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RESEARCH ARTICLE

Compressed Sensing Multiscale Sample Entropy Feature Extraction Method for Underwater Target Radiation Noise

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ABSTRACT Accurate underwater target detection and recognition in complex marine environments has always been a challenge. There is a lot of information in underwater target radiation noise that is important for underwater target recognition. However, the traditional underwater target radiation noise process is inefficient and inaccurate, severely limiting underwater target recognition. This paper proposed a new method for underwater target recognition based on compressed sensing multiscale entropy. For starters, compressing a signal improves its signal-to-noise ratio and broadens its linear spectrum. The multiscale sample entropy for the signal is then calculated after it has been denoised, and the most separated sample entropy is chosen by comparing the different scales of sample entropy to achieve effective underwater target radiation noise recognition. The experimental results show that the feature extraction method proposed in the paper can classify underwater target radiation noise quickly and effectively, improving recognition efficiency.

INDEX TERMS Compressed sensing, multiscale sample entropy, underwater target radiation noise, feature extraction.

I. INTRODUCTION

Humans have explored the seas off the coast with the continuous development of science, technology and the social economy. Classification and recognition of underwater targets are important elements of future duplication. At the same time, with the advancement of science and technology, the signal-to-noise ratio of the underwater target radiation noise is low, which will gradually increase the difficulty of the underwater target classification and recognition. Meanwhile, the marine environment seriously affects sonar's underwater target radiation noise, and the signal-to-noise ratio is extremely low. So the traditional underwater target radiation noise recognition method cannot meet the complex sea conditions by using limited features to identify the target radiation noise. Consequently, in the face of complex sea conditions and the continuous improvement of underwater acoustic target radiation noise, it is more necessary to extract a high-speed and high-precision underwater target radiation noise feature extraction method.

Many researchers have conducted useful investigations in recent years, primarily focusing on wavelet denoising, Fast Fourier Transform (FFT), and multiscale decomposition methods to improve the signal-to-noise ratio of underwater target radiation noise. Zhao *et al.* [1]–[8] proposed a wavelet relative energy criterion, and the results show that after the node segmentation threshold process, the noise band signal and the target band signal can be effectively separated. This method outperforms the global single denoising method in terms of separation and denoising. Kumar *et al.* [3] created a signal denoising method for underwater wireless communication that makes use of the fast Fourier transform and the

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Morlet wavelet, which is based on the continuous wavelet transform. According to the results, the proposed method improves the signal-to-noise ratio by about 12 dB. Despite the fact that the wavelet threshold denoising method is widely used in underwater acoustic signal processing, no response standard specifies the wavelet base or threshold. The choice of different wavelet bases and thresholds has a significant impact on the denoising effect, which causes the underwater target radiation noise recognition to produce a large error. In terms of Fourier analysis, He *et al.* [9], [10] discussed separating forward-scattered waves from direct blasts in the doppler domain using the sliding Blackman window in conjunction with a fast Fourier transform. Liu *et al.* [11]–[13] developed a constant virtual alarm detection approach in marine clutter by exploiting the multiscale Hurst index's sensitivity to target at the appropriate fractional Fourier transform. The multiscale Hurst index of the sea clutter fraction Fourier transform spectrum may distinguish between sea clutter and target, effectively enhancing the signal-to-noise ratio, according to experimental data. Although the Fourier transform performs well in underwater acoustic signal processing, in practical applications, picking the signal's window frequency at the same time limits the Fourier transform's application. In multi-scale decomposition and denoising, Yang *et al.* [14]–[18] integrated Spearman variational modal decomposition, spatial recursive sample entropy, wavelet threshold denoising, and the Savitzky-Golay filter for ship denoising in multi-scale decomposition and denoising. The results demonstrate that this strategy may boost SNR by 8 dB to 13 dB and attract a cleaner and smoother chaotic phase waveform, effectively suppressing marine environment noise in ship radiation noise. In underwater signal processing, the multiscale decomposition method can better characterize the underwater acoustic signal. However, when the denoising treatment is used, the radiated noise line spectrum cannot be completely recovered, limiting the implementation of the multiscale approach. In recent years, the compressed sensing method [19], [20] has been frequently used in underwater acoustic signal denoising. Kim *et al.* [21] investigated the tone signal produced by the mechanical component of the underwater target. The results demonstrate that it obtained better reconstruction accuracy than the classic Fourier transform threshold approach at a low signal-to-noise ratio. Based on compression sensing and wavelet change, Zhao *et al.* [22] developed a filtering strategy for weak signal noise detected in the underwater environment. Furthermore, the experimental results suggest that the method performs well and has a wide range of engineering applications.

Entropy-based approaches have recently been found to be more advantageous in hydroacoustic signal processing [23], [24]. Based on hierarchical entropy, Li *et al.* [25] suggested a method for extracting ship radiated noise features. Furthermore, simulated signal testing is used to characterize the various aspects of traditional entropy. The results suggest that the differences of this method are primarily centered in the signal with better high-frequency performance, which can be employed for ship identification in underwater acoustic signal processing. Feng *et al.* [26] successfully distinguished planetary gearbox defects by combining the phase angle recovered from planetary gear vibrations with sample entropy as a fault detection method for planetary gearboxes under non-smooth operation conditions. Huo *et al.* [27] offer a new entropy measurement approach for rolling bearing failures that is based on fine-to-coarse multiscale permutation entropy (F2CMPE), Laplacian score (LS), and support vector machine (SVM). Rong *et al.* [28] introduced a unique recursive maximum correntropy-based evolving fuzzy system that eliminates the convergence difficulty caused by the learning scale in gradient-based learning and evaluates the system's convergence performance. Li *et al.* [29] proposed a method for performing rolling bearing fault states and identifying fault classes based on refined composite multiscale permutation entropy (RCMPE) and a support vector machine, thereby improving the coarse-grained signal identification process. The multiscale permutation entropy causes the loss of key information in the identification of coarse-grained fault signals, resulting in more accurate fault information identification with better robustness and scalability.

To extract the underwater target radiation noise feature, this research suggested a method that combines compressed sensing denoising with multiscale sample entropy. First, the original signal is compressed, sensing denoising and providing a sparse representation of the original signal's frequency domain, and then the signal is reconstructed to improve the signal-to-noise ratio. The multiscale sample entropy of the signal after denoising was then determined, and the undersea target radiation noise was categorised and detected using the multiscale sample entropy. The method suggested in this paper is fast, has a high identification rate, and is very straightforward to analyze raw data. As a result, it is favourable to the algorithm's general applicability.

The remainder of this paper is structured as follows: The basic theory is provided in section II, signal denoising in section III, entropy extraction from multiscale samples in section IV, results and discussion in section V, and conclusion in section VII.

II. METHOD

A. COMPRESSED SENSING DENOISIN

Compressed sensing is a new data sampling theory that differs from the Nyquil theorem in that it can produce high-dimensional signals at a lower sampling rate. It is a novel concept in the field of future signal processing.

Set an N-dimension signal $x \in R^{N\times 1}$, and transform the signal x with an observation matrix $\varphi \in R^{M\times N}$, where each line of φ is multiplied with the original signal x to obtain an observation value, which contains part of the information of the original signal. Finally, M observations are obtained to form the M-dimension vector $y \in \mathrm{R}^{\mathrm{M}\times 1}$, then y is the observation vector, as shown in Equation 1.

$$y = \varphi_{\mathrm{x}} \tag{1}$$

If the observation vector y has enough information in x, the original signal x can be retrieved from it. When the number of equations in the observation vector y is less than the number of unknowns in the original signal x, the number of solutions is unlimited. In this scenario, the observation vector y cannot determine the initial signal x uniquely. To employ the compressive sensing principle for signal acquisition, sparse representation must be introduced prior to signal reconstruction.

Suppose that there exists a set of orthogonal basis, expand the original signal x on the basis, namely: $\{\Psi_i\}_{i=1}^{N}$ (ψi is the N-dimensional column vector)

$$x = \sum_{i=1}^{N} \theta_i \Psi_i \tag{2}$$

where $\theta_i = \langle x, \Psi_i \rangle = \Psi_i^T x$ is the expansion coefficient? It can be obtained:

$$x = \Psi_\theta \tag{3}$$

where $\Psi = [\Psi_1, \Psi_2, \ldots \Psi_N] \in R^{N\times N}$ is the orthogonal basis, $\theta = [\theta_1, \theta_2, \ldots \theta_N]^T$ is the corresponding expansion coefficient vector, substitute Equation 3 into Equation 1, let $\Phi\Psi = A^{cs}$, where A^{CS} is the compressed sensing information operator, then:

$$y = \Phi\Psi\theta = A^{cs}\theta \tag{4}$$

where θ is sparse, θ can be reconstructed from y. After obtaining θ, the original signal x can be recovered according to Equation 3.

Process flow for compression-sensing denoising:

1) First, assess whether the target radiated noise signal in the water possesses compressibility or sparsity using sparsity-based Discrete Cosine Transform (DCT) and Fast Fourier Transform (FFT).

2) Create several measurement sparse matrices and measure the sparse matrix to acquire the measurement amount f_2.

3) The measurement amount is sparsely represented by DCT discrete cosine and FFT Fourier base following the measurement matrix operation.

4) After sparse base transformation and coding measurement, use the Orthogonal Matching Pursuit (OMP) recovery algorithm to reconstruct the signal f_2.

5) After compressed sensing processing, Fourier transforms the original simulated signal and the reconstructed signal.

6) Finally, the reconstructed signal's signal-to-noise ratio is determined using the signal-to-noise ratio function.

According to the obtained spectrogram, the compressed sensing denoising process is also analyzed according to the calculation of the signal-to-noise ratio reconstructed by the OMP recovery algorithm, and the most suitable measurement matrix and sparse matrix are selected based on the spectrum analysis and the size analysis of the signal-to-noise ratio that is finally calculated. The ship's radiation noise signal has been improved.

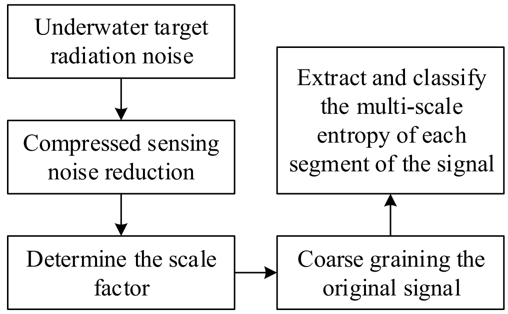

FIGURE 1. Multiscale sample entropy analysis process.

TABLE 1. The data simulation parameters of underwater target radiated noise.

Species	Blade number	Speed (kn)	Blade speed (R/s)	Sampling time (s)	Displacement (T)
1	4	15	25	1	2000
2	5	15	25	1	2000
3	4	10	25	1	2000

B. MULTISCALE SAMPLE ENTROPY

Set a target radiated noise signal X = $[x_1, x_2, \ldots x_N]$, and coarsely grain the underwater target radiation noise signals [30]. Then obtain a coarsely granulated time-series signal.

$$y_j^{(\tau)} = \frac{1}{\tau} \sum\nolimits_{i=(j-1)\tau+1}^{j\tau} x_i, 1 \le j \le N/\tau \tag{5}$$

where N is the length of the original underwater target radiation noise signal; τ is the scale factor; $1 \le j \le N/\tau$; $y_j^{(\tau)}$ is the subsequence with a scale of τ.

When the scale factor is set to one, the signal remains the same. Every coarse-grained signal has a length equal to the original signal length divided by the scale factor. The sample entropy for each coarse-grained signal is then calculated, and the scale factor function is plotted. Figure 1 depicts the multiscale sample entropy analysis process. Process flow for multiscale sample entropy extraction:

1) Separate a set of underwater target radiation noise signals into coarse-grained signals f_3 of length N;

2) Calculate the entropy of each coarse granulated signal f_3 sample of length N;

3) Compare the entropy separability of samples under different scale factors;

4) Use the most separable scale factor as the classification and identification feature of underwater target radiation noise.

III. UNDERWATER TARGET RADIATED NOISE COMPRESSED SENSING DENOISING

Three types of underwater target radiation noise with varying speeds, propeller speed, and displacement are simulated to demonstrate the superiority of the suggested method in this research. These data are sufficient to reflect radiation noise

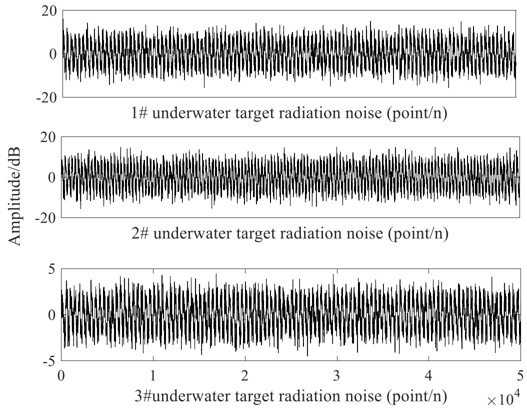

FIGURE 2. Simulating the underwater target radiation noise.

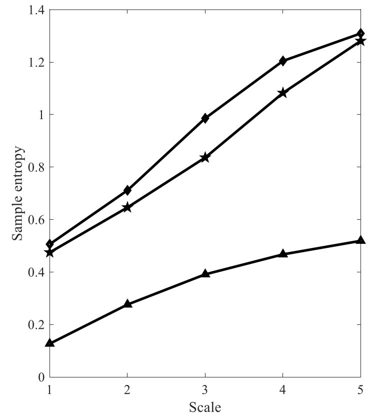

FIGURE 3. Sample entropy at different scales of three different water target radiated nois.

TABLE 2. Calculation results of the different measurement matrices.

Measurement matrix	Calculate the time (min)	Signal-to-noise ratio (dB)
Gaussian matrix	2.753	85.45
Sparse random matrix	2.622	85.48
Toplitz matrix	2.553	84.06
Loop matrix	2.568	83.59
Partial Bernoulli matrix	2.584	84.11
Partial Fourier matrix	2.548	75.22

under the same operating conditions of different underwater targets and the same underwater target, and the data simulation settings are presented in Table 1. The sample time is one second, and the sampling frequency is 50 KHz. The underwater target radiation noise in this article differs from the actual underwater target radiation noise, which is more complex than the actual signal. Because the authors were unable to complete the real signal capture, simulated underwater target radiation noise was utilized in this research to validate the method's practicality. Figure 2 depicts a simulation of underwater target radiation noise.

To extract underwater target radiated noise features, first denoise the ship radiated noise using compression sensing. Compression sensing is a distinct signal sampling approach that uses the Nyquist-specific observation matrix to retrieve underwater target radiated noise without distortion once the original signal x is sparsely represented. The results of the underwater target radiation denoising have been published [31]. Table 2 displays the hysteresis and signal-to-noise ratio results of the various measurement matrices.

It can be seen from the [31], employing the sparse random matrix as a measurement matrix improves calculation time marginally when compared to other measurement matrices. Its signal-to-noise ratio index, on the other hand, achieved 85.48 dB, which was much higher than the other measurement matrices. The linear spectrum of the first type of underwater target radiation noise is not visible after the Fourier transforms directly when using the sparse random matrix as the measurement matrix to address the first underwater target radiation noise. The linear energy is improved after the compressed sensing denoising treatment described in this research, and it can identify the undersea target radiation noise.

IV. EXTRACTION OF THE UNDERWATER TARGET RADIATION NOISE FEATURES

The selection of multiscale entropy parameters is also different for different signals, and it is necessary to study according to the corresponding signals; paper [32] recommends choosing 2 for the dimension m and 0.1-0.25std for the similar tolerance r, where std is the original signal's standard deviation. In this study, the dimension m is chosen by 2, the dimension r is chosen by 0.2 standard deviation, and the scale is determined. As shown in Figure 3.

Figure 3 shows that the multiscale sample entropy of three underwater target radiation noise signals is quite similar when the scale factor is between 1 and 5. When the scale factor is 3, there are obvious changes in the multiscale entropy of three separate underwater target radiation noise signals. As a result, when the scale factor is 3, the multiscale sample entropy of three independent underwater target radiation noise signals exhibits evident separability and may be employed as a feature of underwater target radiation noise signal classification and identification.

V. RESULTS AND DISCUSSION

To validate the suggested method's superiority, the three undersea target radiation noises were first compressed and noise decreased. The three undersea target radiation sounds were then split, each signal into 40 segments, and the time series statistical features and multiple entropy features of each segment calculated and derived; these features are displayed in Table 3. Figure 4 depicts the categorization comparison findings.

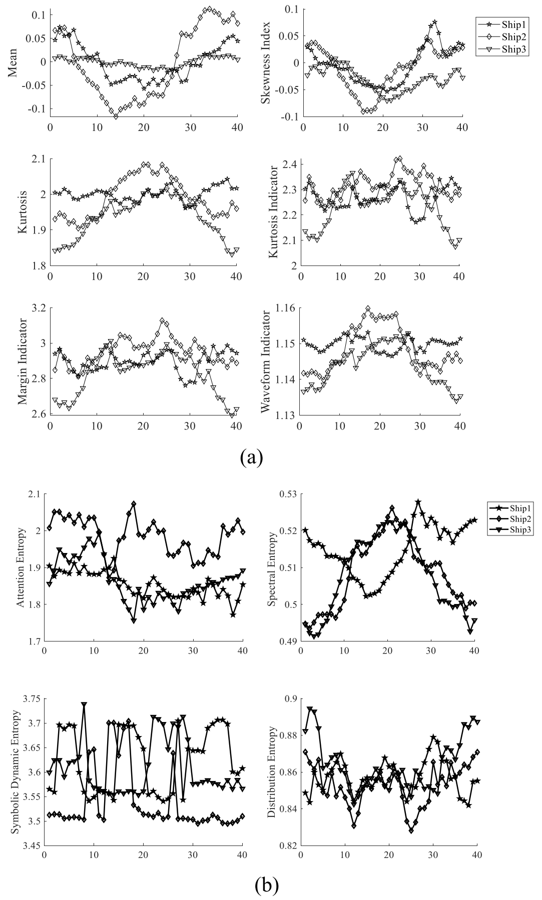

FIGURE 4. **a) Three types of signal classification using time series statistical features as classification features. b) Classification of three signals using entropy features as classification features.**

TABLE 3. **List of various features extracted.**

Temporal statistical feature	Mean, Skewness Index, Kurtosis, Kurtosis Indicator, Margin Indicator, Waveform Indicator
Entropy feature	Attention Entropy, Spectral Entropy, Symbolic Dynamic Entropy, Distribution Entropy

Multiple temporal statistical variables were examined as classification features for the three signals, as shown in Figure 4a, and it was discovered that the three signal samples varied significantly and there was a large crossover, prohibiting accurate classification identification of the three signals. As shown in Figure 4b, even though multiple entropies were used as classification features for the three signals, the three signal samples still fluctuated greatly and could not achieve accurate classification recognition of the signals; thus, using entropies as features cannot achieve accurate classification recognition.

Following compression and noise reduction, the three signals were segmented, with each signal split into 40 segments and each segment extracted with a scale factor of 3 as its multiscale entropy as a feature; the results are displayed in Figure 5.

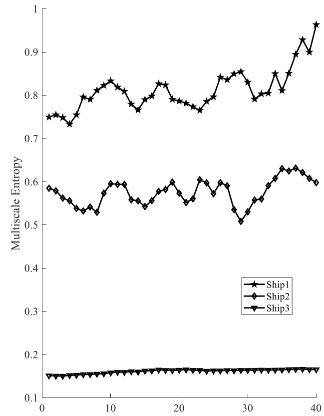

FIGURE 5. **Classification with multi-scale entropy as three signal features.**

As shown in Figure 5, the underwater target radiated noise after compressed sensing denoising process has a smooth arrangement of multi-scale sample entropy, which can reflect the difference in complexity of the original signal and has obvious differentiability. Therefore, the multi-scale entropy can be used as the underwater target radiation noise classification and identification feature.

VI. CONCLUSION

This study presents a novel form of mixed compressive sensing denoising approach for underwater target radiated noise features, as well as a multiscale sample entropy extraction method. It sparsely represents the original signal in the frequency domain using compressed sensing and reconstructs the signal using the observation matrix. It significantly enhances the original signal's signal-to-noise ratio while also employing multiscale sample entropy as a signal feature for underwater target radiated noise. It enables the categorization and identification of underwater target radiated noise while also improving classification accuracy. This approach provides the following advantages after experimental verification of analogue signals:

Combining compression sensing denoising and multiscale sample entropy to recover the features of underwater target radiated noise simplifies and minimizes the computation cost.

When compared to previous methods, the suggested method lowers reliance on the operator and prior knowledge while increasing the accuracy of the extraction of the underwater target radiated noise feature.

Experiment findings suggest that the feature extraction method described in this paper may effectively increase the identification efficiency of underwater target radiation noise.

The approach suggested in this paper enhances signal processing timeliness and underwater target recognition accuracy. Because the noise in this work is simulated, the researchers will continue to gather actual water target radiation noise to test the practicality of the method presented in this paper in true underwater target radiation.

AUTHOR CONTRIBUTIONS

Zhufeng Lei performed the experiment and wrote the article; Xiaofang Lei conceived and designed the research; Chuanghui Zhou and Lyujun Qing investigated the study; Qingyang Zhang wrote, reviewed, and edited the article.

DECLARATION OF CONFLICTING INTERESTS

The author(s) declared no potential conflicts of interest to the research, authorship, and publication of this article.

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