of filter slices. When summed, the frequency slices exactly recreate the original signal.

Figure 1 is a flow chart of the Borga transform algorithm:

1. Compute the complex Fourier spectrum of the input signal (seismic trace) via DFT.
2. For each frequency:
 - Multiply (window) the complex Fourier spectrum with a Gaussian window, centred at the frequency.
 - IDFT of the windowed spectrum.

After repeating for all frequencies we compute a series of frequency slices of the seismic trace. Each one of them contains narrow band-pass information of the signal, such as amplitude strength and location in time. The inverse Borga transform is completed by summing all frequency slices. The inverse process reconstruct the seismic trace exactly, however one should properly scale the area of Gaussian window to one, if the non-zero tails go below 0 Hz or above Nyquist.

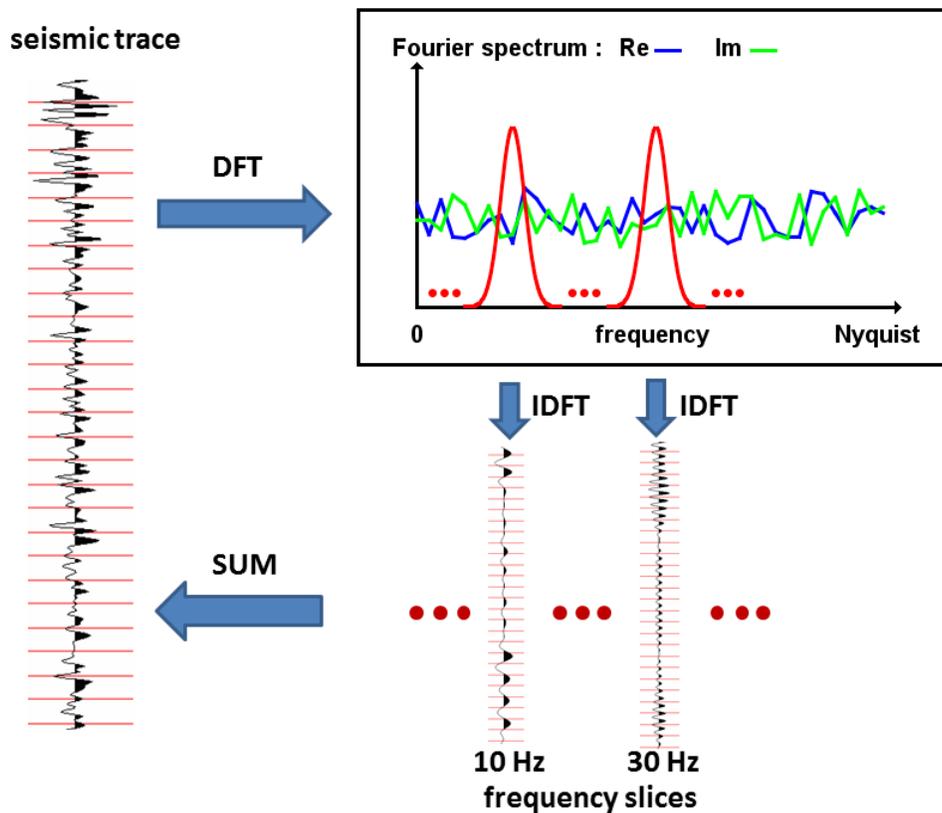


FIG. 1. Flow chart of the Borga transform. A seismic trace can be decomposed into frequency slices by performing DFT, multiplying the complex Fourier spectrum with a Gaussian window and applying IDFT. The inverse Borga transform is performed by summing all the frequency slices.

APPLICATIONS

CMP gather noise attenuation

Figure 2 shows NMO-corrected CMP gathers from the Blackfoot 3D survey (Lawton at all., 1996) and two Borga frequency slices at 10 Hz and 40 Hz. The gather in the middle contains a noisy trace. From the frequency slices we can conclude that the noise is mainly present at the 10 Hz frequency slice, while the 40 Hz looks relatively clean. It is obvious that noise can be band-limited in nature and have abnormal amplitudes at particular Borga frequency slices. For example ground roll is relatively low frequency, while the power line noise has a very narrow, mid-range bandwidth.

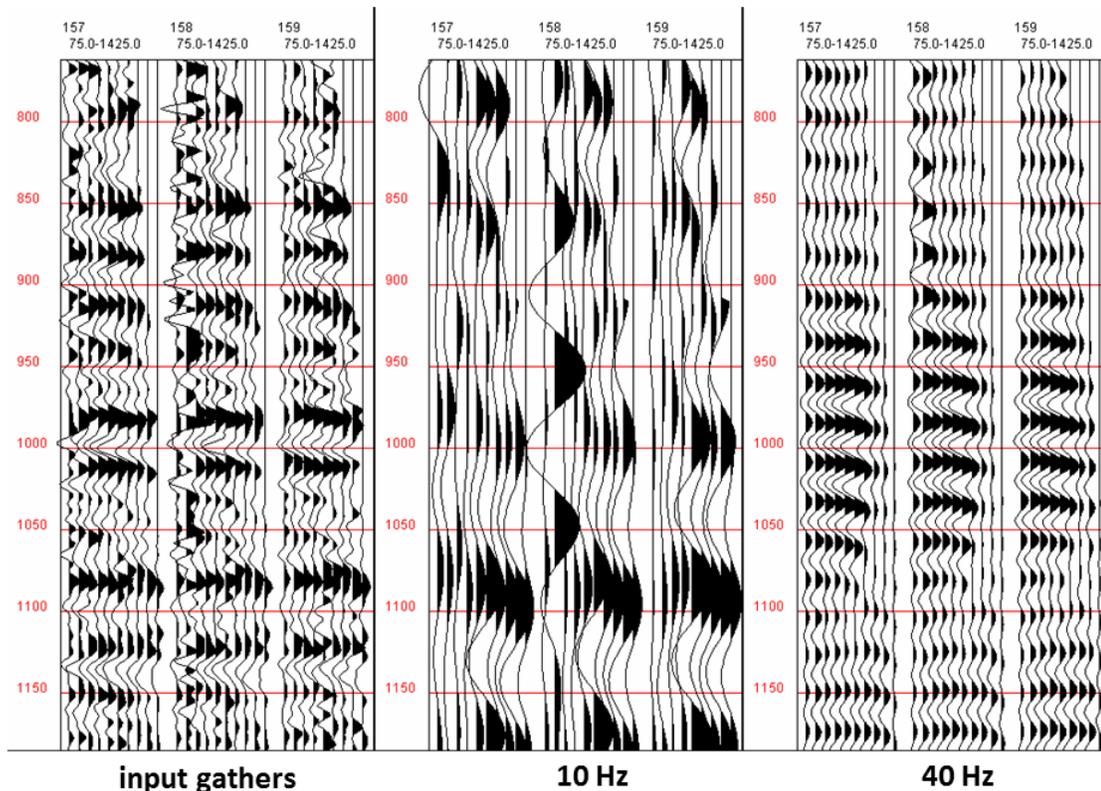


FIG. 2. Blackfoot CMP NMO-corrected gathers and two Borga frequency slices at 10 Hz and 40 Hz. The gather in the middle has a relatively noisy trace. The noise is present at the 10 Hz frequency slice but not in the 40 Hz one.

Aki and Richard (1980) have shown us that within reasonable assumptions the amplitudes for a particular time change in a linear fashion with offset. AVO intercept and gradient analysis are based on the linear assumption.

Based on the above assumptions we can design a noise attenuation method:

1. Start with a CMP NMO-corrected gather.
2. Using the Borga transform, generate frequency sliced gathers.

3. For each frequency slice:
 - For each time:
 - Estimate the amplitude of all samples, based on a linear least-squares fit of nearby samples (the predicted sample is not used in the least-squares).
 - Compute the absolute error between the actual and estimated amplitudes.
 - Correct the amplitude of the sample with the largest error.
 - Repeat until the error is small.
4. Sum noise attenuated frequency sliced gathers to obtain the final result.

Figure 3 shows an example of the process. The input data are CMP NMO-corrected gathers from the Blackfoot survey. The noise attenuated gathers show better signal-to-noise ratio and they are better suited for AVO analysis, inversion, and interpretation.

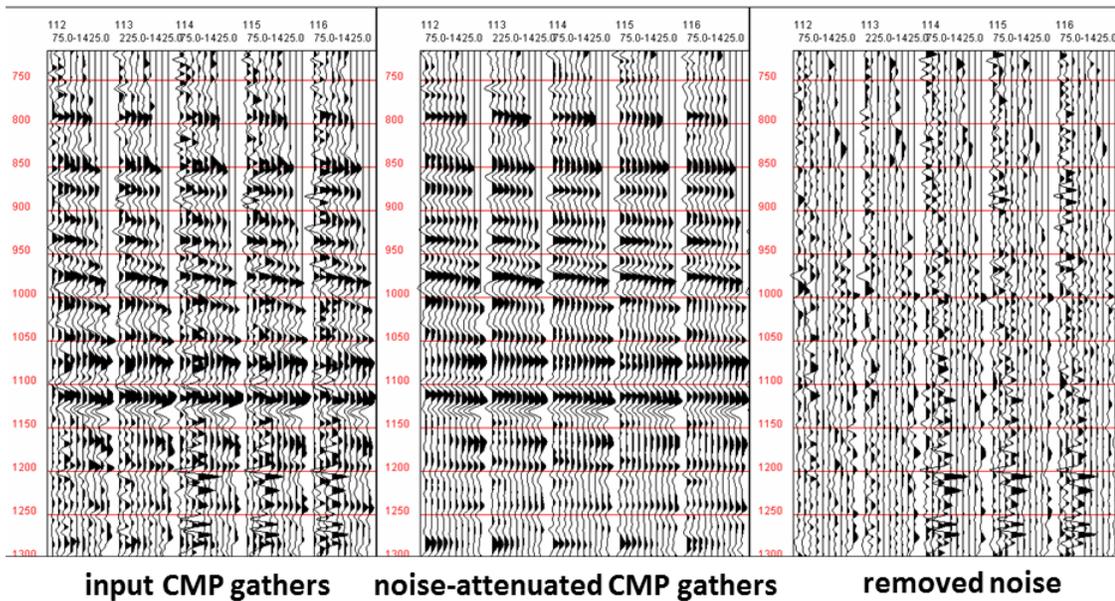


FIG. 3. CMP NMO-corrected gather noise attenuation example from the Blackfoot survey. The noise-attenuated gathers show better signal-to-noise ratio and are better suited for AVO analysis, inversion, and interpretation.

Frequency-dependant high-amplitude data separation

The Borga transform decomposes the single sample seismic amplitude into frequency dependant amplitudes. The ground roll will be present as band-limited high amplitudes. One can separate the data into anomalously high-amplitudes and reasonable amplitudes based on the following process:

1. Apply the Borga transform to a seismic trace.
2. For each sample, sort the frequency-dependant amplitudes in decreasing order. Anomalously high-amplitudes will be in front of the array.
3. Define a cutoff value: pick a reference value at the sample index that is, let say, 10% from the start of the array and multiply it by a scaler, let say 2.
4. Sum all the amplitudes, if an amplitude is above the cutoff value, replace it with the cutoff value, the difference is defined as high-amplitude data.

Figure 4 is an example of the process. In input shot gather has been separated into two shot gathers: one with ‘reasonable’ amplitudes and one with very high amplitudes, mostly ground roll.

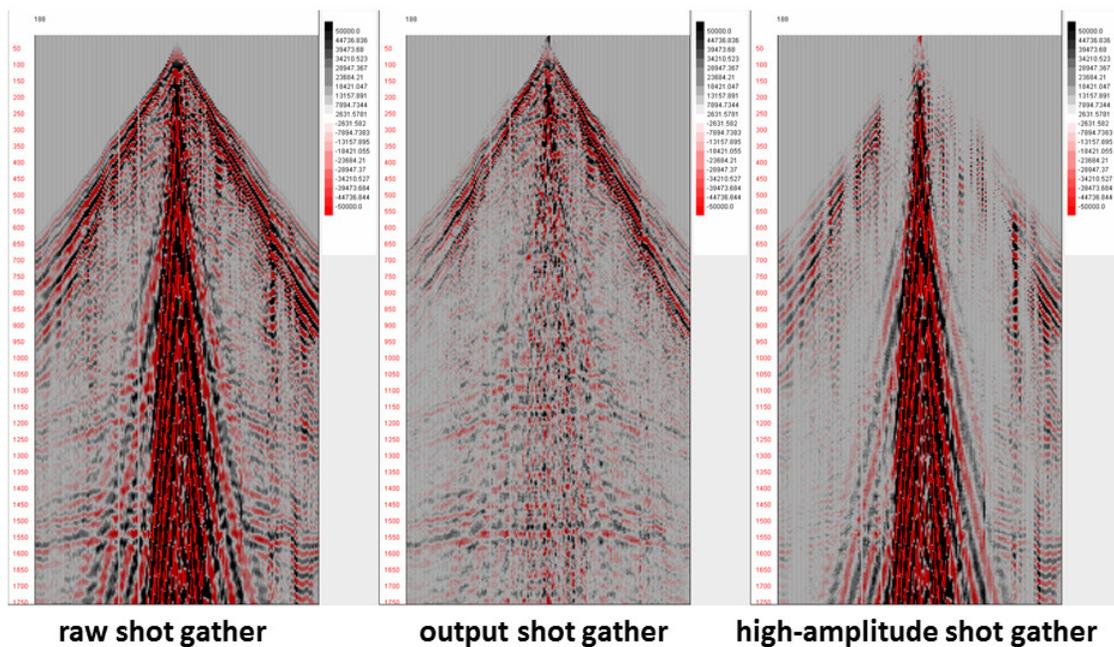


FIG. 4. High-amplitude data separation: input shot gathers has been separated into two gathers, one with ‘reasonable’ amplitudes and one with very high amplitudes, mostly ground roll.

Our tests have shown that some signal, different from ground roll, may leak to the high-frequency amplitude data if too aggressive cutoff is chosen. In its present form the process can be used to remove most of the ground roll with properly chosen cutoff, however more research is required to design a full ground roll attenuation process.

Time-variant spectral whitening

Time-variant spectral whitening (Yilmaz, 2001) is a common seismic processing process used to compensate for frequency dependant amplitude decay. It is commonly applied after spiking deconvolution (Yilmaz, 2001) to improve the flatness of the amplitude spectrum. The process is performed as follows:

- Pick a desired frequency bandwidth to be whitened, for example 8-70 Hz.
- Apply a series of narrow band-pass filters covering the desired bandwidth (frequency panels).
- Compute a time-dependant gain function, $g_f(n)$, for each panel:

$$g_f(n) = \frac{A}{\frac{1}{M} \sum_{n+M/2}^{n-M/2} |a_i|} \quad (1)$$

Where:

A – desired output amplitude level

n – trace sample index

M – window, usually 600-1000 ms

- Apply the gain function to the frequency panel.
- Sum all frequency panels to form the whitened seismic trace.

The design of the narrow band-pass filters and their number is up to the processor. The Borga transform properties make it a natural candidate to perform the TVSW on a seismic trace S, by computing a gain function for each frequency slice:

$$S(t)_{TVSW} = \sum_f g_f(t) S(t) \quad (2)$$

One may wish to restore the amplitudes of the original trace to preserve amplitude-friendly processing. Then the process is defined by:

$$S(t)_{TVSW} = \left[\sum_f g_f(t) S(t) \right] \sum_f \frac{1}{g_f(t)}$$

Figure 5 is an example of the TVSW with Borga frequency slices in the range of 8-60 Hz on a raw shot gather from the Blackfoot survey. This is a simple way to reveal the events hidden by the ground roll and QC the data.

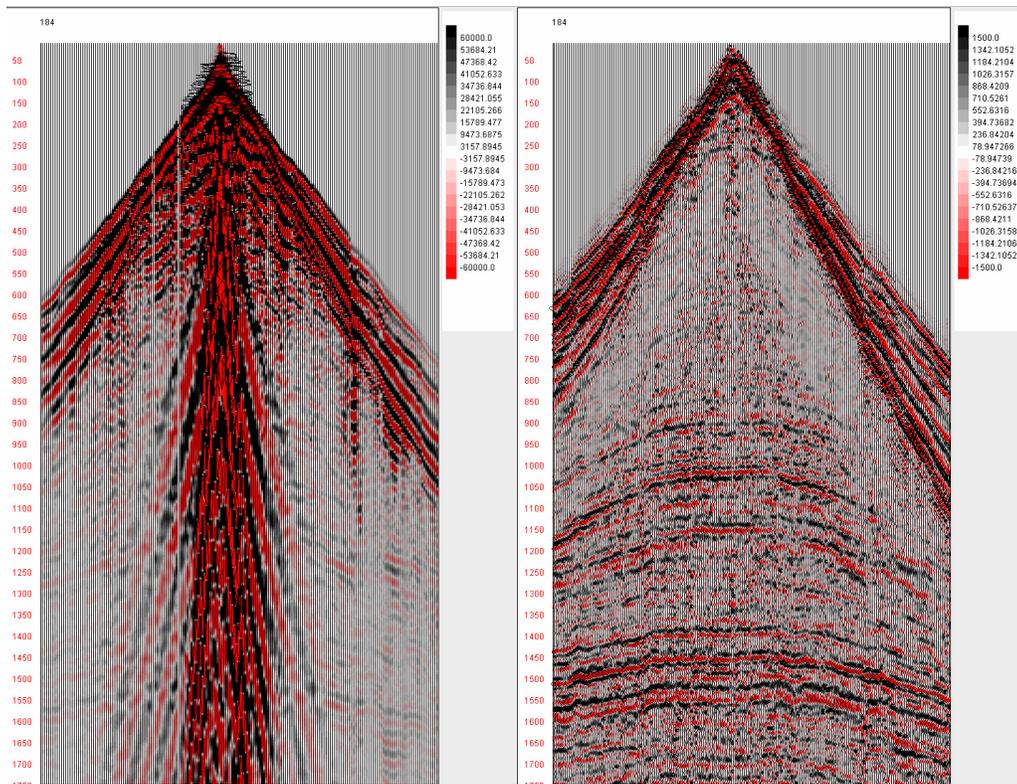


FIG. 5. Blackfoot raw shot record before and after TVSW 8-60 Hz with the Borga transform.

CONCLUSIONS

The Borga transform decomposes the seismic signal into a complete set of filter slices. This property makes the transform a useful tool for designing seismic data processing and analysis algorithms. The presented three processes in this publication show its successful implementation, however we believe that more can be designed and this is a topic of further research.

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