

# Seismic interference noise attenuation based on sparse inversion

Zhigang Zhang\* and Ping Wang (CGG)

## Summary

In marine seismic acquisition, seismic interference (SI) remains a considerable problem when marine seismic data sets are acquired in close vicinity to each other. We present a method for attenuating SI noise using a sparse Tau-P transform. Using a synthetic example, we demonstrate that this method effectively attenuates SI noise while preserving the seismic signals. Further tests on field data confirm the robustness of the method. Compared to the conventional Tau-P based method, our approach leaves less residual noise while still preserving the integrity of the primary signals.

## Introduction

Seismic interference is common in marine seismic surveys when multiple seismic surveys are acquired simultaneously in close proximity of each other. SI noise has a negative impact on seismic signal processing, such as multiple removal, and attenuation of such noise using stacking is unsuccessful when the slope is close to that of signals arriving around the same time. As a result, further processing is required to remove SI noise.

SI noise attenuation has sometimes been put into the same framework as deblending, which is an appealing technique with the potential to achieve a denser shot sampling rate (Berkout, 2008). Often similar algorithms can be applied to both data deblending and SI noise attenuation. Deblending usually resorts to iterative methods, which minimize a cost function and gradually separate signal and noise step-by-step (Baardman et al., 2014; Peng et al., 2014). However, SI noise is often not as strong as blended signals because the seismic sources that generate SI noise are usually not as close as the blended sources. As a result, costly iterative inversion methods are often not necessary for SI noise attenuation.

Identification and attenuation of SI noise can be performed in different domains, such as offset-time ( $x-t$ ), frequency-wavenumber ( $f-k$ ), and Tau-P (Yu, 2011). SI noise can be identified by moveout, slope, or amplitude. A propagation mechanism has also been used to identify and attenuate SI noise (Gulunay, 2008). SI noise attenuation algorithms can be applied in 2D or 3D domains, such as the  $f-x-y$  domain. Additionally, a SI attenuation algorithm has even been applied to 4D data (Kommedal et al., 2007).

Most aforementioned SI noise attenuation methods assume that shot spacing is sufficiently small in the sail line direction, and the geology varies slowly. Therefore, the

signals are coherent in the shot domain, while the SI noise is less coherent across consecutive shots. One approach for SI noise attenuation transforms each input shot gather (spatial windows may be optionally used) into the Tau-P domain. Then SI noise is identified and attenuated by comparing Tau-P coefficients between neighboring shots.

Tau-P transforms have been widely used in seismic signal preprocessing because they offer a good representation of the seismic signals (Gulunay et al., 2007). However, Tau-P transforms also suffer from energy leakage among different slowness values, which limits separability of events with different apparent dips. One solution is to add a sparseness constraint to the Tau-P transform to suppress energy leakage and thus improve the resolution of the Tau-P transform (Herrmann et al., 2000). This strategy was extended to a progressive sparse Tau-P inversion method by Wang and Nimsaila (2014) to improve the stability and efficiency and to better handle weak events.

We propose replacing the regular Tau-P transform with the progressive sparse Tau-P inversion to obtain a more accurate Tau-P representation of the input shot gather for SI noise attenuation. Our synthetic and field data examples show that this method leads to more desirable results than similar methods based on regular Tau-P transform.

## Method

Progressive sparse Tau-P inversion has been proposed for plane-wave decomposition in the presence of strong spatial aliasing (Wang and Nimsaila, 2014). The key is to find a sparse  $f-p_x-p_y$  model,  $M$ , to fit the input data,  $D$ , when inverse Tau-P transformed:

$$D(f; x^i, y^i) = \sum_j e^{-i2\pi f(x^i p_x^j + y^i p_y^j)} M(f; p_x^j, p_y^j), \quad (1)$$

where  $f$  is frequency,  $(x^i, y^i)$  is the receiver location, and  $(p_x^j, p_y^j)$  is the slowness pair ( $i$ : trace index;  $j$ : slowness index). Equation 1 can be solved through a progressive sparse Tau-P inversion process as described by Wang and Nimsaila (2014).

To make the data more suitable for plane wave decomposition, we divide shot gathers into local spatial windows (Figure 1). With coefficients in the Tau-P domain at hand, we compare the amplitude of coefficients of each gather with coefficients of its neighboring gathers to identify SI noise. By assuming that signals are continuous and slowly varying while SI noise is not, we can identify SI noise as outliers in the Tau-P domain. We scale-down those Tau-P coefficients that are considered as SI noise based on

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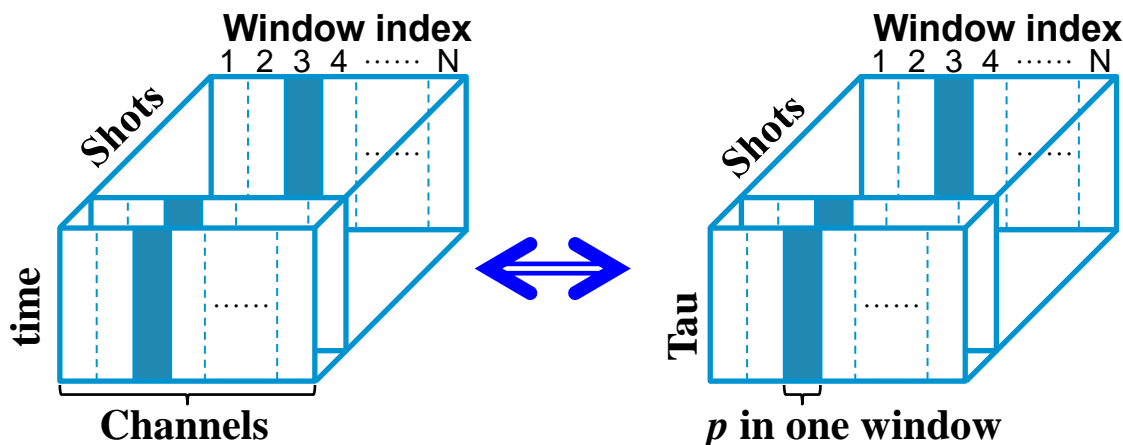


Figure 1: Sketch of our workflow: shot gathers are divided into spatial windows. Data in each window is transformed to the Tau-P domain. The Tau-P coefficients of neighboring shots in each window are compared to identify seismic interference (SI) noise.

the median value in each operation window and then transfer the scaled coefficients in the Tau-P domain back to the offset-time domain. As a result, the SI noise is attenuated, while the signal is preserved. An alternative approach is to generate an SI noise model by transforming the difference between the original and scaled Tau-P coefficients back to the  $x-t$  domain and subsequently removing the SI noise from the original gathers using a subtraction algorithm. The latter approach usually preserves the signal better. Throughout this work, we only show results generated using the first approach.

We summarize our flow as follows:

1. Prepare input shot gathers in the  $(x-t)$  domain.
2. Transform into the Tau-P domain using progressive sparse Tau-P transform.
3. Rearrange Tau-P coefficients into P-shot domain.
4. Identify and scale-down coefficients corresponding to SI noise.
5. Rearrange modified Tau-P coefficients into shot-P domain.
6. Transform the modified Tau-P coefficients back to  $(x-t)$  domain.

### Synthetic data examples

We generated a synthetic data set using the 2004 BP model (Figure 2a). Shot spacing was 50 m, and the maximum offset was 8000 m. The recorded signals included direct arrivals, reflections, and refractions from sediment structures as well as a complex-shaped salt body (Figure 2b). Different types of SI noise were added to the modeled synthetic shot gathers, including linear-shaped SI noise from both the head and tail of the cable boat and curve-shaped SI noise from the side of the cable boat (Figure 2b).

To demonstrate the effectiveness of our method, we increased the amplitude of SI noise to be stronger than what is typically found in field data. Attenuating the SI noise using a regular Tau-P transform with the same workflow resulted in SI noise residuals and signal damage in the output and the difference (Figures 2c and 2d). This was partly caused by the energy leakage problem of the regular Tau-P transform. Our proposed method reasonably attenuated SI noise and left minimal residuals in the output data, even with strong SI noise (Figure 2e). The difference between the input and the output of the proposed method did not show any observable primary damage (Figure 2f).

### Field data examples

Next, we applied our method to data acquired from Garden Banks, Gulf of Mexico with a shot spacing of 150 m (Figure 3a). The noise that arrived earlier than the first arrivals did not affect the processing steps. Therefore, the main objective was to attenuate the SI noise in the lower half of Figure 3a (blue box). After applying the SI attenuation method using a regular Tau-P transform, some residual SI remained (Figure 3b, blue arrows). Although harsher parameters could further attenuate the SI noise residuals, this would result in signal damage. The limited resolution of the regular Tau-P transformation caused by the leakage problem prevented us from clearly separating signal and noise. On the other hand, the progressive sparse Tau-P transform allowed us to find a better balance leaving noise residuals and damaging signal because the sparse Tau-P transform suffered less from the leakage (Figure 3c and 3d). Stacking common middle point (CMP) data together is a powerful tool for evaluating denoised data in seismic signal preprocessing. Random noise is strongly attenuated during stack. However, SI

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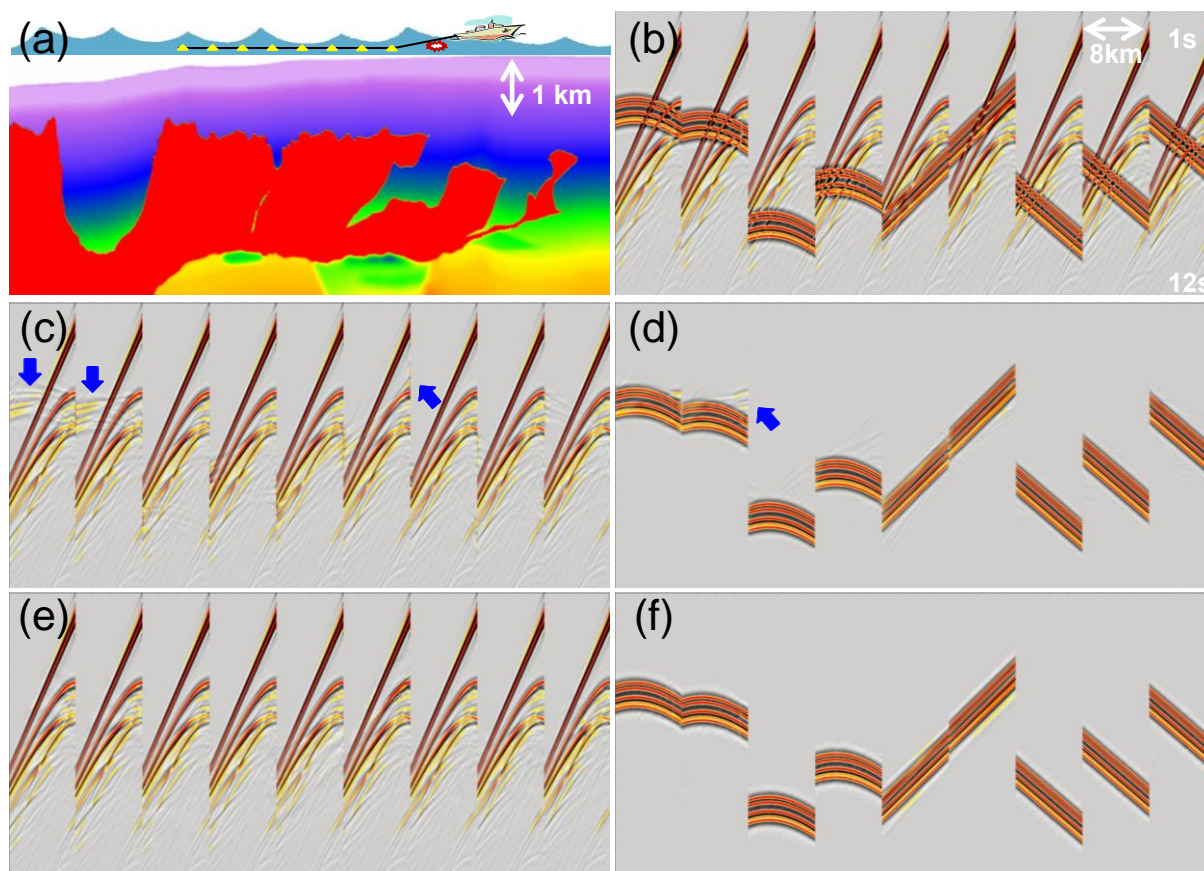


Figure 2: Synthetic test using 2004 BP model. (a) The velocity model. (b) Input data with different shaped SI noise. (c) Output after applying the SI attenuation using regular Tau-P transform. (d) The difference between input (b) and output (c). (e) Output after applying our SI attenuation method. (f) The difference between input (b) and output (e).

noise remains after stacking a sequence of data (Figure 4a). After denoising using a regular Tau-P transform, the signal-to-noise ratio was improved, but residual SI noise was left on the stack (Figure 4b). Compared to the conventional Tau-P transform (Figure 4b), our method left less residual SI noise in the stacked data (Figure 4c and 4d).

### Conclusions

We demonstrated that SI noise can be effectively attenuated by comparing the sparse Tau-P coefficients of neighboring shots. Compared to an equivalent approach based on the regular Tau-P transform, our method works better because the progressive sparse Tau-P inversion provided better separation between events with different dip (noise and signals). This resulted in more accurate removal of SI noise and better preservations of seismic signals. We assume that

the signals of neighboring shots are similar, which is valid as long as the shot spacing is sufficiently small in the sail line direction. When the shot interval is large or in areas where geological structure varies abruptly, seismic events may change rapidly through consecutive shots. In those cases, SI noise removal without damaging signals remains a challenge topic.

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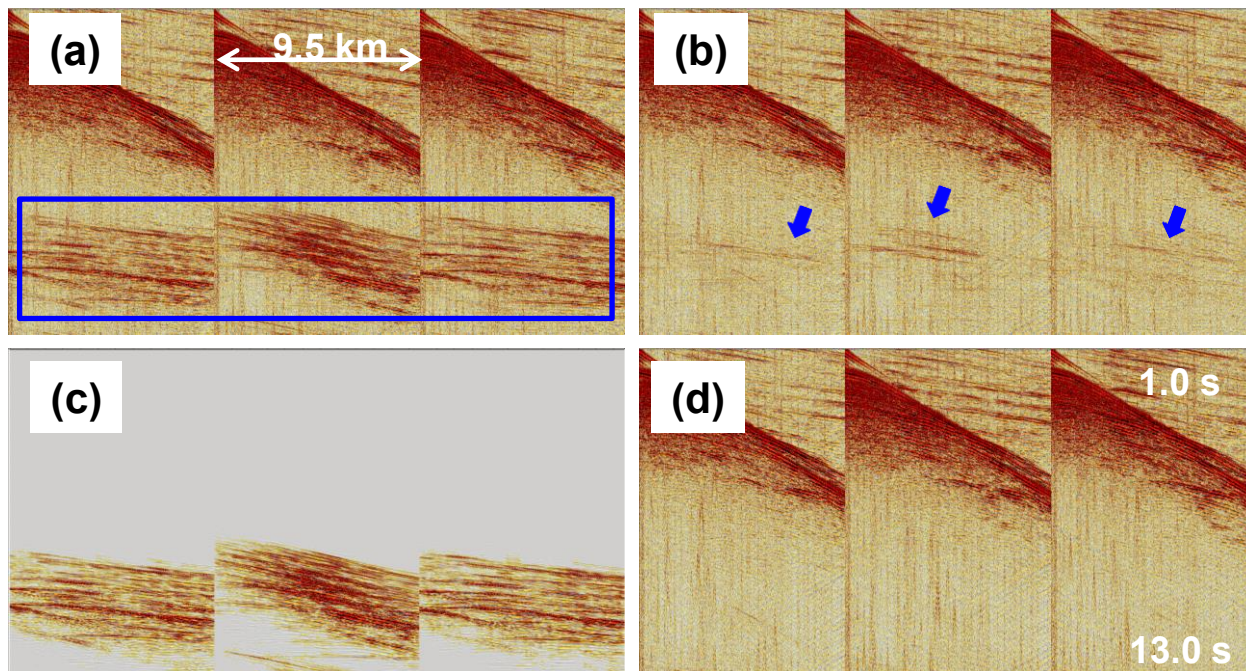


Figure 3: Data from Garden Banks, Gulf of Mexico. (a) Input data with SI noise. (b) Output after applying the SI attenuation method based on conventional Tau-P transform. (c) Difference of (a) and (d). (d) Output after applying our SI attenuation method.

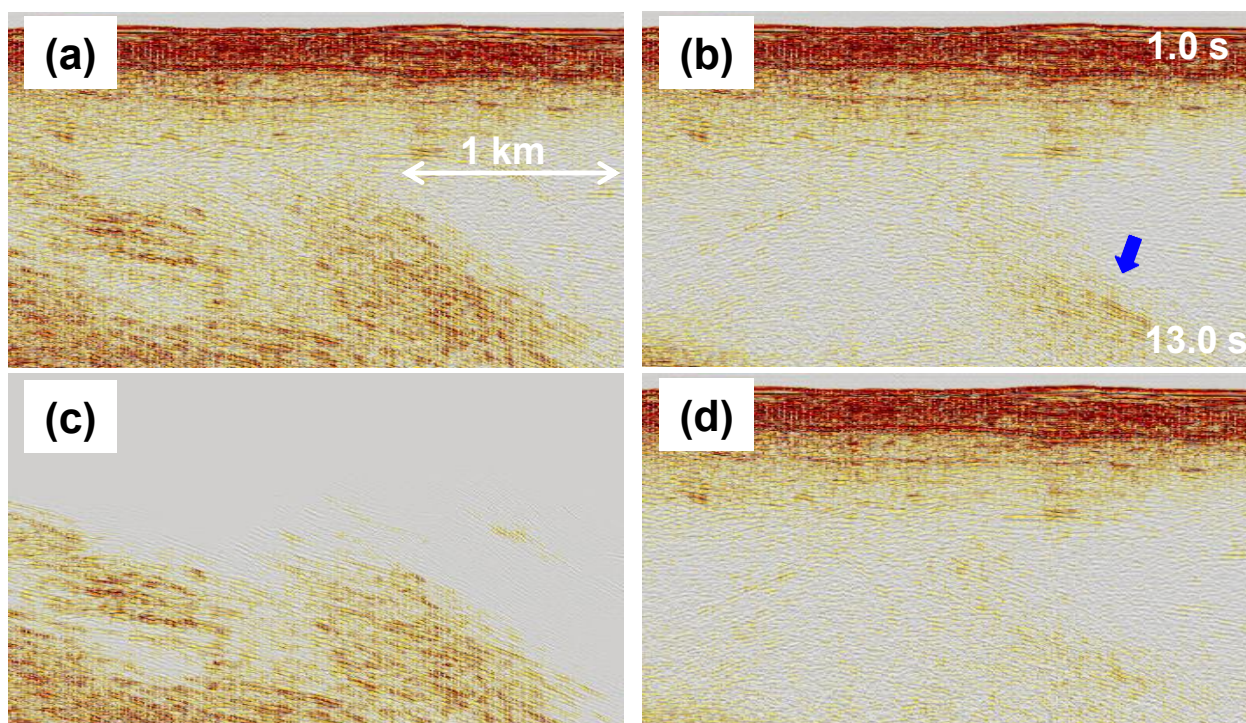


Figure 4: Stacked data from Garden Banks, Gulf of Mexico. (a) Input data SI noise. (b) Output after applying the SI attenuation method based on conventional Tau-P transform. (c) Difference of (a) and (d). (d) Output after applying our SI attenuation method.

## EDITED REFERENCES

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