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An Adaptive-Rank Singular Spectrum Analys [redacted] Simultaneous-Source Data Separation

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***Abstract*— Simultaneous-source exploration improves efficiency and reduces the cost when acquiring seismic data. However, the adjacent shot records interfere with each other, and an efficient deblending way is needed. The traditional truncated singular spectrum analysis (SSA) algorithm is employed in the local window to predict coherent events. After all the local events are predicted, the whole dither noise could be estimated completely. Traditional processing in the time domain complicates deblending. In this letter, a global-frequency SSA is proposed to predict dither noise with a simple iteration scheme. This method will lead to an increase in the rank in the Hankel matrix. Thus, a trigonometric function is introduced to adaptively determine the rank instead of the rank-truncated method. The experiments on actual seismic data show that the proposed method not only improves the deblending performance but also enjoys high efficiency.**

***Index Terms*— Adaptive rank-reduction (RR), simultaneous-source separation, singular spectrum analysis (SSA), trigonometric function.**

I. Introduction

In SEISMIC exploration, the time interval of source excitation is usually set to long enough to prevent crosstalk from adjacent seismic sources, which results in low acquisition efficiency, especially in marine exploration. The simultaneous-source seismic exploration method permits records from different sources to overlap in the time domain so that the acquisition efficiency can be significantly improved [1]–[5]. However, it is necessary to separate the simultaneous-source record that is blended in the time domain for the subsequently traditional process.

Simultaneous-source separation is generally posed as an inversion problem to estimate the coherent signals and then subtract dither noise from the blended gathers. Because of the ill-posed nature of the blending problem, a regularization term is often introduced in the coherent events' estimation procedure. Sparsity promotion and low-rank promotion are the currently often-used regularization terms. Mahdad *et al.* [6] introduced the $f-k$ filter to regularize the coherent events. Zu *et al.* [7] proposed a coherency-pass shaping operator to separate simultaneous source data, but it may leave residual noise when there is strong blending interference. Chen [8] used the seislet-domain shaping regularization to m [redacted] events to the more admissible model. Gan [redacted] seislet frames with two corresponding local [redacted] each signal component. An amplitude-preserv [redacted] Radon transform was incorporated with a regul [redacted] sion method to achieve AVO-preserving deb [redacted] mance [10].

No matter for the seislet transform or oth [redacted] sparsity promotions are based on fixed basis [redacted] their sparsity is depended on the similarity [redacted] and basis functions. Based on the linear event [redacted] low-rank property is demonstrated in the sing [redacted] Its basis functions are driven by the data, [redacted] conducive to data sparsity. Singular spectrum [redacted] has been widely used in denoising and data [redacted] [11], [12]. Cheng and Sacchi [13] introduced [redacted] the simultaneous-source data in the local wind [redacted] in the small local window could be regarded [redacted] low-rank properties. In the Hankel matrix, the [redacted] the number of events, which is difficult to de [redacted] data. Cheng and Sacchi [13] calculated the initi [redacted] size through many simulations. Similar rank- [redacted] strategy deployed in the data reconstruction [redacted] A simple rank increasing (RI) was proposed by [redacted] which sets the initial reconstructed rank to 1 [redacted] rank step by step with iterations. This algorith [redacted] converges slowly.

The local scheme is another strategy in the [redacted] In the small local $t-x$ window, not only [redacted] but also blending noise from another window [redacted] Therefore, it is necessary to estimate all the w [redacted] data before noise prediction, which brings algo [redacted] ity. In this letter, we propose to divide the w [redacted] the spatial domain to simplify the dither no [redacted] subtraction scheme. A trigonometric function [redacted] duced to adaptively estimate the Hankel rank.

II. Method

A. Simultaneous-Source Acquisition Model

Here, the blending model is reviewed in bri [redacted] sources acquisition as example, the two so [redacted] alternatively and pseudosynchronously. The obs [redacted] data D^{obs} with two shots D [redacted]

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Algorithm 1

Inputs: The blended data D^{obs}, dither code Γ and error threshold ε

Initialize: The pseudodeblending data :$D^p = \begin{bmatrix} D^{obs} \\ D^{obs}\Gamma^H \end{bmatrix}$

divide the D^p into a set of local window data $\left\{D_\omega^i, i = 1, 2, \ldots, n\right\}$

Prediction and subtraction iteration:

1. For each local window data D_ω^i in the time domain

   A Transform them to frequency domain

   B For each frequency, execute SSA algorithm.

   C Transform it to time domain and get the estimation $\hat{D}_\omega^i$ of D_ω^i

   (A–C: Many FFT and its inverse are involved here)

2. Patch the $\hat{D}_\omega^i$ into a whole profile and get the current coherent estimation $\hat{D}$
3. Transform $\hat{D}$ into dither noise with operator T and subtract from D^p
4. If $\left\|\hat{D} + \hat{D}T - D^p\right\| \leq \varepsilon$, end, otherwise return 1

(Steps 1–4: Once iteration)

included, no other window crosstalk introduced. The coherent prediction and dither noise subtraction can be all accomplished in this window and avoid the transform between the time and frequency domains. The deblending scheme becomes as simple as in Algorithm 2. It is clear that this scheme is more efficient than Algorithm 1.

C. Adaptive Rank Determination Rule

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