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Transient Electromagnetic Data Noise Suppression Method Based on MPA-VMD-SVD

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ABSTRACT The transient electromagnetic method (TEM) is an efficient physical detection method widely used in underground space detection. However, electromagnetic noise interference poses significant challenges, as the TEM late signal is often submerged in noise, severely impacting the detection accuracy and depth. Therefore, this study proposes a TEM data noise suppression method based on the marine predators algorithm (MPA) to optimize variational mode decomposition (VMD) combined with singular value decomposition (SVD). Firstly, MPA is employed to select the main parameters of VMD. Secondly, the noisy data are decomposed into several intrinsic mode functions using the adaptive variational property of VMD. Finally, the mode containing signal information undergoes SVD to remove residual noise, after which the denoised TEM signal is reconstructed. This study simulates TEM signals with different noise levels for testing. The proposed method is compared to stacking-averaging, wavelet threshold denoising, SVD, empirical mode decomposition, and unoptimized VMD. The results showed that the model exhibits superior noise reduction performance. In addition, measured noise experiments are conducted to verify the practicability of the method. Simulation and field experiments indicated that MPA-VMD-WTD is an effective method for suppressing TEM data noise.

INDEX TERMS Electromagnetic data, noise reduction, VMD, MPA, SVD.

I. INTRODUCTION

With the rapid development of the global economy and the increasing population, underground space development has become an inevitable trend. Geological exploration can prevent geological disasters, protect workers' personal and property safety, provide a scientific basis for underground engineering, and ensure the successful implementation of the project. The transient electromagnetic method (TEM) is an efficient and convenient geophysical exploration method. However, due to the influence of urban environments, substantial noise is present in the collected electromagnetic data, which causes serious interference in the late-stage TEM signal. This noise affects the accuracy of subsequent inversion interpretations, leading to suboptimal exploration results.

Accordingly, researchers have proposed many methods to improve the signal-to-noise ratio (SNR) of TEM late signals. These methods are mainly divided into deep learning algorithms and digital signal processing methods. Chen *et al.* proposed a signal-to-image conversion method to convert the TEM signal into an image and model the noise signal using a deep convolutional neural network (CNN)-based denoising method. This method further incorporates residual learning to enhance denoising performance [1]. Wu *et al.* combined the long short-term memory (LSTM) network with an autoencoder to develop a new neural network structure [2]. Wang *et al.* proposed a TEM deep denoising network based on noise learning, which utilizes a generative adversarial network to learn noise from real signals. The generator constructs a training set by generating noise, improving the generalization ability of neural network-based denoising methods [3]. Sun *et al.* proposed a method that combines the least noise separation algorithm with deep learning [4]. After the SNR of TEM is improved to a certain extent using minimum noise fraction, the spatiotemporal features of the signal are extracted by CNN and gated recursive unit. In addition, a double-loss function is selected as a training guide to achieve TEM data denoising. Pan *et al.* introduced a one-dimensional time-series denoising model, which effectively solves the overfitting phenomenon of convolutional residual networks in one-dimensional time-series denoising using a one-dimensional convolution and a visual transformer encoder architecture [5]. Yan *et al.* proposed a new method combining variational modal decomposition (VMD) optimized by the reptile search algorithm with a deep neural network to identify and eliminate noise [6]. In this method, the optimized VMD decomposes the noisy signal and then integrates CNN and LSTM to extract temporal correlation features, further improving the SNR. Deng *et al.* introduced a semi-airborne TEM signal denoising network based on the variational diffusion model (VDM) [7]. This approach incorporates a supervised fine-tuning strategy based on wavelet transform as a constraint, which improves the model's generalization ability. Although the denoising algorithm based on neural networks performs well, a significant disparity remains between the noise reduction performance of simulated data and field data.

Wei *et al.* utilized VMD and empirical mode decomposition (EMD) to address various noises in the TEM signal [8]. The results showed that VMD outperformed EMD. Feng *et al.* employed the whale optimization algorithm to obtain the optimal parameters of VMD and then applied the Bhattacharyya distance algorithm to identify the effective and noise modes, achieving signal reconstruction [9]. Qi *et al.* proposed a transient electromagnetic signal denoising algorithm based on VMD and wavelet threshold denoising (WTD) [10], where the gray wolf optimization algorithm was employed to determine the optimal parameters of VMD, followed by denoising the mixed mode with WTD, and finally merging the signal with the denoised mode. Wei *et al.* proposed a noise identification and elimination method combining the slime mold algorithm for optimizing VMD with WTD [11]. Xing *et al.* considered the transverse continuity of the multichannel data of the TEM detector and presented a noise processing stream for 2D time-domain electromagnetic data using multivariate variational modal decomposition and multivariate detrended fluctuation analysis, achieving a superior denoising effect compared to single-channel data processing [12]. Tan *et al.* developed an intelligently optimized time-space fractional diffusion model [13], which dynamically thresholds the signal and uses the Harris Hawk algorithm, combined with golden sine and energy-updating algorithm, to determine the optimal filter for each signal stage, yielding better performance than traditional algorithm. Accordingly, modern signal processing methods based on wavelet transform, modal decomposition, and sparse decomposition have been extensively applied in TEM signal noise reduction. However, setting the critical parameters of these denoising algorithms is essential for achieving good results. At present, the key parameters of the algorithm are set based on personal experience, which prevents the achievement of the best denoising effect. Therefore, there is an urgent need to develop a modern digital signal processing method based on the optimization algorithm.

In 2020, Faramarzi *et al.* proposed MPA inspired by the predation law of marine organisms [14]. It solves the optimization problem by simulating the movement and behavior of marine predators during hunting. Conventional intelligent optimization algorithms often encounter the issue of being trapped in a local optimum. In contrast, the population individuals in the MPA adapt their movement mode based on the number of iterations, allowing the MPA to flexibly perform global and local searches in the solution space, avoiding iterative convergence to suboptimal solutions. For this reason, the MPA algorithm is employed in this study to optimize the VMD parameters.

Accordingly, this study proposes a TEM data noise suppression method that utilizes MPA to optimize VMD in combination with singular value decomposition (SVD). The paper's organization is as follows: the second section presents the theoretical background of the MPA-VMD-SVD model; the third section details the simulation experiment results; and the fourth section validates the performance and reliability of the model through field tests.

II. THEORIES AND MODEL

VMD is a modal decomposition method proposed by Dragomiretskiy and Zosso in 2014 [15]. This method adaptively decomposes a complex signal into a set of intrinsic modal functions (IMF), where each IMF corresponds to an independent frequency component within the signal. An IMF is essentially an AM and FM signal, representing the information of the signal within a specific frequency band. This decomposition reflects the local characteristics of the signal across the time scale, which can be expressed as follows:

$$u_k(t) = a_k(t) cos\,(\phi_k(t)) \tag{1}$$

where $u_k(t)$ is the k-th modal function, $a_k(t)$ is the envelope of the k-th IMF component, $\phi_k(t)$ is the phase function of the k-th IMF component.

VMD decomposes the signal by optimizing the variational objective function, which is expressed as:

$$min_{\{u_k\},\{\omega_k\}} \left\{ \sum_{k=1}^{K} \left\| \partial_t \left[\left(\delta(t) + j\frac{1}{\pi t} \right) \times u_k(t) \right] e^{-j\omega_k t} \right\|_2^2 \right\} \tag{2}$$

where ω_k is the center frequency of the k-th modal function, K is the number of decomposed modes, ∂_t is the time derivative, $\delta(t)$ is the unit pulse function. This is a constrained optimization problem, and the constraint for reconstructing the signal $f(t)$ is expressed as:

$$f(t) = \sum_{k=1}^{K} u_k(t) \tag{3}$$

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VMD introduces the Lagrangian function $\mathcal{L}$ to address this constraint. The Lagrangian function not only includes the original objective function but also introduces a penalty factor α and a Lagrange multiplier λ to manage the constraints, which can be expressed as follows:

$$\mathcal{L}(u_k,\omega_k,\lambda)=\sum_{k=1}^{K}\left\|\partial_t\left[\left(\delta(t)+j\frac{1}{\pi t}\right)\times u_k(t)\right]e^{-j\omega_k t}\right\|_2^2 +\frac{\alpha}{2}\left\|f(t)-\sum_{k=1}^{K}u_k(t)\right\|_2^2 +\lambda(t)\left(f(t)-\textstyle\sum_{k=1}^{K}u_k(t)\right) \tag{4}$$

The Lagrangian function forms the foundation of VMD optimization and is solved iteratively using the alternating direction multiplier algorithm (ADMM). This algorithm decomposes the Lagrangian function into sub-problems and optimizes each one alternately. Initially, the current center frequency and the Lagrangian multiplier are fixed, and the signal for each modality is updated. The modal update is expressed as follows:

$$u_k^{n+1}=arg\ \ min_{u_k}\left(\sum_{k=1}^{K}\left\|\partial_t\left[\left(\delta(t)+j\frac{1}{\pi t}\right)\times u_k(t)\right]e^{-j\omega_k t}\right\|_2^2 +\frac{\alpha}{2}\left\|f(t)-\sum_{k=1}^{K}u_k(t)\right\|_2^2\right) \tag{5}$$

Secondly, after fixing the modal function, the center frequency is updated with the expression:

$$\omega_k^{n+1}=\frac{\int_{-\infty}^{\infty}\omega|\hat{u}_k(\omega)|^2 d\omega}{\int_{-\infty}^{\infty}|\hat{u}_k(\omega)|^2 d\omega} \tag{6}$$

where $\hat{u}_k$ is the spectrum of the k-th modal function.

Finally, the Lagrangian multiplier is updated to minimize the error and ensure convergence through the inclusion of a penalty term, ensuring that the superposition of the modes closely approximates the original signal, which is expressed as follows:

$$\lambda^{n+1}(t)=\lambda^n(t)+\tau\left(\textstyle\sum_{k=1}^{K}{u_k}^{n+1}(t)-f(t)\right) \tag{7}$$

where τ is the learning rate, which is utilized to control the speed at which the Lagrange multiplier is updated.

By alternately updating the mode u_k, the center frequency ω_k and the Lagrangian multiplier λ, the value of the Lagrangian function is gradually minimized, yielding the IMF that satisfies the constraints.

The MPA divides the optimization process into three stages, with predators employing distinct hunting strategies at each stage. In the initial stage, the predator utilizes Brownian motion to explore the search space, with its position update formula expressed as follows:

$$Prey_{i,j}=Prey_{i,j}+P\times R\times RB_{i,j}\times\left(Elite_{i,j}-RB_{i,j}\times Prey_{i,j}\right) \tag{8}$$

where $\mathrm{Prey}_{i,j}$ is the position of the i-th prey in the j-th dimension, P is the migration probability, R is the random number in the range [0,1], $\mathrm{RB}_{i,j}$ is the Brownian random number, $\mathrm{Elite}_{i,j}$ is the position of the current best prey in the j-th dimension. During the intermediate phase, the predators use a mixture of Brownian motion and Lévy flight for exploration and exploitation. Half of the predators perform Brownian motion, and their position update formula is expressed as follows:

$$Prey_{i,j}=Elite_{i,j}+P\times CF\times RB_{i,j}\times\left(Elite_{i,j}\times RB_{i,j}-Prey_{i,j}\right) \tag{9}$$

where CF is the control factor that balances exploration and exploitation. The other half of predators make a Levy flight, and their position update formula is described as follows:

$$Prey_{i,j}=Prey_{i,j}+P\times R\times RL_{i,j}\times\left(Elite_{i,j}-RL_{i,j}\times Prey_{i,j}\right) \tag{10}$$

where $\mathrm{RL}_{i,j}$ is the Levy random number. In the later stage, the predators use Levy flight to develop and avoid falling into local optimum, and their position update formula is expressed as follows:

$$Prey_{i,j}=Elite_{i,j}+P\times CF\times RL_{i,j}\times\left(Elite_{i,j}\times RL_{i,j}-Prey_{i,j}\right) \tag{11}$$

MPA also simulates the eddy formation and the effect of fish aggregating devices (FADs) in the ocean. This approach helps the algorithm balance global search and local development, enhancing its ability to locate the global optimal solution. Initially, the predators are classified and assessed to determine each predator’s movement rule. The evaluation conditions are expressed as follows:

$$U_{i,j}=\begin{cases}1\ if\ rand_{i,j}<F\\ 0\ otherwise\end{cases} \tag{12}$$

where $U_{i,j}$ is the element in the judgment matrix, $\mathrm{rand}_{i,j}$ is the random number within the range [0,1], and F is the probability threshold of the FAD effect. When the value of $U_{i,j}$ is 1, the movement of the current predator follows the Eddy formation effect, which is expressed as follows:

$$Prey_{i,j}=\ Prey_{i,j}+CF\times\left(X_{min,j}+rand_{i,j}\times\left(X_{max,j}-X_{min,j}\right)\right) \tag{13}$$

where $X_{\min,j}$ is the lower boundary of the j-th dimension, and $X_{\max,j}$ is the upper boundary of the j-th dimension. When the value of $U_{i,j}$ is 0, the movement of the current predator follows the FADs effect, which is expressed as:

$$Prey_{i,j} = Prey_{i,j} + \left(F \times \left(1 - r_{i,j}\right) + r_{i,j}\right) \times \left(Prey_{\pi_1(i),j} - Prey_{\pi_2(i),j}\right) \quad (14)$$

where $r_{i,j}$ is a random number in the range [0,1], $Prey_{\pi_1(i),j}$ is the position of the first prey in the j-th dimension after random arrangement, $Prey_{\pi_2(i),j}$ is the position of the second prey in the j-th dimension after random arrangement.

As a nonlinear analysis method, sample entropy is mainly utilized to measure signal complexity and uncertainty in time series. The larger the sample entropy value, the higher the complexity and randomness of the signal. In contrast, when the sample entropy is smaller, the signal shows higher repeatability and regularity. In TEM data, it is theoretically feasible to use sample entropy to distinguish between signal and noise because the noise has high randomness and uncertainty, and the effective signal usually conforms to the exponential attenuation law. The formula for calculating the sample entropy is expressed as follows:

$$SampEn(m, r, N) = -\ln\left(\frac{A^{(m)}(r)}{B^{(m)}(r)}\right) \quad (15)$$

where m is the length of the subsequence, r is the similarity tolerance, N is the length of the sequence, $B^{(m)}(r)$ is the probability of two sequences matching m points, and $A^{(m)}(r)$ is the probability of two sequences matching $m+1$ points.

SVD is a matrix factorization method in linear algebra that decomposes data into different components, preserving primary information and eliminating minor noise components. The formula for SVD is expressed as:

$$A = U\Sigma V^T \quad (16)$$

where A is the original matrix, U is the left singular vector matrix, V^T is the right singular vector matrix, and Σ is the diagonal matrix, which contains the singular values of the original matrix. The singular values are arranged from largest to smallest, with larger singular values representing the active components of the signal and smaller singular values corresponding to noise-dependent components. The residual noise in the TEM signal mode is effectively filtered out by truncating the singular values.

Based on the above principles, this study proposes a new noise reduction method, the MPA-VMD-SVD model. Firstly, MPA is employed to optimize the main parameters of VMD by selecting sample entropy as the fitness criterion. Continuous iteration determines the optimal parameter combination, enabling the decomposed mode to achieve the minimum sample entropy. Secondly, VMD decomposes the signal into several modes based on the specified decomposition mode K and the penalty factor α, identifying the mode with the smallest mean square error (MSE) as the signal mode. Finally, the SVD of the mode containing the signal information is performed to remove the residual noise, and the TEM signal, after denoising, is reconstructed. The flowchart of the MPA-VMD-SVD model is shown in Fig. 1.

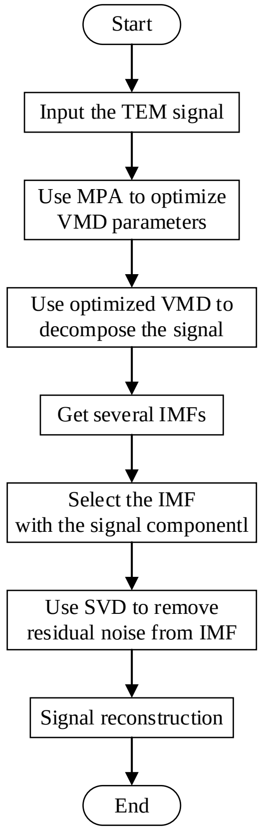

FIGURE 1. **The flowchart of MPA-VMD-SVD.**

III. SIMULATION

In electronics, SNR is commonly utilized to represent the ratio of signal to noise in the data, expressed in dB as:

$$SNR = 10 * log_{10}\frac{\sum s^2(t)}{\sum n^2(t)} \quad (17)$$

where $s(t)$ is the signal sequence and $n(t)$ is the noise sequence. In the actual geological exploration measurement, workers pay more attention to the deeper geological information, and the late TEM signal corresponds to the deep underground information. In addition, the amplitude of the early TEM signal is typically larger, resulting in a higher SNR. In contrast, the late TEM signal is weaker, leading to a lower SNR. Hence, this study emphasizes reducing the noise in the late TEM signal. The improvement in SNR for the last 20% of the data before and after processing is defined as the signal-to-noise improvement ratio (SNIR), a quantitative indicator of the noise reduction effect.

A. SIMULATE SIGNAL AND NOISE

The TEM signal has exponential decay characteristics, with a strong initial signal attenuating rapidly, while the later signal is weak and heavily influenced by noise. Its frequency spectrum ranges from a few hertz to several hundred thousand hertz, with the main components concentrated in the low-frequency range, making it a broadband signal. The waveform and frequency domain diagram are presented in Fig. 2.

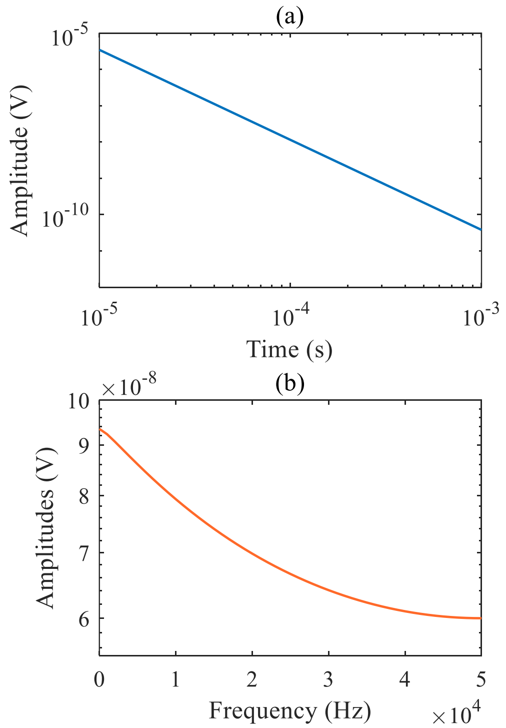

FIGURE 2. Simulated TEM signal. (a) Time domain waveform; (b) Frequency domain diagram.

Random noise is the main component affecting the late TEM signal, often appearing as Gaussian white noise. Gaussian white noise refers to a substantial number of unpredictable disturbances generated randomly, which are Gaussian in nature and widely distributed across various frequencies. The time domain waveform and frequency domain diagram of Gaussian white noise are shown in Fig. 3. The TEM signal combined with Gaussian white noise is depicted in Fig. 4.

This study simulated signals with strong, moderate, and weak noise levels, corresponding to SNR values of 10, 15, and 20 dB, respectively.

B. MPA-VMD OPTIMIZATION PROCESS

The VMD model is optimized using MPA, with the number of predators set to 25 and the maximum number of iterations set to 20. Two parameters are optimized, where the number of decomposed modes K is in the range of [1,10], and the penalty factor α is in the range of [1,50000]. After 20 iterations, the convergence curve of the algorithm is presented in Fig. 5. At the fifth iteration, the minimum value of sample entropy was $7.1301 * 10^{-3}$, corresponding to the optimal decomposition mode number K of 6 and the penalty factor, α of 42489.

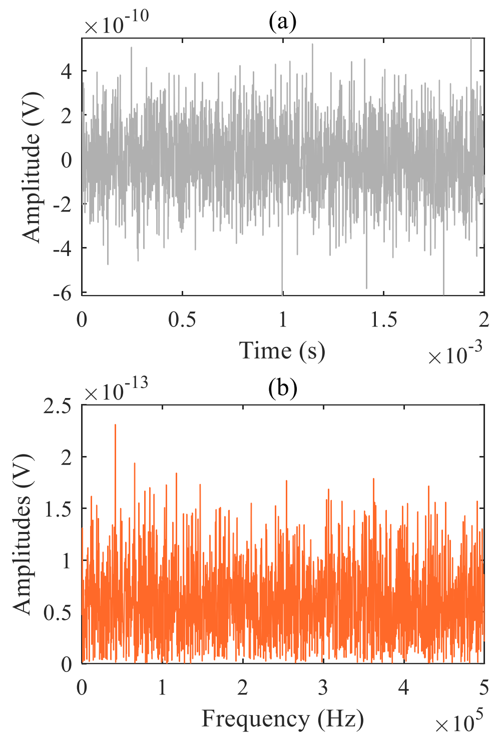

FIGURE 3. Simulated noise. (a) Time domain waveform; (b) Frequency domain diagram.

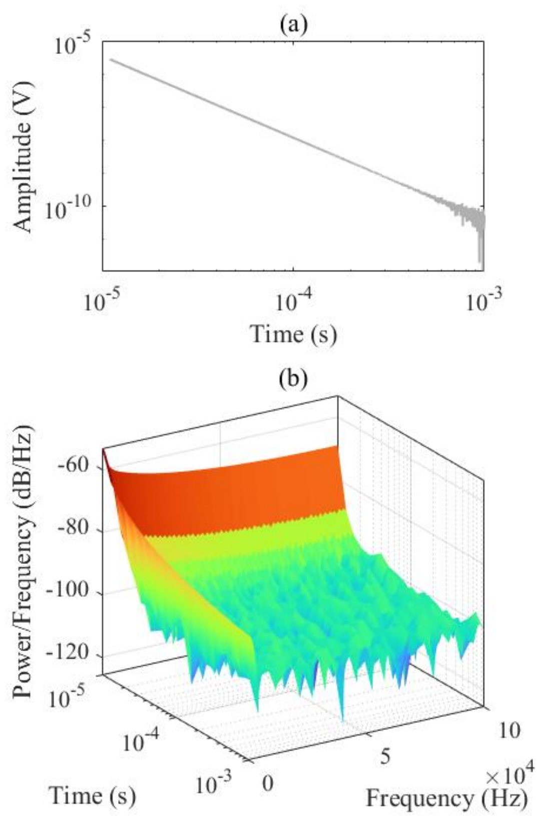

FIGURE 4. Noisy signal. (a) Time domain waveform; (b) Spectrogram.

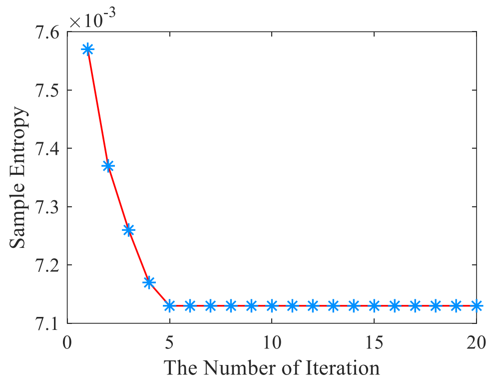

FIGURE 5. Convergence curve of MPA-VMD.

C. MPA-VMD-SVD DENOISING EXPERIMENT

In the previous section, the optimal parameters of the VMD model were determined using MPA. These parameters were applied to VMD to obtain several IMFs, as illustrated in Fig. 6.The MSE of the IMFs derived from the original signal is calculated, and the results are shown in Fig. 7. IMF1 has the smallest MSE compared to the original signal. The Fourier transform is applied to the IMFs, and the resulting spectrum is illustrated in Fig. 8. IMF1 closely matches the original signal, while IMF2–IMF6 corresponds to noise components at different frequencies. Accordingly, VMD effectively extracted the signal components into IMF1 and isolated the noise components into the remaining IMFs.

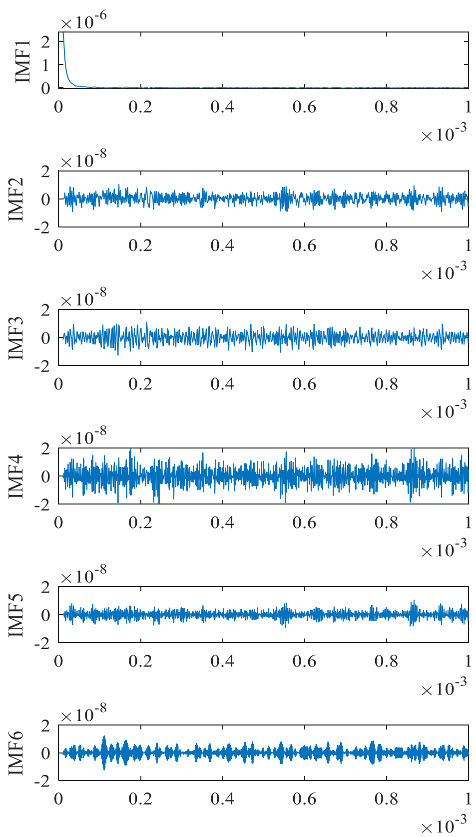

FIGURE 6. Time domain waveforms of each IMF.

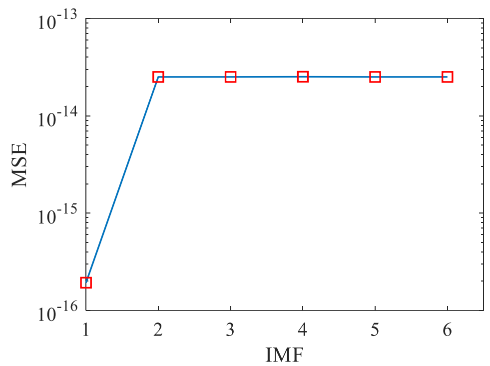

FIGURE 7. MSE of IMFs.

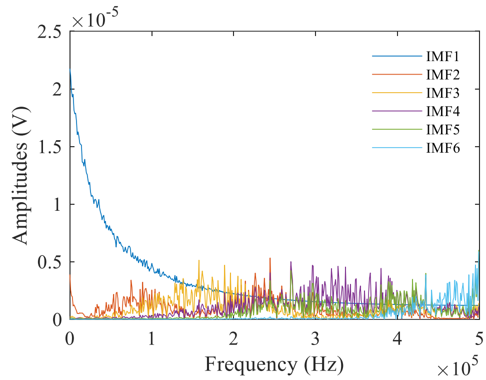

FIGURE 8. Frequency domain diagrams of IMFs.

Then, SVD is employed to process the IMF containing the signal components to filter out the residual signal. The one-dimensional modal sequence is upgraded to a two-dimensional matrix with a window length of half the length of the original sequence. The one-dimensional modal sequence is upgraded to a two-dimensional matrix with a window length of 1000. SVD is then utilized to decompose the reconstructed data, and the distribution of singular values is shown in Fig. 9.

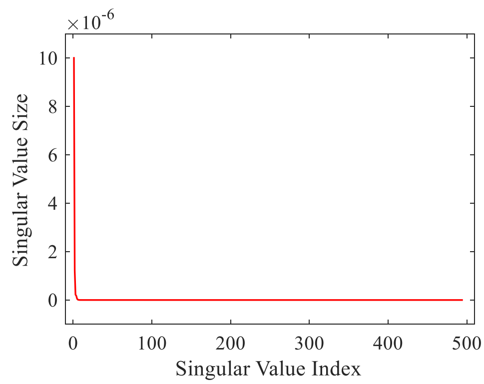

FIGURE 9. The distribution of singular values.

The singular values are subjected to thresholding, where the threshold is set to the average of the singular values to eliminate residual noise components. This method preserves

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the larger singular values associated with the signal components. The MPA-VMD-SVD model is applied to process TEM data noise, and the denoising effect is illustrated in Fig. 10. After denoising, the signal waveform becomes smoother, and the number of glitches is greatly reduced.

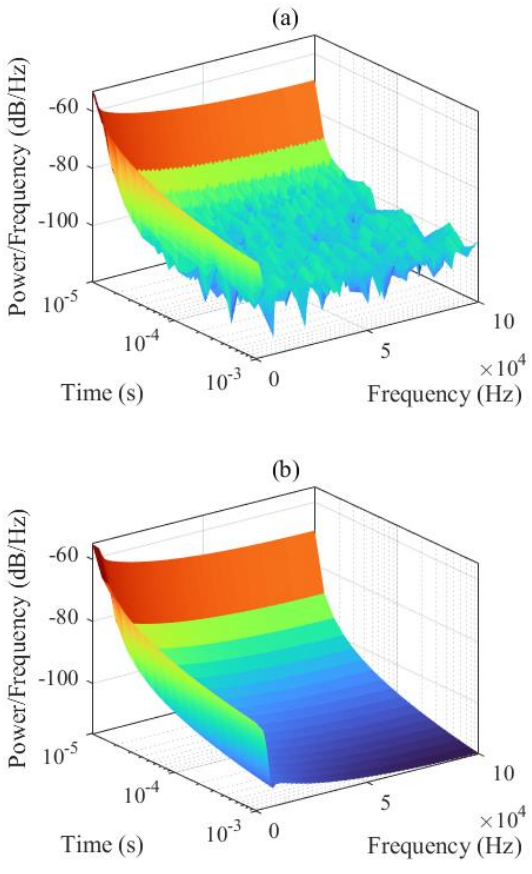

FIGURE 10. **MPA-VMD-SVD simulation noise suppression results. (a) Before; (b) After.**

D. COMPARATIVE ANALYSIS WITH TRADITIONAL ALGORITHM

Several modern digital signal processing algorithms were selected for comparative experiments, including stacking-averaging, WTD, SVD, EMD, and VMD, to verify the superiority of the MPA-VMD-SVD model in addressing TEM data noise. The denoising performance of these algorithms was evaluated under three levels of noise.

Stacking-averaging obtains the denoised signal by summing and averaging 16 channels of signals; however, the processed signal continues to exhibit numerous glitches. WTD decomposes the signal into several layers and uses the threshold function to select specific wavelet coefficients for reconstruction. For the parameter settings, the number of decomposition levels was set to 5, the soft threshold function was selected, and the threshold value was set to 10^{-5}, and Symlet 4 wavelet was used as the decomposition basis function. SVD transforms the one-dimensional time series into a matrix, performs eigenvalue decomposition, applies thresholding, and reconstructs the matrix to obtain denoised data. For this process, the window size was set to 30, and the threshold was set to the average of the eigenvalues. In another setting, the window size was adjusted to 1000, and the threshold was set to the average eigenvalue of the matrix. EMD decomposes the signal into several IMFs based on amplitude, eliminates the IMFs consisting of noise components, and reconstructs the effective signal. Although this method is conceptually simple, it encounters significant waveform distortion in its initial stages. For the unoptimized VMD, the number of decomposition modes K was set to 10, and the penalty factor α was set to 1000. The parameters mentioned above were determined based on human expertise and adjusted to achieve optimal results to ensure a fair comparison among the algorithms in this study.

Fig. 11 shows the test and scaling results under three levels of noise interference. Compared to the traditional algorithm, the signal processed by the MPA-VMD-SVD model demonstrated the best fit to the ideal signal under different conditions and achieved the most effective noise reduction.

Repeated experiments were conducted using the above algorithm. A total of 100 data groups containing three noise levels were processed, and the average SNIR value was calculated. The results are listed in Table 1. The MPA-VMD-SVD model consistently achieved superior processing performance under each noise level, which verifies the effectiveness and stability of the model.

TABLE 1. **The average SNIR of the data processed by the algorithms.**

Model	Strong (10dB)	Moderate (15dB)	Weak (20dB)
Stacking-averaging	12.05	12.04	12.04
EMD	11.53	10.87	9.74
WTD	18.27	18.29	18.25
SVD	21.83	21.80	21.85
VMD	7.56	5.57	3.21
MPA-VMD-SVD	41.77	39.56	36.92

The simulated noise experimental results fully prove that the MPA-VMD-SVD model effectively preserves the original information of the early TEM signal while accurately restoring the attenuation trend of the late signal to the greatest extent. Compared to traditional denoising algorithms, the model exhibits superior noise suppression performance, making it more suitable for processing TEM data.

IV. FIELD NOISE TEST

Experiments on field noise were conducted to verify the performance of the proposed model. The field noise data samples were obtained from the Key Laboratory of Geo-Information Detection Instruments, Ministry of Education, Jilin University. The time-domain waveform and frequency-domain diagram are presented in Fig. 12.

The processing results for pure noise samples are shown in Fig. 13. The SNIR of the signals processed using stacking-averaging, EMD, WTD, SVD, VMD, and MPA-VMD-SVD were 16.39, 16.35, 21.05, 24.74, 10.64, and 45.79 dB, respectively. Compared to traditional algorithms, the signal curve processed by MPA-VMD-SVD is closer to the ideal signal, achieving the maximum SNIR. The experimental results demonstrate the superiority of this method.

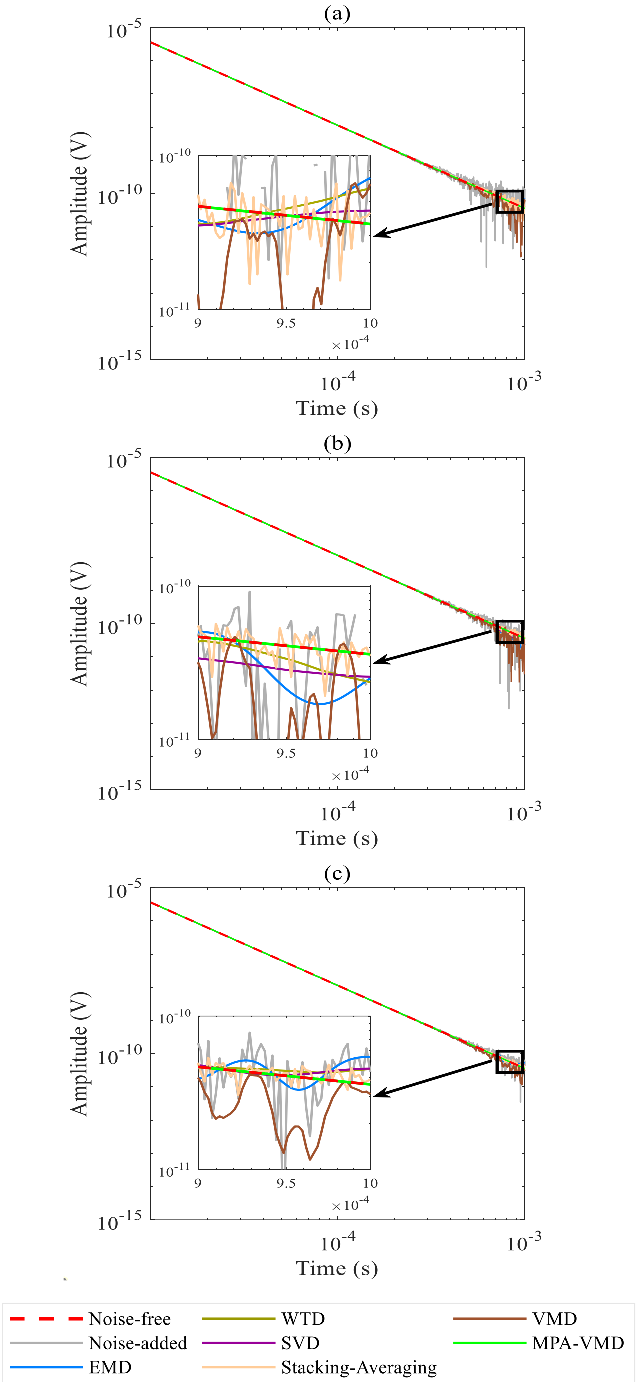

FIGURE 11. **Comparison of simulation noise suppression effect with traditional algorithms. (a) Strong noise; (b) Moderate noise; (c) Weak noise.**

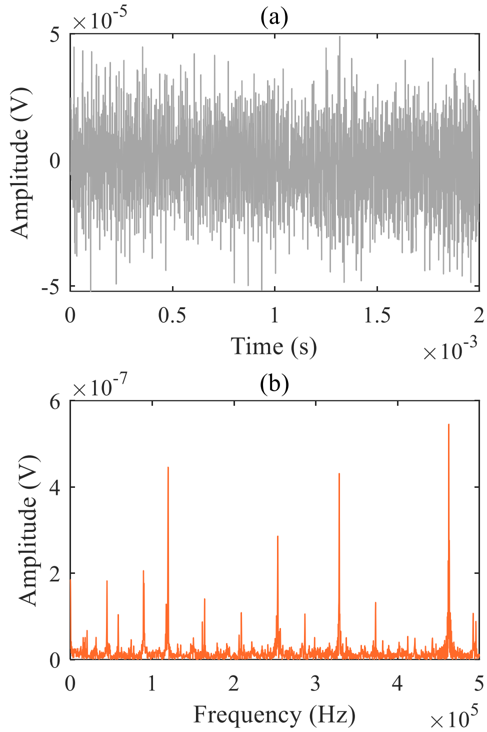

FIGURE 12. **Field noise data. (a) Time domain waveform; (b) Frequency domain diagram.**

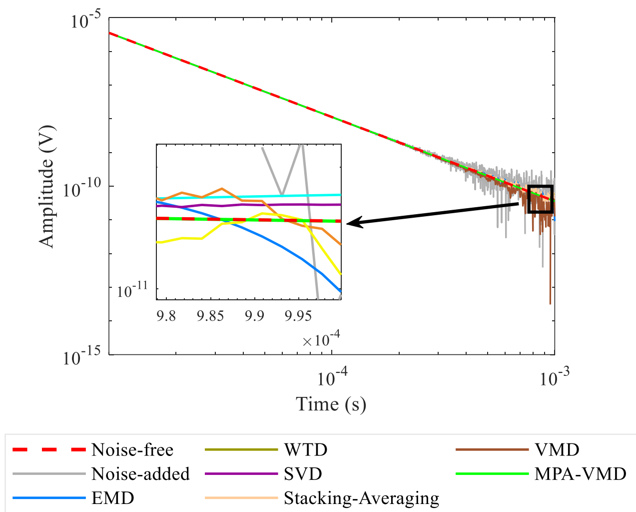

FIGURE 13. **Comparison of field noise suppression effect to traditional algorithms.**

V. CONCLUSIONS

This study proposes the MPA-VMD-SVD noise reduction model to address the challenge of parameter selection when applying modern digital processing algorithms to TEM data noise. The MPA is utilized to efficiently identify the optimal global solution and optimize the parameters of VMD. SVD is then applied to filter out residual noise in the signal modes, enhancing the accuracy of signal-noise separation. This research categorizes noise into three levels: strong, moderate, and weak. Several traditional algorithms are selected for comparative experiments, with SNIR used as an evaluation metric to analyze the noise reduction performance on both simulated and field data. The experimental results show that the MPA-VMD-SVD can suppress the TEM late signal noise and effectively recover the signal attenuation trend under different SNR conditions. This method exhibits superior performance, providing an innovative TEM data noise suppression solution.

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