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## Application of Curvelet Denoising to 3D Post-stack Data Acquired in Hardrock Environment

A. Górszczyk\* (Institute of Geophysics, Polish Academy of Science) & M. Malinowski (Institute of Geophysics, Polish Academy of Science)

### SUMMARY

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Seismic data acquired in hardrock environment are demanding for processing. Frequently occurring lack of clear coherent events hinders imaging and interpretation. Additional difficulty arises from the presence of significant amount of cultural noise (e.g. associated with exploration and processing of ore) which corrupt the data. For this purpose we demonstrate our noise attenuation approach based on 2D Discrete Curvelet Transform (DCT) by applying it to 3D post-stack seismic data from active mining camp. DCT introduce minimal overlapping between coefficients representing signal and noise in the curvelet domain, hence being well-suited for data denoising. Forward DCT is applied in sequences to inline, crossline and time slice sections. 3D DMO volume after curvelet denoising is much easier to interpret, e.g. it's easier to follow diffracted energy originating at ore lenses. We believe that the presented approach of running 2D DCT for 3D data might be also a sufficient substitution for a more expensive 3D DCT.

## Introduction

Contamination of seismic signal with noise of various origin is one of the main challenges encountered during processing and interpretation of seismic data. Data acquired in hardrock environment are typically characterized by a high level of cultural noise due to the active mine operations. Moreover, reflections in a hardrock medium are usually sparse and discontinuous, with a lot of scattered (diffracted) energy. Therefore, processing of such data requires non-standard approaches.

Several authors (e.g. Herrmann et al., 2008; Kumar et al., 2011; Neelamani et al., 2008) already proved robustness of Discrete Curvelet Transform (DCT) (Candès et al., 2006) for attenuating random noise in seismic data. Here we demonstrate curvelet-based noise attenuation approach by applying 2D DCT to 3D post-stack seismic data acquired in the Flin Flon mining camp (White et al. 2012).

## Method

In the curvelet domain coherent energy appears as relatively small number of high value coefficients whereas random noise maps into large collection of small coefficients. Since the values of noise coefficients significantly differ at each curvelet scale, single threshold level is not sufficient for optimal signal and noise separation. Therefore in our algorithm we introduce *scale-adaptive* thresholding supplemented by additional *angle-adaptive* thresholding; the latter being based on the F-K spectra of the data.

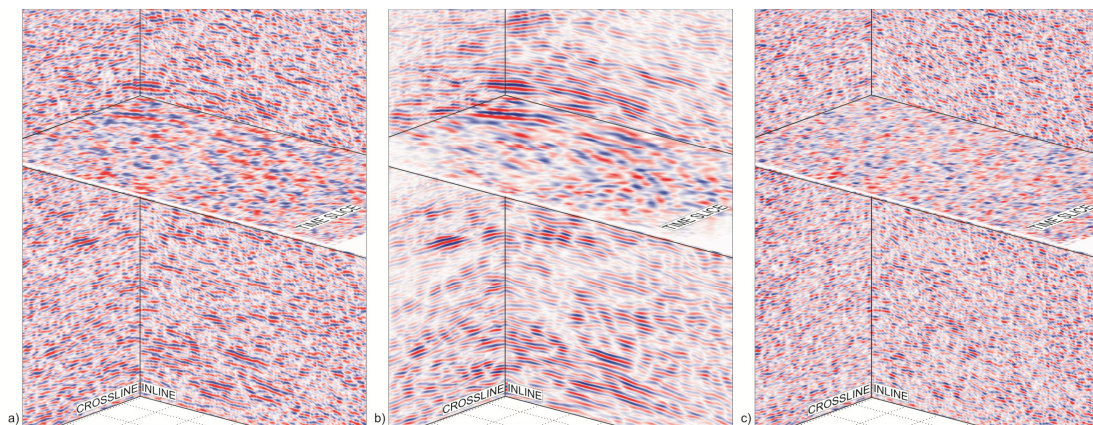
## Application to the Flin Flon 3D survey

We applied our curvelet-based *scale-adaptive* denoising algorithm to a real 3D data set acquired in a complex geological setting. The data comprise a 3D DMO stack volume from a 17 km<sup>2</sup> survey acquired in a hardrock environment (Flin Flon mining camp, Manitoba, Canada; White et al. 2012). Due to high cultural noise associated with production and processing of ore and active town operation, data are relatively noisy. DMO stack was post-processed with a F-XY deconvolution, but remains relatively noisy. Our approach to 3D data noise attenuation was a consequence of initial experiments with applying curvelet based denoising to time slices. Visible and measurable improvement of SNR in inline and crossline sections obtained from filtered horizontal slices encouraged us to employ 2D DCT to denoise 3D data. For the Flin Flon dataset (171 inlines spaced every 25 m, 340 crosslines spaced every 12.5 m) we started by filtering the inline sections. Afterwards, data were denoised in the crossline sections. This was done due to the fact that signal may be more difficult to capture on the time slices than on the vertical sections especially in case of hard rock data lacking clear coherent events. Such approach allowed to boost coherent energy before final filtering of the time slices.

Due to the number of sections and slices optimal thresholding was more challenging in this case. Individual adjustment of the threshold for each portion of data would be impractical and very time-consuming. To solve this problem we took the advantage of the fact that samples from the same data set present approximately similar characteristic in frequency and curvelet domain. After reviewing the frequency spectra and vectors of curvelet coefficients of selected samples, we opted for partitioning into 6 scales for inlines and crosslines and 5 scales for time slices. The number of angles was set to default which is 16 at 2<sup>nd</sup> coarsest scale and doubling every second scale. Threshold level was initially set to preserve only the highest 2% of all curvelet coefficients obtained from each input section or slice. After a few tests we concluded that the inline and crossline sections are denoised efficiently when stronger attenuation of the coarsest and the finest scale coefficient is applied. For scales 1, 2, 6 (inlines filtering) and 1, 5, 6 (crosslines filtering) threshold levels were multiplied by  $\epsilon=1.5$ . In case of time slices we noticed that filtering performed better while preserving more coefficients from the coarser scales, hence threshold levels for scales 4, 5 were multiplied by the same constant  $\epsilon=1.5$ . Final increase of the mean SNR after filtration with the scale-adaptive thresholds compared to the global

thresholding was equal to 12% when measured for inlines and 27% when estimated for crosslines. It validates our earlier conclusions that introducing more than one threshold level translates into improved results.

Figure 1 shows a fence-plot of the 3D volume used for filtering. Comparing data before (Fig. 1a) and after (Fig. 1b) noise attenuation we observe high improvement of signal quality in all directions. The recorded data is highly contaminated with noise so that the reflectors, discontinuous and crooked due to the geology of the area, are dominated by incoherent energy. Curvelet noise attenuation enhances the strong amplitude reflections and makes it easier to interpret the data. Difference between input and output data (Fig. 1c) shows the amount and the incoherent character of the energy separated from the signal.



**Figure 1** (a)(b) Fence-diagram of 3D DMO volume before and after noise attenuation respectively. (c) Energy considered as noise and extracted from input data.

## Conclusions

Curvelet-based denoising is a robust technique to increase S/N ratio of seismic data and it proves to work well in case of low S/N ratio data, such as the one acquired in hardrock environment. Flin Flon 3D volume after curvelet denoising is much easier to interpret, e.g. it's easier to follow diffracted energy originating at ore lenses. We believe that the presented approach of running 2D DCT for 3D data might be also a sufficient substitution for a more expensive 3D DCT.

## Acknowledgements

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