

## Seismic data denoising via shearlet transform and data-driven tight frame

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### Summary

We propose a sort of double sparsity dictionary (DSD) to deal with random noise of seismic exploration, which consists of shearlet transform and data-driven tight frame (DDTF). We train the DDTF dictionary in the domain of shearlet transform to improve the robustness of the dictionary. Furthermore, the function of hard-thresholding is applied to find dictionary coefficients and cut small shearlet coefficients. Finally, we verified the reliability of the proposed approach by a synthetic data denoising example.

### Introduction

Seismic data often suffer from random noise, which seriously interferes with the sequential seismic processing (e.g. deblending, migration, stacking, dynamic correction and static correction). In seismic data denoising, sparse representation is an effective method to attenuate random noise, especially for DSD. According to DSD, we combine the shearlet transform with DDTF to form a DSD and then apply hard-thresholding to attenuate the random noise.

### Denoising by DSD

Seismic data denoising by DSD can be formulated as follow (Chen et al., 2016):

$$\arg \min_{D, A} \|Y - \Phi^{-1} D^T A\|_F^2, s.t. \begin{cases} \|a_i\|_0 \leq t_0 \\ D^T D = I \end{cases}, \quad (1)$$

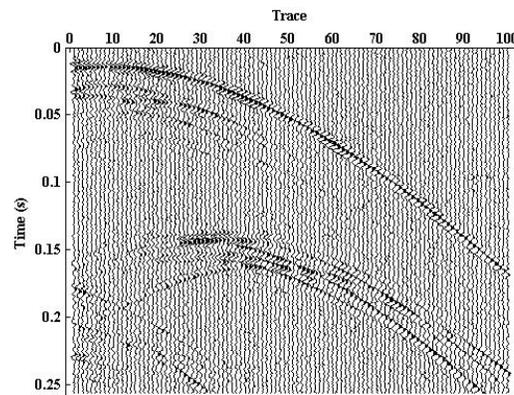
where  $Y$ ,  $\Phi$ ,  $D$ ,  $A$  and  $I$  denote noise data, shearlet transform, dictionary, dictionary coefficients and identity matrix, respectively. The superscript  $^{-1}$  stands for inverse transform and  $^T$  stands for transpose. Moreover,  $a_i$  is the  $i$ -th column of  $A$  and  $t_0$  is the amount of nonzero entry. We solve the equation (1) by alternately and obtain the result (Cai et al., 2014):

$$\begin{cases} \Phi Y (X^k)^T = U \Sigma V^T \\ D^{k+1} = UV^T \\ X^{k+1} = \Phi^{-1} H_\lambda \left[ (D^{k+1})^T \Phi Y \right] \end{cases}, \quad (2)$$

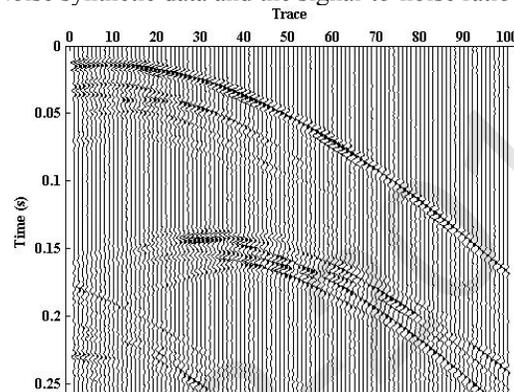
where  $\Phi Y (X^k)^T = U \Sigma V^T$  stands for singular value decomposition. The symbol  $H_\lambda(\bullet)$  denotes hard-thresholding function, and superscript  $^k$  denotes iteration.

### Synthetic data example

The noise synthetic data as shown in Figure 1 includes 100 traces, 256 time samples per trace and the temporal interval is 0.001 s. Next, we applied the proposed approach to attenuate the random noise, and the result is shown in Figure 2. As we can see in Figure 2, much random noise is moved, and it is worth noting that events are protected well.



**Figure 1.** Noise synthetic data and the signal-to-noise ratio (SNR) is 3 dB.



**Figure 2.** Denoising and the SNR is 13.2308 dB.

## Conclusions

The proposed approach has an outstanding performance in seismic data denoising, which attenuates much random noise and saves the energy of events well. Owing to its good result, we predict that it will be widely applied to seismic data denoising in the future.

## References

- Cai J F, Ji H, Shen Z, et al., 2014, Data-driven tight frame construction and image denoising, *Applied and Computational Harmonic Analysis*, 37(1): 89-105.
- Chen Y, Ma J, Fomel S., 2016, Double-sparsity dictionary for seismic noise attenuation, *Geophysics*, 81(2): V103-V116.