An algorithm for 252Cf-Source-Driven neutron signal denoising based on Compressive Sensing: Postprint

Authors: LI Peng-Cheng, WEI Biao, FENG Peng, HE Peng, MI De-Ling

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Abstract

As photoelectrically detected 252Cf-source-driven neutron signals always contain noise, a denoising algorithm is proposed based on compressive sensing for the noised neutron signal. In the algorithm, Empirical Mode Decomposition (EMD) is applied to decompose the noised neutron signal and then find out the noised Intrinsic Mode Function (IMF) automatically. Thus, we only need to use the basis pursuit denoising (BPDN) algorithm to denoise these IMFs. For this reason, the proposed algorithm can be called EMDCSDN (Empirical Mode Decomposition Compressive Sensing Denoising). In addition, five indicators are employed to evaluate the denoising effect. The results show that the EMDCSDN algorithm is more effective than the other denoising algorithms including BPDN. This study provides a new approach for signal denoising at the front-end.

Full Text

Preamble

An Algorithm for ^{252}Cf-Source-Driven Neutron Signal Denoising Based on Compressive Sensing

LI Peng-Cheng (李鹏程),† WEI Biao (魏彪), FENG Peng (冯鹏), HE Peng (何鹏), and MI De-Ling (米德伶)

Key Laboratory of Opto-electronics Technology and System, Ministry of Education, Chongqing University, Chongqing 400044, China

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Abstract: Photoelectrically detected ^{252}Cf-source-driven neutron signals invariably contain noise. To address this, we propose a denoising algorithm based on compressive sensing. The algorithm employs Empirical Mode Decomposition (EMD) to decompose the noisy neutron signal and automatically identify the noisy Intrinsic Mode Functions (IMFs). Subsequently, only these noisy IMFs are processed using the Basis Pursuit Denoising (BPDN) algorithm. Consequently, we designate this approach the EMDCSDN (Empirical Mode Decomposition Compressive Sensing Denoising) algorithm.

We evaluate the denoising performance using five quantitative indicators. The results demonstrate that EMDCSDN outperforms other denoising algorithms, including BPDN alone. This study provides a novel front-end approach for signal denoising.

Keywords: ^{252}Cf-source-driven neutron signal, Empirical mode decomposition, Compressive sensing, Denoising

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Introduction

Photoelectric detection and imaging technology have been widely employed in Nuclear Material Identification Systems (NMIS) for neutron signal detection and nuclear component analysis. Time-frequency methods have been utilized to analyze neutron signals and identify properties of nuclear materials [1, 2], while tomographic imaging has been implemented to provide additional geometric information about nuclear components, thereby enhancing NMIS accuracy [3–5]. However, measurement processes inevitably introduce noise from external environments, detectors, and electronic devices, which can obscure weak but useful information. Consequently, denoising neutron signals is essential for improving NMIS accuracy.

Beyond circuit-level and technical denoising methods, traditional algorithms typically represent noisy signals in a transform domain and apply thresholding for denoising. Fast Fourier Transform (FFT) filtering and wavelet shrinkage have thus been applied to neutron signal denoising [6]. Additionally, a novel algorithm called EMDSD (Empirical Mode Decomposition Double Smoothness Detecting) has been proposed specifically for neutron signals [7]. Nevertheless, these conventional algorithms cannot automatically adjust their decomposition bases.

In recent years, compressive sensing (CS) has emerged as a state-of-the-art paradigm for sparse sampling and reconstruction [8, 9]. CS approaches have opened numerous research avenues in underdetermined systems and found practical applications in image processing, wireless communication, data streaming, and medical imaging. CS has also been applied to image denoising [10–14], with several new algorithms derived from the Basis Pursuit Denoising (BPDN) framework [17]. Although these methods target signals across all frequencies, compressive reconstruction errors tend to increase, potentially reintroducing noise into the signal.

Fortunately, Empirical Mode Decomposition (EMD) can decompose signals into Intrinsic Mode Functions (IMFs) ranging from finer temporal scales (high-frequency IMFs) to coarser ones (low-frequency IMFs). Since noise predominantly resides in high-frequency IMFs, the BPDN algorithm can be selectively applied to denoise only these components. In this paper, we propose the EMD-CSDN algorithm and compare its performance with several existing denoising methods to verify its robustness.

Methodology

A. Materials

Neutron signals from ^{252}Cf-source-driven nuclear material fission are detected using photoelectric detectors. We designed a ^{252}Cf-source-driven verification system to identify properties of ^{235}U (Fig. 1 Figure 1: see original paper). The system comprises a ^{252}Cf neutron source, an ionization chamber, scintillation neutron detectors, a workstation equipped with a high-speed (1 GHz) data acquisition card and large-capacity disk array, verification software, and a user interface (UI) system. Three detectors are positioned around the fissile material, with the target-detector distance d and the inter-detector angle α adjustable according to measurement requirements (Fig. 1(b)).

Figure 2 [Figure 2: see original paper] illustrates a noisy neutron pulse signal acquired by the ^{252}Cf-source-driven verification system. For experimental purposes, the EMDCSDN algorithm is applied to denoise this signal. Since the pure neutron signal is unknown, we treat a curve-fitted version of the noisy signal as the ground truth for evaluation. All materials are used without further purification.

B. Basis Pursuit Denoising

Compressive sensing represents an advanced theory for sparse sampling and reconstruction. Specifically, let $\mathbf{x} = \{x_1, x_2, \dots, x_N\}$, $\mathbf{x} \in \mathbb{R}^N$ with $\mathbf{x} = \Psi\alpha$, where α contains only K non-zero elements and $K \ll N$. The signal $\mathbf{x}$ is called K-sparse with respect to transform Ψ. Random measurements $\mathbf{y} = \{y_1, y_2, \dots, y_M\}$, $\mathbf{y} \in \mathbb{R}^M$ are generated by:

$$\mathbf{y} = \Phi\mathbf{x},$$

where $\Phi \in \mathbb{R}^{M\times N}$, and the number of measurements $M \ll N$. Recovering $\mathbf{x}$ from $\mathbf{y}$ is an ill-posed problem. In CS theory, a K-sparse signal $\mathbf{x}$ can be recovered from $M = O[K\log(N/K)]$ measurements provided that Φ satisfies the Restricted Isometry Property (RIP). Reconstruction can be achieved with high probability by solving the following convex optimization:

$$\alpha = \arg\min \|\alpha\|_1, \quad \text{subject to} \quad \mathbf{y} = \Phi\Psi\alpha,$$

where $\|\alpha\|_1$ denotes the ℓ_1-norm of vector α.

For noisy neutron signals, the compressive sensing process can be described as follows. Assume the noisy neutron signal $\mathbf{x} = \mathbf{s} + \mathbf{n} = \Psi\alpha + \mathbf{n}$, where $\mathbf{s}$ is the original signal, $\mathbf{n}$ denotes additive Gaussian white noise, and Ψ is the sparse basis. Consequently, compressive sampling is defined as:

$$\mathbf{y} = \Phi(\mathbf{s} + \mathbf{n}) = \Phi\mathbf{s} + \Phi\mathbf{n} = \Phi\mathbf{s} + \mathbf{z} = \Phi\Psi\alpha + \mathbf{z},$$

where $\mathbf{z}$ is sampling noise and $\|\mathbf{z}\|_2 \leq \varepsilon$.

With noisy or imperfect data, exact fitting of the linear system is impossible. Instead, the Basis Pursuit constraint is relaxed to obtain the Basis Pursuit Denoising problem:

$$\min \|\alpha\|_1 \quad \text{subject to} \quad \|\mathbf{y} - \Phi\Psi\alpha\|_2 \leq \varepsilon.$$

An efficient algorithm using Spectral Projected Gradient (SPG) solves BPDN [17]. This method converges much faster and maintains constant memory requirements across iterations. However, most signal frequencies are pure and require no denoising. Applying BPDN to all frequencies would recontaminate the signal and potentially filter out useful information. Therefore, we propose a new denoising algorithm based on compressive sensing that targets only the noisy frequency components.

C. EMDCSDN Algorithm

The Hilbert-Huang Transform (HHT) is a novel time-frequency analysis technique proposed by Huang [18], with Empirical Mode Decomposition as its core component. EMD' s advantage lies in deriving basis functions from the signal itself, making the analysis more adaptive compared to wavelet methods with fixed basis functions. Any signal can be decomposed into a finite number of IMFs that yield meaningful instantaneous frequencies:

$$x(t) = \sum_{j=1}^{N} \mathrm{IMF}_j + \mathrm{res},$$

where *res* represents the EMD residual.

Figure 3 [Figure 3: see original paper] shows the IMFs of a neutron signal decomposed by EMD. Only the first few high-frequency IMFs appear noisy, while the remaining IMFs are pure. Although EMD possesses inherent filtering characteristics, noisy IMFs cannot be filtered directly. Therefore, we must identify the noisy IMFs before applying BPDN for denoising.

The EMDCSDN algorithm is presented in Fig. 4 [Figure 4: see original paper]. The IMF selector is designed based on characteristics of white noise [19]. One key characteristic is that $\Gamma_i = E_i P_i$ remains constant, where E_i is the energy density and P_i is the period of the IMFs:

$$E_i = \sum_{j=1}^{N} [C_i(j)]^2, \quad P_i = \frac{n_{\max}(i) + n_{\min}(i)}{N},$$

where N, C, $n_{\min}$, and $n_{\max}$ denote the length, amplitude, number of maxima, and number of minima of the IMFs, respectively.

If $R_i = |(\Gamma_i - \bar{\Gamma})/\bar{\Gamma}| \geq 1$, then $\Gamma_j (j = 1, 2, \dots, i-1)$ is constant and the first $i-1$ IMFs are noisy, where $\bar{\Gamma}$ is the mean of Γ_j. This IMF selector automatically identifies noisy components. Figure 5 [Figure 5: see original paper] shows $R_3 > 1$, indicating that for the noisy neutron signal, IMF_1 and IMF_2 require denoising. By narrowing the denoising scope, EMDCSDN reduces compressive sensing reconstruction error and improves overall performance.

Algorithm 1: EMDCSDN Algorithm for Neutron Signal

Input: Noisy neutron signal $\mathbf{x}$
Output: Denoised neutron signal $\mathbf{x}_D$

1. Decompose $\mathbf{x}$ into IMFs ($\text{IMF}_j, j = 1, 2, \dots, N$) and residual *res*
2. Select noisy IMFs ($\text{IMF}_c, c = 1, 2, \dots, C$) and pure IMFs ($\text{IMF}_p, p = 1, 2, \dots, P$) using the IMF selector, where $C + P = N$
3. Apply BPDN algorithm to denoise the noisy IMFs, producing denoised IMFs $D\text{IMF}_c, c = 1, 2, \dots, C$
4. Reconstruct: $\mathbf{x}_D = \sum_{c=1}^{C} D\text{IMF}_c + \sum_{p=1}^{P} \text{IMF}_p + \text{res}$

D. Denoising Evaluation

Signal-to-noise ratio (SNR), peak signal-to-noise ratio (PSNR), and mean squared error (MSE) are commonly used to evaluate denoising performance. However, these three indicators alone are insufficient, as high SNR may indicate that useful information has been filtered out. Therefore, two additional indicators–smoothness of curve (SOC) and correlation coefficient (CC)–should be included:

$$\text{SOC} = \frac{\sum_{i=1}^{N-1} [\hat{x}(i+1) - \hat{x}(i)]^2}{\sum_{i=1}^{N-1} [x(i+1) - x(i)]^2}$$

$$\text{CC} = \frac{\sum (x_i - \bar{x})(\hat{x}_i - \bar{\hat{x}})}{\sqrt{\sum (x_i - \bar{x})^2 \cdot \sum (\hat{x}_i - \bar{\hat{x}})^2}}$$

where $\mathbf{x}$ is the original noisy signal and $\hat{\mathbf{x}}$ is the denoised signal. For CC, larger values are better, while for SOC, smaller values indicate superior denoising. Comprehensive evaluation requires consideration of all five indicators.

Results and Discussion

For the noisy neutron signal $\mathbf{x} \in \mathbb{R}^N$ with elements $x[n], n = 1, 2, \ldots, N$ and $N = 1024$, let M denote the number of compressive samples, yielding a compressive sampling rate of M/N.

As previously determined, the first two IMFs (IMF_1, IMF_2) are noisy. Therefore, BPDN is applied only to these components. Figure 6 [Figure 6: see original paper] shows the denoising results for $M/N = 0.65$, where DN denotes denoising.

Figure 7 [Figure 7: see original paper] presents the overall denoising result for the neutron signal using EMDCSDN. However, visual inspection alone cannot fully characterize performance, necessitating evaluation using the five quantitative indicators.

Different compressive sampling rates produce varying denoising effects. Figure 8 [Figure 8: see original paper] illustrates EMDCSDN performance across different M/N values using dual Y-axes: the left axis represents MSE, SOC, and CC, while the right axis shows SNR. SNR and CC increase with M/N, whereas MSE and SOC decrease. Optimal performance occurs at $M/N = 0.75$, where SNR and CC reach their maxima and MSE and SOC reach their minima. However, for applications requiring lower sampling rates, $M/N = 0.65$ offers comparable performance and may be preferable. We select $M/N = 0.75$ for our final evaluation.

EMDCSDN is compared against four alternative algorithms: (1) EMD Filter (EMDF), which directly filters noisy IMFs; (2) Basis Pursuit Denoising (BPDN) using the SPGL1 algorithm; (3) Wavelet Threshold Denoising (WTDN), which applies thresholding in the wavelet domain; and (4) EMD Wavelet Denoising (EMDWTDN), which uses WTDN on noisy IMFs before reconstructing with all IMFs. Table 1 summarizes the comparative performance.

Table 1 reveals that EMDF, while simple, is less effective because it filters out useful information along with noise. EMDWTDN outperforms WTDN, confirming that EMD enhances denoising effectiveness. EMDCSDN achieves the best overall performance across all five indicators, validating the benefits of both EMD and automatic noisy IMF selection, albeit with slightly longer processing time.

Conclusion

We have proposed a novel denoising algorithm, EMDCSDN, for noisy neutron signals. This method modifies the traditional BPDN approach by automatically selecting and denoising only the noisy IMFs, making the algorithm more targeted and reducing compressive sensing reconstruction error. Evaluated using five comprehensive indicators, EMDCSDN demonstrates superior effectiveness compared to existing algorithms while also reducing sampling costs. The EMDCSDN framework is applicable to other denoising tasks beyond neutron signal processing.

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Note: Figure translations are in progress. See original paper for figures.