Underwater magnetic target signal denoising based on modified wavelet decomposition and reconstruction algorithm

Tao Qin¹, pingjun Cao¹, yuzhu Zhang¹, zhanxin Liu¹, zhengxiang Chen¹, xuebin Zhang¹, Ke Dou¹, Hao Dong¹
¹Yichang Testing Technique Research Institute, Yichang, China
Email: 1539397903@qq.com

Abstract: Noise reduction is crucial for magnetic anomaly signal detection of underwater ferromagnetic target. Modified wavelet decomposition and reconstruction algorithm is proposed to suppress the colored noise and improve the signal to noise ratio. Hamming window is employed to make the preprocessed signal continuous. Evaluation index based on signal-to-noise ratio function is selected, wavelet decomposition and reconstruction algorithm iterates adaptively to select the optimal order of decomposition and reconstruction. The experiment result emphasizes that the signal-to-noise ratio of novel algorithm is 71.6dB. In this particle, we provide a new method to improve signal-to-noise ratio and enhance real-time signal processing for underwater target magnetic anomaly signal detection.

1. Introduction
The significance of signal detection of underwater ferromagnetic target is self-evident, which is one of primary method to detect unknown targets in the ocean circulation. But the magnetic interference of ocean is complex that makes difficult to detect the target signal accurately. In the ocean circulation, there include all kinds of magnetic interference source which are the eddy magnetic field produced by sea water, the magnetic field of a magnetic object, the magnetic field generated by cloud movement in the atmosphere and earth's magnetic field. Because the target magnetic anomaly signal is very weak, the signals of objective is drowned in the interference signals. It is necessary to improve the signal to noise ratio in order to obtain the magnetic anomaly characteristics of targets.

Currently, some researchers have explored many methods to acquire the perfect performance of SNR of magnetic anomaly signal. As far as we know, A.Shinker and L. Frumkis el.at utilize a three-axis magnetometer to detect the magnetic targets which is assumed as a magnetic dipole. They propose a fusion algorithm of Orthogonal Basis Function and filter to extract objective signals under the interference of white noise [1]. At the same time, A.Shinker also proposes entropy filter and high order crossing method which are used to process the magnetic anomaly signals[2-3]. In the context of some specific interference, the noise reduction effect of proposed algorithms is outstanding by analyzing the SNR of methods. Xin Xu introduces a new model that applies Deep Learning to detection and denoising of magnetic anomaly. The end-to-end deep learning framework is consisted of a binary classification network and a regression network which realize function of magnetic anomaly detection and geomagnetic noise suppression, respectively[4]. In addition, Xin Zheng uses a method that is a combination of wavelet analysis and orthonormalized basis function algorithm to extract and recognize the target magnetic anomaly signals[5]. Compared with the traditional orthonormalized basis function algorithm for magnetic anomaly detection, this new way reduces the false alarms.

Under certain background of magnetic interference, most of the existing magnetic anomaly
detection algorithms have a wonderful SNR. Due to the complexity and diversity of marine magnetic interference, most of these methods fail to give true advantage. What is more, magnetic anomaly detection of underwater moving targets needs the superduper real time and low-down false alarm rate. So we propose a novel algorithm that is modified wavelet decomposition and reconstruction to reduce the influence of interference for underwater magnetic target signals.

2. Sample data acquisition
We apply a Three-Axis-magnetometer to detect the magnetic anomaly signals of ship[6-7]. In the procession of detection, detected target is assumed as a magnetic dipole. The experimental site is chosen as Zhourshan in Hangzhou city, which has a wonderful magnetic interference environment. Merchant ships that travels at a fixed speed is chose as target. The sampling frequency of the target is 5000Hz. Fig.1 is the target magnetic anomaly signal sample data graph.

![Fig.1 Target magnetic anomaly signal sample data graph](image)

Fig.1 emphasizes that external interference has adverse effect on the target signal. The characteristic signal of target magnetic anomaly is almost submerged by the interference signal.

3. Modified wavelet decomposition and reconstruction algorithm
Wavelet decomposition and reconstruction algorithm have a strong ability for noise suppression and signal extraction[8]. It is able to associate time domain with frequency domain by analysis with wavelet decomposition and reconstruction algorithm[9]. In this particle, we improve the wavelet in order to sure high real-time performance.

3.1. Theory of wavelet decomposition
Assuming that target signal is \( f(t) \). Hypothesis \( V_0 \) is the fine-scale space under consideration, i.e. the scale factor \( j \). The corresponding scale function and wavelet function are defined as \( \phi_{j,k} \) and \( \psi_{j,k} \), respectively [10-11].

\[
\phi_{j,k}(t) = 2^{j/2} \phi(2^j - k) = 2^{j/2} \sqrt{2} \sum_{n \in Z} h_n \phi(2^{j+1} t - 2k - n) \\
= \sum_{n \in Z} h_n \phi_{j+1,2k+n}(t) = \sum_{n \in Z} h_{n+2k} \phi_{j+1,n}(t)
\]

(1)
\begin{align}
\psi_{j,k}(t) &= 2^{j/2} \psi(2^j - k) = 2^{j/2} \sqrt{2} \sum_{n \in \mathbb{Z}} g_n \varphi(2^{j+1} t - 2k - n) \\
&= \sum_{n \in \mathbb{Z}} g_n \varphi_{j+1,2k+n}(t) = \sum_{n \in \mathbb{Z}} g_{n-2k} \varphi_{j+1,n}(t) \\
A_j^d f &= \langle f(t), \varphi_{j,k} \rangle, \quad D_j = \langle f(t), \psi_{j,k} \rangle, \quad k \in \mathbb{Z} \quad (3)
\end{align}

Among them, \( h_n \) and \( g_n \) is the basis function, \( A_j^d f \) is called the fuzzy component, \( D_j f \) is called the detail component. The two-scale difference Equations (1) and (2) are utilized to calculate the wavelet expansion coefficients \( A_j^d f \) and \( D_j f \) of signal \( f(t) \). Then there is Equation (4).

\[
\begin{align*}
A_j^d f &= \sum_{n \in \mathbb{Z}} h_{n-2k} A_{j+1}^d f \\
D_j f &= \sum_{n \in \mathbb{Z}} g_{n-2k} A_{j+1}^d f \
\end{align*} \quad j = 0, \pm 1, \pm 2, \ldots \quad (4)
\]

Through the derivation of the Equations, the concrete process of wavelet decomposition can be expressed in detail by using the Fig. 2.

3.2. Theory of wavelet reconstruction

When \( f(t) \) is decomposed, reconstruction algorithm is applied to reconstruct the decomposed signal by the coefficients \( A_j^d f \) and \( D_j f \). Equation (5) is the wavelet reconstruction algorithm[12].

\[
A_{j+1}^d f(n) = \sum_{k \in \mathbb{Z}} h_{n-2k} A_j^d f(n) + \sum_{k \in \mathbb{Z}} g_{n-2k} D_j f(n) \quad (5)
\]

Wavelet reconstruction algorithm is the inverse process of wavelet decomposition algorithm. Fig. 3 is a schematic diagram of the reconstructed wavelet signal.

3.3. Improved algorithm

In order to satisfy the needs of real-time and effectiveness of noise suppression, the algorithm is improved by increasing Hamming window to select appropriate signal length, and elect signal-to-noise ratio (SNR) as evaluation criterion to judge the number of layers of wavelet decomposition[13-14]. Hamming window insures consecutiveness of processed target magnetic anomaly signal. Normally, the Hamming window has a length of 512 sample points. Moreover, by iteration of the algorithm, order of wavelet decomposition and reconstruction is determined through the SNR of signal of wavelet reconstruction. Evaluation function is Equation (6).
4. Results analysis

We utilize the modified wavelet decomposition and reconstruction algorithm to suppress noise of the underwater magnetic target signal. The adaptive iterative operation of wavelet algorithm determines the order of wavelet. The target magnetic anomaly signal is adaptively decomposed by the wavelet decomposition algorithm, and the wavelet reconstruction
Fig. 6  $j = 2$

Fig. 7  $j = 3$
Fig. 8  \( j = 4 \)

Fig. 9  \( j = 5 \)
Fig. 10  \( j = 6 \)

The algorithm is used to reconstruct the decomposed wavelet coefficients to obtain the reconstructed target magnetic anomaly signal at each layer. Fig.11 shows the result of SNR with different scale factors.

By the comprehensive analysis of the experimental results, it can be concluded that when the scale factor is 5, the improved algorithm has the best noise reduction effect on the target magnetic anomaly signal and gets the highest signal-to-noise ratio. Fig.9 shows the noise reduction diagram of magnetic anomaly signal with scale factor of 5. Compared with other scale factor values, the target magnetic anomaly signals in the figure not only have clear and smooth curves, but also retain the details of the target magnetic anomaly signals.

5. conclusion

We make use of the improved wavelet decomposition and reconstruction to reduce the interference of ocean magnetic noise for target magnetic anomaly signal. Though analyze the result of experiment, a conclusion is obtained that the modified wavelet algorithm has a perfect ability to suppress the colored
noise, and the real-time performance of filtering algorithm is improved. Besides, based on the signal-to-noise ratio function as the evaluation index, the improved wavelet decomposition and reconstruction algorithm can adaptively determine the order of the decomposed signal, which has better accuracy than empirical parameters. The result of performance manifests that the signal to noise ratio of improved algorithm is 71.6 dB for target magnetic anomaly detection.

Reference

[1] Sheinker A, Frumkis L, Ginzburg B, et al. Magnetic anomaly detection using a three-axis magnetometer[J]. IEEE Transactions on Magnetics, 2009, 45(1): 160-167.

[2] A. Sheinker, Ginzburg B, Salomonski N, et al. Magnetic anomaly detection using high-order crossing method[J]. IEEE Transactions on Geoscience and Remote Sensing, 2011, 50(4): 1095-1103.

[3] Sheinker, Arie, et al. "Magnetic anomaly detection using entropy filter." Measurement science and technology 19.4 (2008): 045205.

[4] Xu X, Huang L, Liu X, et al. DeepMAD: Deep Learning for Magnetic Anomaly Detection and Denoising[J]. IEEE Access, 2020, 8: 121257-121266.

[5] Zheng X, Xu Q, Zhou M, et al. An orthonormalized basis function algorithm based on wavelet analysis for Magnetic Anomaly Detection[C]/2017 10th International Congress on Image and Signal Processing, BioMedical Engineering and Informatics (CISP-BMEI). IEEE, 2017: 1-5.

[6] Farissi M S, Carletta S, Nascetti A, et al. Implementation and Hardware-In-The-Loop Simulation of a Magnetic Detumbling and Pointing Control Based on Three-Axis Magnetometer Data[J]. Aerospace, 2019, 6(12): 133.

[7] Zhang Q, Li X, Pan H L, et al. Detection of vehicle tracks by a three-axis magnetometer[J]. Sensors and Actuators A: Physical, 2018, 276: 83-90.

[8] Zhang D. Wavelet transform[M]//Fundamentals of Image Data Mining. Springer, Cham, 2019: 35-44.

[9] H. Toda and Z. Zhang, "Tight Wavelet Frame Using Complex wavelet Designed in Free Shape on Frequency Domain," 2019 International Conference on Wavelet Analysis and Pattern Recognition (ICWAPR), Kobe, Japan, 2019, pp. 1-6.

[10] González-Audícana, María, et al. "Fusion of multispectral and panchromatic images using improved IHS and PCA mergers based on wavelet decomposition." IEEE Transactions on Geoscience and Remote sensing 42.6 (2004): 1291-1299.

[11] CusidÓCusido, Jordi, et al. "Fault detection in induction machines using power spectral density in wavelet decomposition." IEEE Transactions on Industrial Electronics 55.2 (2008): 633-643.

[12] Keylock, C. J. "Characterizing the structure of nonlinear systems using gradual wavelet reconstruction." Nonlinear Processes in Geophysics 17.6 (2010): 615.

[13] Hansen, Anders Christian, and Laura Thesing. "On the stable sampling rate for binary measurements and wavelet reconstruction." Applied and Computational Harmonic Analysis 48.2 (2020): 630-654.

[14] Holighaus, Nicki, et al. "Characterization of analytic wavelet transforms and a new phaseless reconstruction algorithm." IEEE Transactions on Signal processing 67.15 (2019): 3894-3908.