Research Article

Feature Extraction of Ship Radiation Signals Based on Wavelet Packet Decomposition and Energy Entropy

Yuxing Li ^{1,2}, Feiyue Ning ¹, Xinru Jiang ¹ and Yingmin Yi ^{1,2}

¹School of Automation and Information Engineering, Xi'an University of Technology, Xi'an 710048, China

²Shaanxi Key Laboratory of Complex System Control and Intelligent Information Processing, Xi'an University of Technology, Xi'an 710048, China

Correspondence should be addressed to Yingmin Yi; yiym@xaut.edu.cn

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The analysis of ship radiation signals to identify ships is an important research content of underwater acoustic signal processing. The traditional fast Fourier transform (FFT) is not suitable for analyzing non-stationary, non-Gaussian, and nonlinear signal processing. In order to realize the feature extraction and accurate classification of ship radiation signals with higher accuracy, a feature extraction method of ship radiation signals based on wavelet packet decomposition and energy entropy is proposed in this paper. According to wavelet packet decomposition, the ship radiation signal is decomposed into different frequency bands, and its energy entropy feature is extracted. As for comparisons, the center frequency and permutation entropy are also used as features to be extracted, then the k -nearest neighbor is applied to classify and recognize the extracted results. Based on the comparisons of wavelet packet decomposition, the center frequency, permutation entropy, and the k -nearest neighbor are used for classification and recognition. The experimental results present that, when comparing with center frequency and permutation entropy, the method based on energy entropy has the best availability, with the highest average recognition rate for four types of ship radiation signals, up to 98%.

1. Introduction

In the development of science and technology, underwater acoustic signal processing plays an extremely important role in the human exploration of the ocean and plays a great role in military and marine life research [1, 2]. Since the radiated noise signal of a ship contains a lot of information about the ship's characteristics, it has become one of the important indicators to measure the ship's performance, and it is widely used as the information source of passive sonar for the detection, tracking, and classification of ship targets [3, 4], so the feature extraction of the ship radiated noise signal has always been an important research content in the field of underwater acoustic signal processing, which has important theoretical and practical significance [5–8].

In general, many nonlinear, dynamic, and statistical parameters can be extracted as features of ship's radiated noise and for signal classification, such as the Lempel Ziv

complexity (LZC) [9, 10], Lyapunov exponent [11], correlation coefficient analysis [12], spectral kurtosis [13, 14], and the entropy-based complexity, among which the entropy-based complexity has attracted widespread attention. Entropy, as an indicator of the complexity of time series, can quantify the randomness of a time series, and greater entropy also represents greater irregularity [15, 16]. Some commonly used entropies include approximate entropy [17], sample entropy [18], and permutation entropy [15]. Compared with approximate entropy and sample entropy, the arrangement is not easily affected by the length of the time series, and the calculation time is relatively short, so it has been applied in many fields [19–21]. However, the PE only considers the order of amplitude values and ignores some information of amplitude values. Therefore, the traditional PE algorithm should be improved [22].

Since the late 1980s, many scholars have also applied spectrum analysis to underwater acoustic target feature

extraction, such as extracting the line spectrum and modulation spectrum of underwater target radiated noise by using acoustic power spectrum [23], Wigner-Ville distribution (WVD) [24], bispectrum and high-order spectrum analysis [25], empirical mode decomposition (EMD) [26], and wavelet or wavelet packet decomposition [27]. In particular, as a preprocessor, wavelet packet decomposition can divide the frequency space into various finite frequency bands to realize the time-frequency localization of the signal. It can decompose not only the low frequency but also the high frequency of the signal, and adaptively select the corresponding frequency band according to the analyzed signal, which has good time-frequency characteristics. Hence, wavelet packet decomposition is also widely used in signal feature extraction in various fields [28–30].

In this paper, we introduce the wavelet packet decomposition on the basis of energy entropy and calculate the corresponding PE value for each frequency band after decomposition and use it as a feature. Finally, the k-nearest neighbor (KNN) algorithm is introduced and used as a classifier to verify the validity of the extracted features. A large number of comparative experimental results also prove the effectiveness of the feature extraction method proposed in this paper.

The train of thought of this paper is given as follows: Section 2 gives an introduction to wavelet packet decomposition; Section 3 proposes a feature extraction method based on PE and wavelet packet decomposition; Section 4 verifies the effectiveness of the feature extraction method proposed in this paper through comparative experiments; Section 5 embraces main conclusions obtained.

2. Wavelet Packet Decomposition

Wavelet packet decomposition, also known as an optimal sub-band tree structure, is a further optimization of the wavelet transform. The main algorithm idea is on the basis of the wavelet transform, in each stage of signal decomposition, not only the low-frequency sub-band is further decomposed, but also the high-frequency sub-band is further decomposed. The original signal is decomposed by the optimal signal decomposition path, which was calculated by minimizing a cost function.

h_k and g_k is the filter coefficient of the scale function, $g_k = (-1)^k h_{1-k}$. The wavelet function is equivalent to high-pass filtering the signal to preserve the change details, while the scaling function is equivalent to low-pass filtering the signal to preserve the smooth shape. The basic function of the wavelet is actually formed by scaling and translating the scale function and the wavelet function. The size of the shift is related to the current scaling degree.

The scaling function $\psi(x)$ and wavelet function $\varphi(x)$ satisfy the following equations:

$$\begin{aligned}\phi(x) &= \sqrt{2} \sum_k h_k \phi(2x - k), \\ \psi(x) &= \sqrt{2} \sum_k g_k \phi(2x - k).\end{aligned}\quad (1)$$

The time-domain signal $\mu(x)$ can be decomposed recursively as

$$\begin{aligned}\mu_{j,2n}(x) &= \sum_k h_k \mu_{j-1,n}(2x - k), \\ \mu_{j,2n+1}(x) &= \sum_k g_k \mu_{j-1,n}(2x - k),\end{aligned}\quad (2)$$

where $n = 0, 1, \dots, 2(j-1) - 1$, g_k , h_k is low pass filter and high pass filter, respectively. When $n = 0$, $\mu_{0,0}(x) = \varphi(x)$, $\mu_{0,1}(x) = \psi(x)$, $\mu_{j,n}(x)$ denotes the wavelet coefficients at the j^{th} level, n^{th} frequency band. The recursive function set $\{\mu_n(x)\}_{n \in \mathbb{Z}}$ defined in the abovementioned formula is the wavelet packet defined by the orthogonal scaling function. Figure 1 shows an example of a three-layer wavelet packet decomposition of signals.

From Figure 1, the wavelet packet of the signal is decomposed into three layers into eight frequency bands, and each layer is decomposed into two parts, high-frequency and low-frequency. The high-frequency and low-frequency coefficients of wavelet packet coefficients are decomposed again, unlike the wavelet decomposition, which only decomposes low-frequency coefficients.

3. Proposed Feature Extraction Method

Let $P = \{P_1, P_2, \dots, P_n\}$ be a probability distribution, its information entropy $H(P)$ can be expressed as

$$H(P) = - \sum_{i=1}^n P_i \ln P_i. \quad (3)$$

The difference of signal in time-frequency distribution can be expressed by the uncertainty of energy distribution in different frequency bands. Therefore, a feature extraction method of ship radiated signal based on wavelet packet decomposition and energy entropy is proposed in this paper. The wavelet packet is used to decompose ship signals to obtain different frequency bands. Energy entropy, as a feature, is used to estimate the uncertainty of ship signal frequency band energy distribution. The specific steps of the proposed feature extraction method are as follows:

- (1) The ship signal is decomposed into M frequency bands by wavelet packet decomposition. In this paper, a three-layer wavelet packet decomposition is performed, where the M value is 8. The sum of the energy of the M frequency bands is equal to the total energy of the ship signal.
- (2) The energy proportion of each frequency band signal is calculated by

$$C_i = \frac{E_i}{E}. \quad (4)$$

E_i is the energy of the i^{th} frequency band signal; E is the total energy of ship signal; C_i is the proportion of the i^{th} band signal to the total energy of the ship signal.

The total energy of the ship signal can be expressed as

$$E = \sum_{i=1}^M E_i. \quad (5)$$

M is the number of signals in different frequency bands obtained after wavelet packet decomposition.

- (3) The energy entropy of the ship signal after wavelet packet decomposition is calculated by the definition of information entropy, which can be defined as

$$H(C) = - \sum_{i=1}^M C_i \ln C_i. \quad (6)$$

- (4) To demonstrate the effectiveness of the proposed feature extraction method, the k -nearest neighbor algorithm is used in the classification of the energy entropy features of ship signals to obtain the identification results. Given a training data set, for a new input instance, K instances closest to the instance are found in the training data set. Most of the K instances belong to a class, and the input instance is classified into this class.

4. Feature Extraction of Ship Radiated Noise

4.1. Ship Radiation Signals. In this paper, feature extraction and classification identification are carried out for four types of measured ship radiation signals (SRS), named SRS1, SRS2, SRS3, and SRS4. The signal lengths of the first and second types are 1380000, the third type is 28282835, and the fourth type is 164160, and the sampling frequency is 44.1 kHz. Data points within 5001 to 1000000 of the four types of SRS are taken, Figure 2 presents four types of SRS after normalization.

4.2. Wavelet Packet Decomposition of Ship Radiation Signal. For the wavelet packet decomposition of four types of SRS, 100 samples are extracted from each type of SRS, each sample contains 5000 sampling points. One sample for each type of SRS is processed with the wavelet packet decomposition, using the DB2 wavelet basis function, each sample is decomposed into eight frequency bands (FB), named FB1, FB2, FB3, FB4, FB5, FB6, FB7, and FB8. The wavelet packet decomposition results of four types of SRS are shown in Figure 3 (1 sample). For the four types of SRS, the amplitudes in different FB have obvious differences, FB1 has the lowest frequency.

4.3. Feature Extraction Experiment. The energy entropy feature of each FB is extracted, center frequency (CF) and permutation entropy (PE) are used as comparative features.

4.3.1. Energy Entropy. Four types of SRS are extracted from the perspective of energy, the energy proportion is calculated for each FB. Figure 4 displays the energy distribution of four types of SRS (1 sample).

From Figure 4, for the four types of SRS, FB1 has the highest energy; the energy of SRS1 and SRS4 in FB2 is greater than that of SRS2 and SRS3; for FB2 of the four types of SRS, SRS4 has the most energy distribution, and similarly, for FB3 and FB4, SRS4 is also the highest; in the eight FB, the energy distributions of SRS2 are almost all concentrated in FB1, while those of SRS4 are more dispersed. Figure 5 exhibits the energy entropy of 100 samples for four types of ship signals.

In the light of Figure 5, there is a big difference in energy entropy among the four types of SRS; SRS2 has the smallest range of sample distribution, and has great stability; most samples of SRS1 are distributed between 0.4 and 0.7, while a small number of samples of SRS3 and SRS4 also appears in this range; there is a clear order of the energy entropy of the samples for the four kinds of SRS.

4.3.2. Center Frequency. The CF feature extraction is performed for each FB of the four types of SRS, and the CF of each FB for the four types of SRS is shown in Figure 6.

As presented in Figure 6, for the four types of SRS, the CF under the same FB is different; for SRS2, the CF of FB7 and 8 is very different from the other three types of SRS; the CF distribution of samples in FB4 and FB6 is similar, the CF of SRS1 and SRS2 are close, and so are SRS3 and SRS4, but there is an obvious gap between the two groups; the CF distribution of the samples for SRS1 and SRS3 are very dispersed in each FB.

4.3.3. Permutation Entropy. PE mainly includes three parameters: data length, embedding dimension, and delay time, which are 5000, 3, and 1, respectively, in this experiment. Figure 7 indicates the PE of each FB for the four types of SRS.

As exhibited in Figure 7, the PE for the four types of SRS in the same FB is very close; the PE of the SRS2 coincides less with the range of PE distributions from the other SRS in FB1 and 7; SRS3 has a difference in its PE from the other SRS in FB5; the distribution of PE of samples for each type of SRS in each FB is very scattered.

4.4. Analysis of Classification and Recognition Results

4.4.1. K-Nearest Neighbor. KNN is one of the machine learning methods that classify each record in a data collection. The principle is that if a majority of the K most similar samples in a feature space belong to a class, then that sample also belongs to that class. This method is simple and easy to understand and implement, and K is set to 5 in this

FIGURE 1: Three-layer wavelet packet decomposition.

FIGURE 2: Four types of SRS after normalization. (a) SRS1. (b) SRS2. (c) SRS3. (d) SRS4.

paper. 50 samples of each type of SRS are selected as the training set and the remaining 50 as the test samples to classify and identify the four types of SRS. The recognition rate of each feature extraction method is obtained to compare and prove the effectiveness of the proposed method. The recognition rates of the energy entropy for four types of SRS are presented in Table 1.

According to Table 1, the recognition rate for each type of SRS is greater than 90%, the recognition rates of SRS1 and

SRS2 are 100%; the average recognition rate is 98%; it is indicated that all the four types of SRS have good recognition results. The recognition rates of CF for four types of SRS are demonstrated in Table 2.

From Table 2, for the CF of each FB, the highest recognition rates of SRS1 and SRS4 is only 74%, the recognition rate of SRS2 reaches 100%; for SRS3, the recognition rates of each FB have a great difference; the highest average recognition rate of the four SRS is only 72%, which is difficult to

(a)

(b)

FIGURE 3: Continued.

(c)

(d)

FIGURE 3: Wavelet packet decomposition results of four types of SRS (1 sample). (a) SRS1. (b) SRS2. (c) SRS3. (d) SRS4.

distinguish between the four SRS. The recognition rates of PE of four types of SRS are displayed in Table 3.

As can be seen from Table 3, overall, only FB6 had the highest average recognition rate of 52%, and the other FB

average recognition rates are below 50%; the recognition rates of PE for SRS1 is less than 60%, for SRS3 and SRS4 is less than 70%; only the highest recognition rate of SRS2 is 86%; the recognition results make it hard to classify and

FIGURE 4: Energy distribution of four types of SRS (1 sample). (a) SRS1. (b) SRS2. (c) SRS3. (d) SRS4.

FIGURE 5: Energy entropy of 100 samples for four types of SRS.

recognize the four types of SRS as well. For comparison, the highest recognition rates of the three methods are displayed in Table 4.

It is known from Table 4 that the feature extraction based on wavelet packet decomposition and energy entropy can effectively identify four types of SRS with the highest recognition rate of 98%, much better than the other two.

4.4.2. Random Forest. In this subsection, the random forest (RF) method is introduced to compare with KNN, RF is a machine learning method that integrates multiple trees by the idea of ensemble learning. Its basic unit is the decision tree, and its essence is an important branch of machine learning—ensemble learning method and the number of trees in this paper is set to 25. As in Section 4.4.1, 50 training samples and 50 test samples for each type of SRS are taken. The recognition rates of the energy entropy for four types of SRS are presented in Table 5.

Table 5 shows that the recognition rates of both SRS1 and SRS2 reached 100%; for each type of SRS, the recognition

FIGURE 6: CF of each FB for the four types of SRS. (a) FB1. (b) FB2. (c) FB3. (d) FB4. (e) FB5. (f) FB6. (g) FB7. (h) FB8.

FIGURE 7: PE of each FB for the four types of SRS. (a) FB1. (b) FB2. (c) FB3. (d) FB4. (e) FB5. (f) FB6. (g) FB7. (h) FB8.

TABLE 1: The recognition rates of energy entropy for four types of SRS.

SRS1	SRS2	SRS3	SRS4	Average
100%	100%	94%	98%	98%

TABLE 2: The recognition rates of CF for four types of SRS.

	SRS1 (%)	SRS2 (%)	SRS3 (%)	SRS4 (%)	Average (%)
FB1	62	98	54	74	72
FB2	74	88	36	38	59
FB3	66	90	64	42	65.5
FB4	52	56	40	52	50
FB5	48	44	98	68	64.5
FB6	48	56	72	56	58
FB7	34	98	26	48	51.5
FB8	40	100	42	66	62

TABLE 3: The recognition rates of PE for four types of SRS.

	SRS1 (%)	SRS2 (%)	SRS3 (%)	SRS4 (%)	Average (%)
FB1	20	80	42	46	47
FB2	30	20	38	36	31
FB3	56	64	22	32	43.5
FB4	26	46	38	34	36
FB5	34	32	64	40	42.5
FB6	38	42	60	68	52
FB7	32	86	42	36	49
FB8	24	60	20	34	34.5

TABLE 4: The highest recognition rates of the three feature extraction methods.

Energy entropy	CF	PE
98%	72%	52%

TABLE 5: The recognition rates of energy entropy for four types of SRS (Random forests).

SRS1	SRS2	SRS3	SRS4	Average
100%	100%	94%	96%	97.5%

TABLE 6: The recognition rates of CF for four types of SRS (Random forests).

	SRS1 (%)	SRS2 (%)	SRS3 (%)	SRS4 (%)	Average (%)
FB1	72	98	42	76	72
FB2	74	88	36	32	57.5
FB3	72	92	68	36	67
FB4	58	46	56	48	52
FB5	50	40	98	60	62
FB6	54	52	84	38	57
FB7	46	98	16	50	52.5
FB8	50	100	38	52	60

rates were generally higher than 90%, and the average recognition rate reached 97.5%, which verified the effectiveness of the feature extraction method proposed in this paper.

The recognition rates of CF for four types of SRS are displayed in Table 6. From Table 6, it can be seen that the

highest average recognition rate of the four SRSs is 72% and the lowest is only 52%; there is a significant difference in the recognition rate of each FB of SRS3; in FB7, the recognition rate of SRS2 is 98%, but the recognition rate of SRS3 is only 16%; these results imply that it is difficult to distinguish one SRS from another.

Table 7 shows the recognition rate of PE for the four types of SRSs, from Table 7, the recognition rate of PE is very low, none of the results has a recognition rate over 50%; the highest recognition rate for SRS3 is 48%; for SRS1 and SRS4, the recognition rate is below 40%; the highest average recognition rate is 38.5%, which indicates that the classification of the four types of SRSs by PE of random forest is very difficult.

The highest recognition rates of the three methods are shown in Table 8. As we can see from Table 8, with the recognition rate of 97.5%, the energy entropy can recognize the SRS better than the other two features. The above results show that the influence of the classifier is not dominant, and the energy entropy-based feature extraction method proposed in this paper still has the highest recognition rate compared with the CF and PE in the comparison experiments with RF as the classifier.

5. Discussion

In this paper, energy entropy, CF and PE are used to extract the features for each FB of SRS. Energy entropy has a very significant effect in identifying the SRS. The CF is presented as a method other than entropy. The PE can easily and accurately locate the time when the system changes abruptly, and it can amplify the small changes of the signal. PE and energy entropy are in the form of entropy, so the results of permutation entropy and energy entropy are compared in this paper to prove the effectiveness of energy entropy. From the comparison results of recognition rates, we can see that energy entropy has better separability as an extracted feature compared to PE.

In the classification comparison experiment, we calculate the recognition rate while introducing different classifiers for comparison. For energy entropy, the recognition result of KNN is 98%, while the recognition result of random forest is 97.5%. Both classifiers prove the effectiveness of the feature extraction method proposed in this paper, but the result of KNN is better than RF, while the recognition results of CF and PE also prove this point.

Finally, we introduce cross-validation to avoid overfitting. Different numbers of training samples are randomly selected from 100 samples, and the rest are used as test samples. To reduce randomness, the cycle is repeated 20 times to compare whether the standard deviations are close under different numbers of training samples. The classification results of the proposed feature extraction method using a different number of samples for training are shown in Table 9.

As can be seen from the table, the average recognition rate at the end is similar for different training sample numbers, and the standard deviation fluctuates just a little, indicating that there is no overfitting problem. We can also

TABLE 7: The recognition rates of PE for four types of SRS (Random forests).

	SRS1 (%)	SRS2 (%)	SRS3 (%)	SRS4 (%)	Average (%)
FB1	26	48	40	28	35.5
FB2	32	28	24	20	26
FB3	20	34	20	20	23.5
FB4	20	34	32	30	29
FB5	30	28	36	30	31
FB6	36	38	48	32	38.5
FB7	34	46	34	30	36
FB8	16	24	18	28	21.5

TABLE 8: The highest recognition rates of the three feature extraction methods (Random forests).

Energy entropy 97.5%	CF 72%	PE 38.5%
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TABLE 9: The classification results of the proposed feature extraction method using a different number of samples for training.

Number of training samples	80	70	60	50	40	30
Average accuracy	95.125%	96.009%	95.000%	95.400%	95.625%	95.553%
Standard deviation	0.0205	0.01848	0.0163	0.0086	0.01025	0.00971

observe that when we select 50 training samples, the recognition rate reaches 95.4% with the standard deviation of 0.0086, which is the most stable group under each combination in Table 9. Considering the average recognition rate and standard deviation, we select 50 samples for training and the remaining 50 for testing, so as to verify the advantages of the feature extraction method proposed in this paper.

6. Conclusions

According to this paper, the wavelet packet decomposition is integrated with energy entropy to extract features of four types of SRS. By comparing with CE and PE, the effectiveness of EE is testified, and the major conclusions are summarized as follows:

- (1) In view of the advantages of wavelet analysis theory in non-stationary signal analysis and processing, and based on this theory, this paper presents an analysis method of SRS by combining energy entropy.
- (2) Observing the conditions of figures and contrasting the recognition rates, it can be found that, when compared with CF and PE, the energy entropy can reflect the energy distribution of each FB from a macro perspective, which is more valid.
- (3) Compared with other feature extraction methods, the feature extraction method of wavelet packet decomposition and energy entropy proposed in this paper has the highest recognition rate of 98%, at least 26% higher. As a result, the availability of the new method can be fully confirmed.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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