Application of Semi-Airborne Frequency Domain Electromagnetic Data Based on Improved Ant-Colony-Optimized Wavelet Threshold Denoising Method

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ABSTRACT The semi-airborne frequency domain electromagnetic detection method is a popular electromagnetic detection method in which the transmission system is excited on the ground and the reception system coil is in the air to measure the vertical magnetic field signals in the frequency domain. In the field exploration, the semi-airborne frequency domain electromagnetic detection system is vulnerable to low-frequency motion noise, power-line interference, industrial noise, astronomical noise, and many other interferences, which leads to a very low signal-to-noise ratio of the detection data. Owing to the overlap between the effective signal and several types of noise in the time-frequency domain in the semi-airborne frequency domain of the detected signal, the conventional denoising methods are limited and cannot meet practical needs. Therefore, an integrated denoising method based on the improved ant-colony-optimized wavelet threshold is proposed. The method first separates the low-frequency noise of motion using the wavelet’s high-scale component for noise reduction. Other interference noise types, such as power-line interference, industrial noise and astronomical noise, are also reduced using the improved ant-colony-optimized wavelet threshold method. The experimental results show that the proposed integrated denoising method exhibits good suppression effects on several types of noise, can effectively improve the signal-to-noise ratio of the data, and improve the field data inversion accuracy.

INDEX TERMS Semi-airborne frequency-domain electromagnetic method, wavelet transform, noise reduction, ant colony optimization.

I. INTRODUCTION

As an important part of geophysical exploration technology, the semi-airborne frequency domain electromagnetic (SAFEM) detection method achieves rapid acquisition of geodetic electrical information and rapid investigation of deep subsurface structures within a large depth range in complex terrain conditions. This is achieved by placing a high-power artificial electromagnetic source on the ground as the transmission excitation system and by mounting a small size and lightweight receiving coil on an aircraft to collect the airborne magnetic field signal [1], [2], [3]. This method has numerous advantages, including the broad detection range, adaptability to complex terrain, high-spatial resolution, convenient field wiring of the airborne electromagnetic method, high-signal-to-noise ratio (SNR), broad exploration depth range, and large transmission magnetic moment of the terrestrial electromagnetic method, and also increases the safety and simplification of the cost compared with the conventional airborne electromagnetic method [4], [5], [6]. When subjected to the excitation of artificial field sources, the airborne receiving system is relatively lightweight and can be mounted on more versatile unmanned aerial platforms.
Prior publications [7], [8] introduced the semi-airborne electromagnetic detection system based on a helicopter platform developed by eight joint-research collaborators, including the University of Münster and Leibniz Institute of Applied Geophysics in Germany. References [9], [10], and [11] introduced the semi-airborne electromagnetic detection system in the frequency domain based on a multisource emission and unmanned aircraft platform developed by Jilin University and presented the related field detection and application features. As the semi-airborne frequency domain electromagnetic detection conducts electromagnetic measurements using unmanned aerial vehicle (UAV)-mounted reception equipment during the exploration process, it is susceptible to noise interferences, such as low-frequency motion noise [12], power-line interference [13], and astronomical noise [14]. Noise can affect the SNR of detected data considerably and limit the detection effect; therefore, it is crucial to study low-frequency noise suppression methods to improve the detection accuracy of the system. At present, most researchers mainly focus on the noise reduction research of transient electromagnetic detection data [15], [16], [17], and the literature on noise processing of detected electromagnetic data in the frequency domain is limited. Yin et al. addressed the relationship between the attitude pod changes and motion noise and proposed a geometric correction method based on the analysis of the response characteristics of aerial frequency-domain EM method [18]. Liu et al. [19] optimized the design of a hollow coil sensor to suppress astronomical noise induced during measurements. The aforementioned methods can suppress specific noise to some extent, but the overall noise reduction effect for semi-airborne frequency domain electromagnetic detection data is not satisfactory. To improve the noise-reduction effect of frequency domain electromagnetic detection data, Wang [20] investigated the effect of power-line noise on semi-airborne frequency-domain electromagnetic data. Cai et al. [21] proposed a wavelet transform (WT) threshold method to improve the problem of poor noise-reduction effects of traditional filters applied on the Earth’s power-line interference signals. Kang [22] used wavelet transform for noise reduction of motion noise interference in semi-airborne (frequency-domain) electromagnetic data. The aforementioned method verifies the effectiveness of the wavelet transform method for noise reduction in detected frequency-domain electromagnetic data, as it can eliminate the interference of single noise on electromagnetic data to a certain extent and provide some guidance for noise reduction in semi-airborne frequency domain, electromagnetic data. However, the literature only discusses the applicability of wavelet transforms to cope with a single noise type in the electromagnetic detection process, and the removal of other noise types from frequency-domain electromagnetic detection data has not been quantified. In addition, a large number of other methods exist for noise suppression of frequency domain electromagnetic signals, such as mode decomposition algorithms [23], etc. However, the empirical mode decomposition is adaptive decomposition, which is a data-driven method. If there are differences in electromagnetic data, the results of mode decomposition vary tremendously [24]. And the mode mixing phenomenon of empirical mode decomposition is serious. Although ensemble empirical mode decomposition [25] is proposed to solve the modal aliasing problem, the residual noise remaining in the signal is larger when the signal is reconstructed. These methods have certain limitations in terms of noise reduction in conjunction with frequency electromagnetic detection data; accordingly, it is difficult to meet the interpretation accuracy and application effects of semi-airborne frequency domain electromagnetic detection. Therefore, the study of noise reduction methods has become the key to semi-airborne frequency-domain-based electromagnetic detection to effectively suppress multiple interference noise types in electromagnetic data.

To solve the interference problems of low-frequency motion noise, power-line interference, industrial noise and astronomical noise in semi airborne electromagnetic detection data, a integrated denoising method based on wavelet transform is proposed in this paper. The main contributions are as follows: according to the different time-frequency characteristics of noise in the semi airborne electromagnetic detection data, wavelet high scale components and wavelet threshold methods are respectively used to reduce low frequency motion noise and other interference noises. When using high scale components of wavelet to suppress motion noise, the effects of different wavelet basis and decomposition scales on noise reduction are discussed. In order to improve the denoising effect and solve the problems of difficult threshold selection and poor filtering effect in actual data, an improved ACO algorithm is designed to optimize the wavelet threshold function when using wavelet threshold method to denoise other interference noises. After experimental verification, the proposed integrated noise reduction method is shown to exhibit a good suppression effect on a variety of noise types, and can meet the needs of noise suppression of semi-airborne frequency domain electromagnetic data.

II. SAFEM DETECTION METHOD

The structure of the semi-airborne frequency domain electromagnetic detection system is shown in Fig. 1. This mainly includes the ground-transmission and the air-reception systems. The measurement area is located near the mid-pipeline of the transmitting conductor. To increase the signal strength, ground-to-air transmission systems usually use grounded long wire sources, including ground electrodes, transmission wires, and transmitters. The length of the wire is usually in the range of 1–3 km, the transmitting current is tens of amperes, and the transmitting frequency is in the range of 0.01–10 kHz. The airborne receiving system includes the magnetic field acquisition system and the flight platform. The magnetic field acquisition system is suspended below the flight platform based on a soft connection structure. As the ground and air acquisition systems are relatively lightweight,
the flight platform can choose a flexible and convenient rotorcraft UAV system. Typically, the airborne receiving system (based on the rotorcraft platform) has a flight speed in the range of 3–10 m/s, and a flight altitude in the range of 30–150 m. Based on the combination of low-altitude, near-surface, and low-speed high-density measurements, the ground-to-air UAV measurement system can enhance effectively the perception and discrimination of spatially anomalous targets.

According to the principle of electromagnetic induction, the spatial magnetic field response is proportional to the amplitude of the emitted current. For a long wire source, the emission current \( I(f) \) is

\[
I(f) = \frac{U}{\sqrt{R^2 + (2\pi f L)^2}} \quad (1)
\]

where \( U \) is the voltage at the output of the transmitter, \( R \) is the load resistance of the transmitting system, \( L \) is the inductance of the long wire (typical value = 3 mH/km ), and \( f \) is the transmitting frequency.

When the magnetic induction intensity at the spatial position is determined, the voltage signal \( V_s(f) \) at the output of the airborne magnetic field receiving system is

\[
V_s(f) = 2\pi \xi f K(f) B_z(f) \quad (2)
\]

where \( \xi \) denotes an imaginary number, \( B_z(f) \) is the magnetic induction intensity received in the air, and \( K(f) \) is the magnetic sensitivity coefficient of the measuring device, which is related to the signal frequency and determined by the parameters of the measuring sensor and the measuring device.

III. DENOISING METHOD BASED ON OPTIMIZED WT

Semi-airborne frequency domain electromagnetic exploration data is a non-stationary noise. Wavelet transform is able to analyze the non-stationary noise signal while decomposing the signal on multiple scales [26]. The wavelet transform analyzes the time resolution and frequency resolution of the reasonably compromised signal at high and low frequencies by multiscale analysis. In the high frequency part, the signal gives a high temporal resolution due to its short duration and strong variation characteristics. In the low frequency part, the signal is given a higher frequency resolution because of its long duration and slow variation.

The advantage of wavelet transform is that certain aspects of the problem can be fully highlighted by the transform. The method enables the localized analysis of temporal (spatial) frequencies and the gradual multi-scale refinement of the signal by means of a telescoping translation operation, eventually reaching temporal subdivision at high frequencies and frequency subdivision at low frequencies. In addition, the method automatically adapts to the requirements of time-frequency signal analysis so that it can focus on arbitrary details of the signal.

The wavelet transform noise reduction method is based on the variation of the characteristics of the effective signal and noise at different scales of wavelet coefficients to achieve
the purpose of data noise reduction. The wavelet transform noise reduction method is capable of handling oscillating and varying nonstationary signals, and is used to suppress accurately a wide range of noise types in semi-airborne frequency domain, electromagnetic data by performing multiscale signal decompositions.

In actual explorations, in addition to the target signal excited by the artificial field source at the receiving location, motion, astronomical, industrial and power-line interferences are also included, as shown in Fig. 2. This causes signal motion, astronomical, industrial and power-line interferences excited by the artificial field source at the receiving location, electromagnetic data by performing multiscale signal analysis, and is used to suppress accurately a wide range of noise types in semi-airborne frequency domain to improve the detection accuracy of the system.

In view of the distribution characteristics of electromagnetic detection noise in the semi-airborne frequency domain, a comprehensive noise reduction method based on wavelet transform is proposed to suppress multiple noises in this paper. The wavelet function has the advantage of time-frequency localization, and can accurately identify the noise in the signal range for signals exhibiting different trends. Therefore, the wavelet transform is used to denoise the electromagnetic signal in the time and frequency domains to reduce the effects of motion, power-line, and astronomical noise on the effective signal, as shown in Fig. 3.

A. MOTION NOISE REDUCTION

Given that the reception system of semi-airborne frequency domain, electromagnetic detection uses a rotary-wing UAV to carry the receiving system in the air to conduct motion measurements, motion platform noise is inevitably introduced into the reception system. The energy of the baseline drift caused by motion noise is mainly concentrated in the high-scale, low-frequency component, and the multiresolution property of wavelets can realize the decomposition of noise-containing signals in a step-by-step manner, i.e., it is decomposed into subsignals at different frequency bands.

Assume that the frequency domain electromagnetic detection data containing motion noise is \( Y(t) \)

\[
Y(t) = s(t) + n(t)
\]

where \( t \) denotes time, \( s(t) \) is the effective information, and \( n(t) \) is the noise information.

The coefficients after the wavelet transform are then expressed as follows:

\[
W_{i,j}(Y) = W_{i,j}(s) + W_{i,j}(n)
\]

where \( W_{i,j}(s) \) is the wavelet transform coefficient of the effective signal and \( W_{i,j}(n) \) is the wavelet transform coefficient of the noisy signal.

The motion noise in the semi-airborne frequency-domain electromagnetic detected data is mainly concentrated in the high-scale, low-frequency component. Accordingly, layer-by-layer decomposition of the noise-containing signal can be achieved based on the multiresolution characteristics of wavelets, that is, it is decomposed into different frequency bands of subsignals according to the frequency. The approximate part of the low-frequency mapped signal information and the detailed part of the high-frequency mapped signal information both correspond to the scale coefficients and wavelet coefficients of the function, respectively. The schematic of the wavelet decomposition process (classified according to the level) is shown in Fig. 4, where CA is the low-frequency information, and CD are the high-frequency wavelet coefficients.

The noise-reduction effect of the wavelet function is crucial with the choice of wavelet basis function and scale parameters. The commonly used wavelet basis classes are the haar, Sym4, Sym8, db2, and coif5 wavelet basis functions. To achieve the best noise-reduction effect for frequency domain, semi-airborne electromagnetic data, the effects of wavelet basis and scale parameters on the noise-reduction effect of frequency domain, semi-airborne electromagnetic data in different combinations are discussed next. In this study, the SNR was chosen as the evaluation index to quantify the differences of different combinations of decomposition scales and basis functions on the noise-reduction effects of simulated signals, and the noise-reduction scheme with the largest SNR improvement was selected.

The SNR is the ratio of useful signal power to noise power:

\[
SNR = 10 \cdot \log_{10} \left[ \frac{\sum_{k=1}^{N} s_{k}^2}{\sum_{k=1}^{N} (g_{k} - s_{k})^2} \right]
\]

where \( s_{k} \) is the noise-free signal, \( g_{k} \) is the noise-reduced signal, and \( N \) is the number of sample points, \( k = 1, 2, \ldots, N \).

1) WAVELET BASE SELECTION

In the semi-airborne electromagnetic detection system, the reception sampling rate was typically set to 31250 Hz, and the transmission frequencies were 32 Hz, 64 Hz, 128 Hz, 256 Hz, etc. According to the Nyquist sampling theorem, the signal frequency information ranges from 0 to 15625 Hz. As the system low-frequency motion noise frequency is mainly concentrated in the frequency band (frequency values <20 Hz), and the minimum transmission frequency is 32 Hz, this meets the requirements associated with the removal of the low-frequency motion baseline.

Different wavelet bases have different time–frequency characteristics. To select the most suitable wavelet basis for semi-airborne electromagnetic signal data in the frequency domain, this study selected different wavelet basis functions for the simulated signal and calculated the SNR before and after noise reduction, and compared the optimal wavelet basis functions based on the aforementioned noise reduction evaluation rule. The signal was simulated by adding Gaussian noise to the effective signal, and the noise-reduction scheme with the largest SNR improvement was selected.

**Appendix**

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white noise and low-frequency motion noise with an SNR equal to 80 dB at 32 Hz, 64 Hz, 128 Hz, and 256 Hz to test the effect of common wavelet basis haar, Sym4, Sym8, db2 and coif5 functions on the data collected from semi-aircraft, frequency-domain electromagnetic detection.

Fig. 5 shows the time-domain comparison of the noise-containing signal with several wavelet functions after baseline correction. The small picture in the figure is the enlarged picture of the first time period in Fig. 5 (spanning 0.5 s). As shown, the low-frequency motion noise of the original noise-containing signal is much larger than the signal level, and several wavelet bases have the ability to suppress the motion noise signal. However, the comparison of the noise reduction abilities of several wavelet bases showed that the
coif5 wavelet base had the best noise-reduction effect and could reduce the interference of motion noise to the maximum extent. To be able to compare the noise reduction effect of wavelet bases more intuitively, Fig.6 shows a comparison of the spectrum of the noise-containing signal with several wavelet functions after baseline correction. From the figure, it can be inferred that both the coif5 and sym8 wavelets can eliminate effectively the leakage of low-frequency motion noise in the high-frequency band for the interference of very strong motion noise, thus resulting in a considerable reduction of the system noise level in the 20–500 Hz frequency band.

To quantify the effect of noise reduction of wavelet basis functions, the SNR results of different wavelet basis functions at different frequency points are listed in Table 1. As indicated, the SNR of coif5 wavelet basis at 32, 64, 128 and 256 Hz is the highest among several wavelet basis functions; thus, the coif5 wavelet basis has the best noise reduction effect.

2) SCALE PARAMETER SELECTION
The scale parameter of the wavelet transform is the key parameter for scaling operation on wavelet function. A larger scale factor generates a stretched wavelet, and a smaller scale factor generates a contracted wavelet. In addition, there is a certain proportional inverse relationship between scale and frequency, which is defined as

$$ f_s = \frac{F_c \times f_s}{s} $$

where $f_s$ denotes the actual frequency, $F_c$ denotes the wavelet center frequency, $f_s$ denotes the sampling frequency, and $s$ denotes the scale factor. Larger scale factors correspond to lower frequencies whereas smaller scale factors correspond to higher frequencies.

To examine whether the signal noise cutoff frequency obtained after the scale factor of coif5 wavelet basis completes the reconstruction of low-frequency motion noise meeting the requirements of the noise reduction algorithm, the noise reduction effect of different scales of the coif5 wavelet basis (shown in Fig. 7) was compared herein to obtain the best scale parameters applicable to the noise reduction of semi-airborne frequency-domain electromagnetic detection data. Fig. 7 shows that when the number of decomposition layers is 10, the cut-off frequency of the reconstructed signal noise is 15 Hz, which is lower than the minimum emission frequency point of 32 Hz, and therefore meets the requirements of noise reduction. The cut-off frequency of other decomposition layers is greater than 32 Hz, and the noise reduction result considerably affects the detection accuracy of the semi-airborne frequency-domain electromagnetic detection system at 32 Hz. Therefore, this study selected $s = 10$ as the best scale parameter for the motion noise suppression process.
In summary, the capacity of the coif5 wavelet to remove motion noise in the low-frequency band is significantly better than several other wavelets. Moreover, the cutoff frequency of the signal noise obtained when the decomposition scale is 10 is lower than the minimum emission frequency; these findings meet the requirement of removing the low-frequency motion baseline. Therefore, it is very feasible and effective to select 10-layer coif5 wavelets to suppress motion noise when processing semi-airborne frequency-domain, electromagnetic data.

**B. OTHER NOISE REMOVAL**

The wavelet threshold method can be used to reduce the interfering noise signals. For the interference signals, such as power-line and astronomical noise in semi-airborne frequency-domain electromagnetic detection data. To improve the noise-reduction effect, an adaptive ACO algorithm was designed in this study to optimize the threshold function of wavelets.

1) TRADITIONAL THRESHOLD DENOISING METHOD

There are two commonly used threshold functions used to filter out noise signals, namely, the hard and the soft threshold functions, as described below. Hard threshold function:

\[
\hat{W}_{i,j} = \begin{cases} 
W_{i,j}, & |W_{i,j}| \geq \lambda_i \\
0, & |W_{i,j}| < \lambda_i 
\end{cases}
\]  \( (7) \)

where \( \lambda_i \) denotes the selected threshold value for layer \( i \). Soft threshold function:

\[
\hat{W}_{i,j} = \begin{cases} 
\text{sgn}(W_{i,j}) \cdot (|W_{i,j}| - \lambda_i), & |W_{i,j}| \geq \lambda_i \\
0, & |W_{i,j}| < \lambda_i 
\end{cases}
\]  \( (8) \)

where \( \text{sgn}(.) \) is a symbolic function.

The conventional soft and hard wavelet threshold denoising methods have advantages associated with simple calculation processes and obvious noise-suppression effect. However, both of them also have obvious defects. The breakpoint problem of the hard threshold function makes it discontinuous, and the signal obtained by reconstruction contains oscillations. The soft threshold function is associated with the problem of constant deviation, which directly affects noise reduction. To overcome this drawback, this study proposes a threshold noise-reduction method based on improved ACO to obtain a more appropriate threshold value based on the estimated SNR of the noise-containing signal.
2) THRESHOLD DENOISING METHOD WITH IMPROVED ACO

The ACO algorithm is a stochastic class search algorithm inspired by the collective behavior of ant colonies in nature [27]. Compared with other heuristic algorithms such as genetic algorithm [28] and particle swarm optimization [29], the ant colony optimization algorithm adopts a positive feedback mechanism, which is one of the most significant features different from other algorithms. The positive feedback process makes the differences in the initial parameters expand continuously, and at the same time guides the whole system to evolve toward the optimal solution. The ant colony optimization algorithm is essentially a parallel algorithm and can be viewed as a distributed multi-individual system. The algorithm performs independent solution search processes at multiple points in the problem space, which not only increases the reliability of the algorithm, but also makes the algorithm have a strong global search capability. In addition, the algorithm has strong robustness in solution performance, which is one of the important factors for adopting the ant colony optimization algorithm in this paper. In the basic ACO algorithm, the artificial ant selects the direction of movement according to the concentration of pheromones on the path when it searches for a path. The higher the concentration is, the higher the probability of selecting that direction of movement is. If the pheromone intensity on the path of ant $z$ from node $i$ to node $j$ at moment $t$ is $\rho_{i,j}(t)$, then the probability of transfer from node $i$ to node $j$ is

$$p_{i,j}(t) = \begin{cases} \frac{\rho_{i,j}(t)}{\sum_{s \in A_z} \rho_{i,s}(t)}, & j \in A_z \\ 0, & \text{otherwise} \end{cases}$$

where $\alpha$ denotes the pheromone trajectory weighting factor. After $m$ moments, the ants complete a cyclic iterative search, and the pheromones of each road segment can be adjusted appropriately according to the pheromone update equation.

$$\rho_{i,j}(t + m) = (1 - \gamma) \cdot \rho_{i,j}(t) + \Delta \rho_{i,j}(t + m)$$

$$\Delta \rho_{i,j}(t + m) = \sum_{l=1}^{m} \Delta \rho_{i,j}^l$$

$$\Delta \rho_{i,j}^l = \begin{cases} \frac{Q}{F_j}, & i \to j \\ 0, & \text{otherwise} \end{cases}$$

where $\gamma$ represents the persistence of the pheromone locus. $\Delta \rho_{i,j}(t + m)$ denotes the pheromone trajectory increment.
on the path from node \( i \) to node \( j \) in this iteration of search, denotes the pheromone left by ant \( l \) on the path from node \( i \) to node \( j \) in this iteration of search, \( Q \) denotes the pheromone trajectory intensity factor, and \( F_l \) denotes the corresponding fitness value of ant \( l \) in this search iteration.

Although the positive feedback mechanism of the traditional ant colony algorithm helps speed up the convergence of the algorithm, it can lead to the over-enhancement of the pheromone trajectory. The reduction of population diversity and the weakening of global search ability make the algorithm vulnerable to premature convergence or premature maturity owing to local optimality. In view of the shortcomings of the traditional ant colony algorithm, the local pheromone and global pheromone updated methods of the ant colony algorithm are improved.

In the path finding process, the local pheromone update on the path of an ant from node \( i \) to \( j \) is given by
\[
\rho_{ij}(t+1) = (1 - \gamma) \cdot \rho_{ij}(t) + \gamma \cdot \rho_0
\]  
(13)
where \( \rho_0 \) denotes the initial pheromone value. The purpose of pheromone local update is to reduce the pheromone concentration of the visited paths and increase the pheromone concentration of unvisited paths.

After completing this iterative path search, the ant performs a global update of the path pheromone according to the following equation.
\[
\rho_{ij}(t + m) = (1 - \gamma) \cdot \rho_{ij}(t) + \gamma \cdot \Delta \rho_{ij}(t + m)
\]  
(14)

The wavelet threshold based on the improved ACO algorithm optimization is defined as
\[
\hat{W}_{ij} = \begin{cases} 
\text{sgn}(W_{ij}) \cdot (|W_{ij} - \beta|), & |W_{ij}| \geq \mu_i \\
0, & |W_{ij}| < \mu_i
\end{cases}
\]  
(15)

where \( \mu \) denotes the threshold value optimized based on the improved ACO algorithm, and \( a \) and \( b \) are the adjustment parameters. The main indicator used to evaluate the signal quality after denoising is the SNR and its comparison between the reconstructed and the original signal. Therefore, the SNR is used as the objective function of the improved ACO algorithm in this study. The larger the SNR value is, the better the selection of \( \mu \) is. The other parameters of the ant colony optimization algorithm are set as follows: the number of ant colonies is 20, the pheromone trajectory persistence \( \gamma = 0.01 \), the pheromone trajectory intensity factor \( Q = 1.0 \), the pheromone trajectory weighting factor \( \alpha = 0.5 \), the number of ants allowed to update pheromones sequentially \( m = 5 \), and the maximum number of iterations is 50.

To verify the effectiveness of the optimized wavelet threshold noise reduction method based on the improved ACO
algorithm, this study compared the noise reduction effects of soft thresholding, hard threshold, ant-colony- and improved ant-colony-optimized thresholds on power-line and astronomical noise, as shown in Fig. 8. The red circle in the figure indicates the transmitting and receiving frequency points of the semi airborne electromagnetic detection system. As indicated, the noise reduction methods based on ant-colony- and improved ant-colony-optimized threshold yield better effects compared with the noise reduction approaches with soft and hard thresholds. To quantify the performances of wavelet threshold noise reduction methods, the SNR values of several threshold methods are listed in Table 2. As indicated, the SNR values obtained for the proposed improved ant-colony-optimized threshold are higher than several other thresholds, thus illustrating the superiority of the proposed noise reduction method. Using the 32 Hz frequency as an example, the SNR values of the improved ant-colony–optimized threshold were improved by 163.6%, 7.4%, and 3.6%, respectively, compared with the hard, soft, and ant-colony-optimized thresholds.

### IV. APPLICATION EXAMPLES

The semi-airborne frequency-domain electromagnetic data collected from the central coal mine of Changzhi, Shanxi Province in June 2022 were selected for processing and analysis. The field construction layout is shown in Fig. 9. The exploration task of this work area was the detection of the roof layer of the coal seam.

The transmission frequencies of 32, 64, 128 and 256 Hz are used in the experiment. Owing to the complex environment in the selected study area, the frequency-domain data were subject to interferences from unmanned aircraft flights, human activities, and other factors, and the SNR of the original data was low. For the field measurement data with strong noise interference, the integrated noise reduction method based on wavelet transform proposed herein was used for processing. Fig. 10 compares the signal of measurement line 9 before and after noise reduction. As can be seen from the figure, compared with the hard thresholding, soft thresholding and ACO optimized thresholding methods, the proposed method can effectively suppress the interference of motion, power-line, and astronomical noise in the actual field practice, and can significantly improve the effective SNR at the transmission frequency, thus illustrating the effectiveness of the method for noise reduction of semi-airborne frequency-domain, electromagnetic data.

In addition, to verify the influence of the noise reduction on the inversion accuracy of the data, Fig. 11 shows the apparent resistivity imaging map based on the original data and different noise-reduction methods at an elevation of 1053 m. Fig. 11(a) shows that the inversion results have false low-resistance anomalies due to the existence of motion, power frequency, and sky power noise. In addition, although the roof of the coal seam shown in the black box is visible at elevations in the range of 550–600 m, the boundary with the surrounding strata is not clear. To improve the inversion
accuracy, the hard threshold denoising method, the threshold
denoising method based on ACO, and the method proposed
in this study were used for noise reduction, and the results are
compared, as shown in Fig. 11(b)-(d), respectively. As shown,
the apparent resistivity inversion by the noise reduction
method in this study is consistent and continuous, and the
inversion results eliminate the false low-resistivity anomaly,
thus making the boundary division of the coal seam roof
clearer. In combination with regional hydrogeological data
and known borehole side data, it can be clearly shown that the
coal mine has obvious water rich abnormal area at elevations
in the range of 750–850 m. Compared with this method,
the noise reduction effects of the hard threshold denoising
and ant-colony-optimized threshold denoising method were
not ideal. The filtering scale of the hard threshold denoising
method was too large, and the image details were lost.
The ACO threshold noise-reduction method could restore
the real stratum conditions more effectively, but the noise
was not completely reduced; therefore, there were existing
false low-resistivity anomalies in the image, and the interface
division of coal seam roof was not as clear as that associated
with this method.

V. CONCLUSION
In this study, a wavelet transform-based, integrated
noise-reduction method was proposed for the reduction of
low-frequency motion, power-line, and astronomical noise in semi-airborne electromagnetic data in the frequency domain. By analyzing the time–frequency characteristics and distributions of several types of noise, the proposed method first used wavelet high-scale components to reduce motion noise; the wavelet threshold method was then used to reduce other interference noise types. To obtain better noise reduction effects, a method was designed to improve the ACO algorithm to optimize the wavelet threshold function to solve the problem of difficult threshold selection and poor filtering effects in the actual data. After the verification of simulation and actual measurement data, the integrated noise reduction method proposed in this study demonstrated its capacity to suppress the noise in the semi-airborne, frequency-domain electromagnetic data, and effectively improved the inversion accuracy of the data.

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