Feature extraction method of ship radiated noise based on BOA-VMD and slope entropy

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Although the technical requirements for the feature extraction of ship radiated noise (SRN) in the fields of national defense and economy increase with each passing day, the complexity of the marine environment makes the feature extraction of SRN difficult. The traditional feature extraction method based on variational mode decomposition (VMD) is widely used in the feature extraction of SRN. Nevertheless, the use of VMD is greatly affected by parameters. In this paper, the butterfly optimization algorithm (BOA) is introduced to optimize VMD, which is called BOA-VMD algorithm, and realizes the optimal selection of VMD parameters K and α. To further improve the efficiency of feature extraction method, combined with slope entropy (SE), a feature extraction method of SRN based on BOA-VMD and SE is proposed. The experimental results of the simulated signal show that the BOA-VMD algorithm has a smaller envelope entropy value and better decomposition effect than the genetic algorithm (GA) and particle swarm optimization (PSO). The experimental results of feature extraction of SRN show that the highest recognition rate of the four entropy values improve with the increase of the number of extracted features, compared with the three entropy values of dispersion entropy (DE), fluctuation dispersion entropy (FDE) and permutation entropy (PE), the SRN feature extraction method based on BOA-VMD and SE has the highest recognition rate under different quantity features, and the recognition rate has reached 100% under three features.

KEYWORDS

ship radiated noise, slope entropy, feature extraction, variational mode decomposition, butterfly optimization algorithm

1 Introduction

Due to the complexity of the generation principle of underwater acoustic signals and the diversity of components, it is difficult to identify ship radiated noise (SRN) [1, 2]. The key to the recognition of SRN lies in the feature extraction method [3]. Traditional feature extraction methods usually use DEMON spectral analysis, wavelet transform, Fourier transform, empirical mode decomposition (EMD) and other signal processing algorithms, which are based on feature differences to classify and identify SRN. However, wavelet transform cannot guarantee time accuracy and frequency accuracy at the same time.

Fourier transform has trouble in dealing with non-stationary signals, and EMD has modal aliasing in the processing of SRN signals.

To overcome the above shortcomings, Konstantin Dragomiretskiy et al. proposed the variational mode decomposition (VMD) in 2014 [4], which adaptively decomposes the complex signal into several intrinsic mode functions (IMF), thereby overcoming the mode mixing [5, 6]. VMD is suitable for processing complex hydroacoustic signal, such as feature extraction of SRN [7]. However, its decomposition effect is greatly affected by the number of decompositions K and the penalty factor α. In order to solve the parameter selection problem of VMD, many scholars have combined intelligent optimization algorithms [8] with VMD [9–13], and proposed some modified algorithms for VMD, such as using genetic algorithm (GA) to optimize VMD in the field of SRN and using particle swarm optimization algorithm (PSO) to optimize VMD in the field of fault detection [14, 15]. These methods have proved to be able to solve the problem of parameter selection of VMD and improve the decomposition effect of VMD. In 2019, the butterfly optimization algorithm (BOA) [16] was proposed, which is a butterfly-based foraging strategy that uses its sense of smell to locate food. Compared with GA and PSO, BOA has higher convergence accuracy and faster convergence speed. However, it has not yet been applied to optimize the parameter selection of VMD.

In the field of underwater acoustic signal processing, entropy is used to describe the complexity of the time series and is often used as eigenvalues for feature extraction [17–20], among which permutation entropy (PE) [21], dispersion entropy (DE) [22], fluctuation dispersion entropy (FDE) [23] and others have been widely used in this field. Moreover, a large number of experimental studies have also proved that the entropy-based feature extraction method [24] is more effective than traditional methods [25–27]. Slope entropy (SE) [28], as a new type of entropy estimator, was proposed by David Cuesta-Frau in 2019. It assigns symbols based on the slope between two continuous data samples, and has good time series classification performance [29]. In 2022, SE was applied for the first time, and combined with PE to achieve double feature extraction of SRN [30], which verifies the effectiveness of SE. However, the feature extraction methods still are based on the original signal, and the features of each mode of the signal are not deeply excavated. To solve this problem, a method combining VMD and SE is proposed to extract the features of SRN [31], which is more effective than the method based on SE of the original signal. However, intelligent optimization algorithm has not been introduced to improve the decomposition efficiency of VMD.

In order to solve the parameters selection problem of VMD and further improve the feature extraction efficiency of SRN, BOA is introduced to optimize the parameters of VMD, called BOA-VMD, in addition, combined with SE, a feature extraction method of SRN based on BOA-VMD and SE is proposed. The

structure of this paper is as follows. Section 2 expounds the principle and step of various algorithms used in this paper. Section 3 exhibits the steps of the feature extraction method proposed in this paper. In Section 4, the simulation signal decomposition experiment and result analysis are introduced. Section 5 demonstrates the experiment and result analysis of single feature, dual feature and three feature extraction of SRN. Finally, the last Section draws the conclusion of this paper.

2 Algorithm

2.1 Butterfly optimization algorithm-variational mode decomposition algorithm

Since the parameters K and α of VMD directly affect the result of signal decomposition, we add BOA to optimize the parameters selection of VMD, called the BOA-VMD. The fitness function of the BOA-VMD is the average envelope entropy value of all IMF components after decomposition. The smaller the envelope entropy value, the better the decomposition effect. On the contrary, the larger the envelope entropy value, the worse the decomposition effect. The expression for the average envelope entropy is as follows:

$$Y_i = \frac{1}{K} \sum_{j=1}^{K} H_{en}(j) \tag{1}$$

where, K represents the number of IMF components after decomposition, $H_{en}(j)$ is the envelope entropy value of the jth IMF component.

The expression for the envelope entropy value $H_{en}(j)$ of the signal p_j is as follows:

$$\begin{cases} H_{en}(j) = -\sum_{j=1}^{N} p_j \lg p_j \\ p_j = a(j) \bigg/ \sum_{j=1}^{N} a(j) \end{cases} \tag{2}$$

where, N represents the sampling point, $a(j)$ is the envelope signal obtained by Hilbert modulation of the signal $IMF(j)$, and p_j denotes the normalized sequence of $a(j)$.

The algorithm steps of BOA-VMD are as follows:

(1) Set the range of parameters in VMD, with the parameter $[K, \alpha]$ as the position of the butterfly.

(2) Initialize the parameters in BOA, including population size G, number of iterations N, sensory modality C, stimulus intensity I, etc.

(3) Initialize the population, and use the average envelope entropy value of all IMF components as the fitness function for optimization.

FIGURE 1
Symbol allocation diagram.
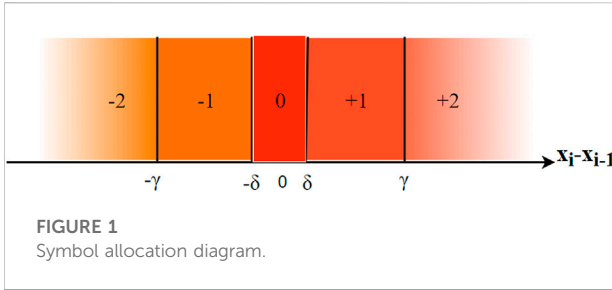
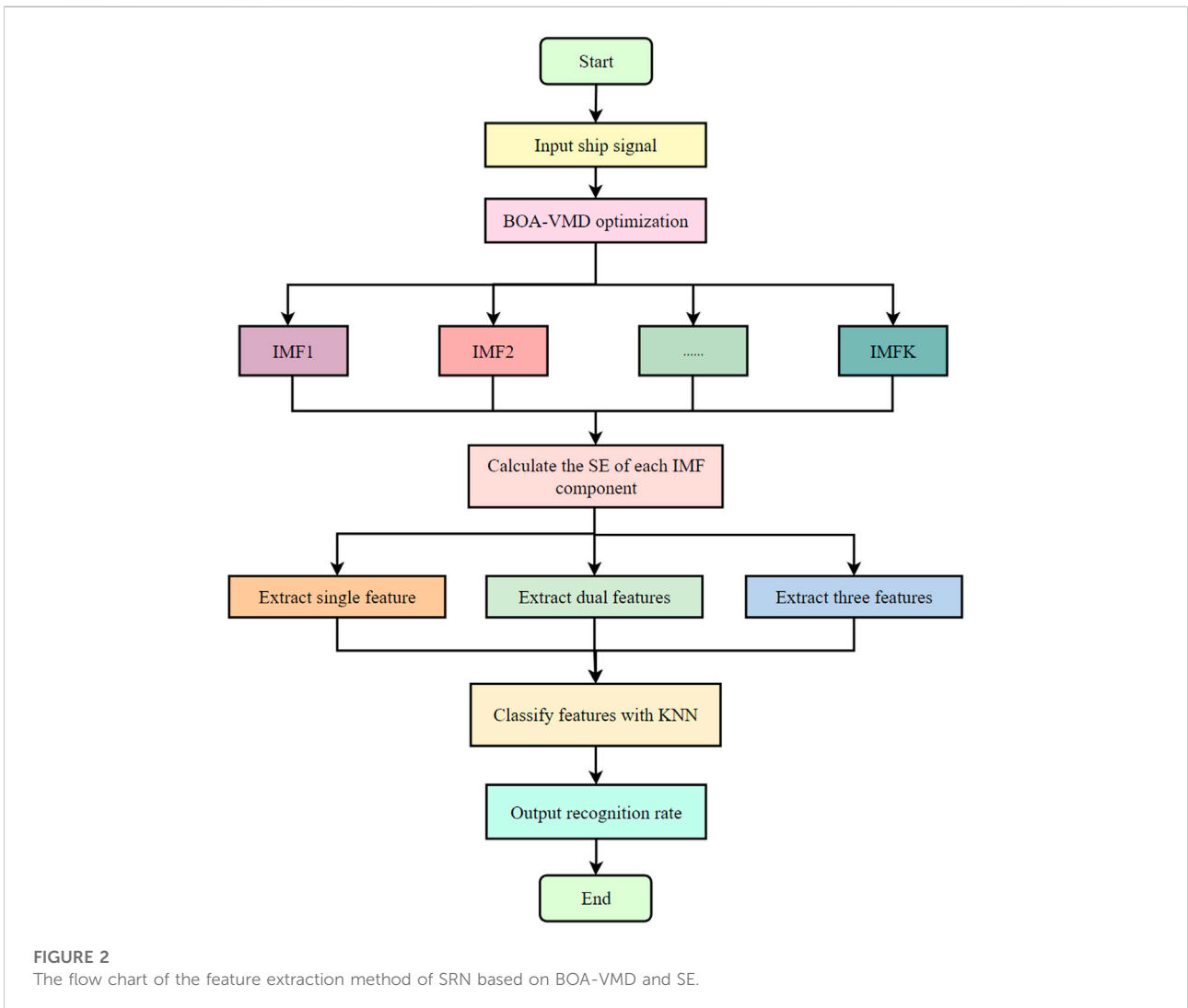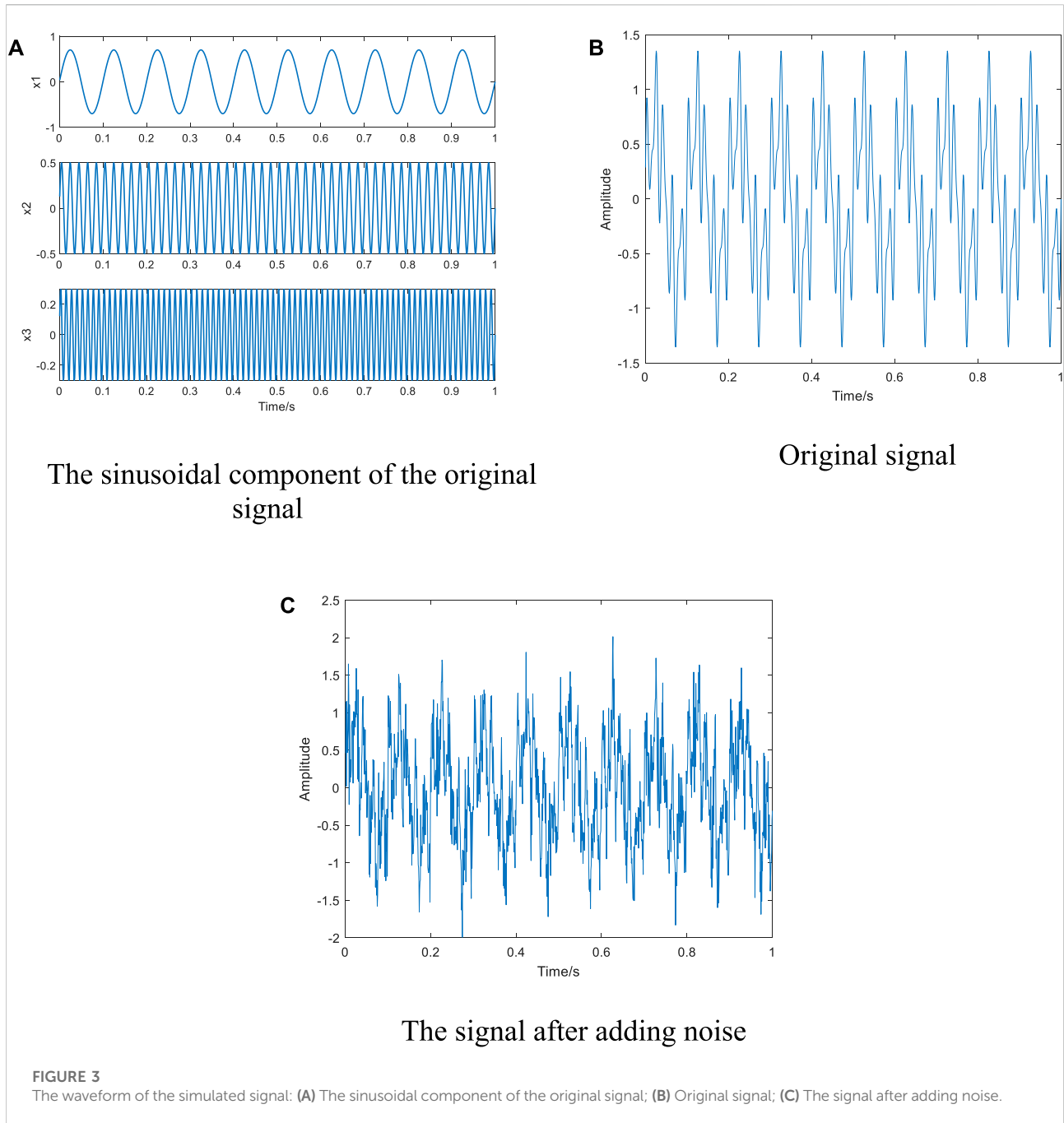(4) Calculate the fitness value of each butterfly under VMD decomposition, compare the size of the fitness value, and update the range of parameters $[K, \alpha]$ and the position and fragrance of the butterfly.

(5) Repeat step (4) until the number of iterations reaches the set maximum value, and output the optimal parameter combination $[K, \alpha]$ of VMD.

2.2 Slope entropy

SE, as a new type of entropy estimator, was proposed by David Cuesta-Frau in 2019. Its purpose is to solve the problem that the time series amplitude information is ignored in the calculation of permutation entropy. SE uses a new encoding method that is based on the slope of two consecutive data samples and maintains the symbolic representation of subsequences. The SE contains five symbols, namely (± 2), (± 1), and 0. The configuration rule of symbols stipulates that the horizontal increment between consecutive samples is 1, and the vertical increment, that is, the difference, is represented by the parameter γ threshold. In this paper, γ is taken as 1 (45°). It is represented by the parameter δ threshold near 0, and the value of δ in this paper is 1×10^{-3}.

For two continuous values x_i, x_{i-1} in a continuous time series, if $x_i - x_i > + \gamma$, the sign is +2; if $+\delta < x_i - x_{i-1} \leq + \gamma$, the sign is +1; if $|x_i - x_{i-1}| \leq \delta$, the sign is 0; if $-\gamma \leq x_i - x_{i-1} \leq -\delta$,

FIGURE 2
The flow chart of the feature extraction method of SRN based on BOA–VMD and SE.

FIGURE 3
The waveform of the simulated signal: **(A)** The sinusoidal component of the original signal; **(B)** Original signal; **(C)** The signal after adding noise.

the sign is −1; if $x_i - x_{i-1} < -\gamma$, the sign is −2. The symbol allocation diagram is shown in Figure 1.

The symbols cover the range of slopes of line segments for two consecutive input data samples, and the relative frequency of each pattern found is then mapped to a true value using the method of Shannon entropy. The calculation steps are as follows.

(1) Input a time series of length N: $X = \{x_1, x_2, x_3 \ldots x_N\}$, set the embedding dimension to m, so that K subsequences of length m can be extracted:$X_1 = \{x_1, x_2 \ldots x_m\}$, $X_2 = \{x_2, x_3 \ldots x_{m+1}\}$ $\ldots X_k = \{x_k, x_{k+1} \ldots x_N\}$,where $k = N - m + 1$

(2) Calculate $x_i - x_{i-1}$, and then compare the calculated results with γ and δ by the principle of symbol assignment to obtain the k new sequences. The new sequence is:$S_1 = \{s_1, s_2 \ldots s_{m-1}\}$, $S_2 = \{s_2, s_3 \ldots s_m\} \ldots S_k = \{s_k, s_{k+1} \ldots s_{N-1}\}$.Where $k = N - m + 1$, $s_k = x_{k+1} - x_k$. The new sequence contains $n = 5^{m-1}$ of different types, and the number of occurrences of each type is $k_1, k_2 \ldots k_n$.
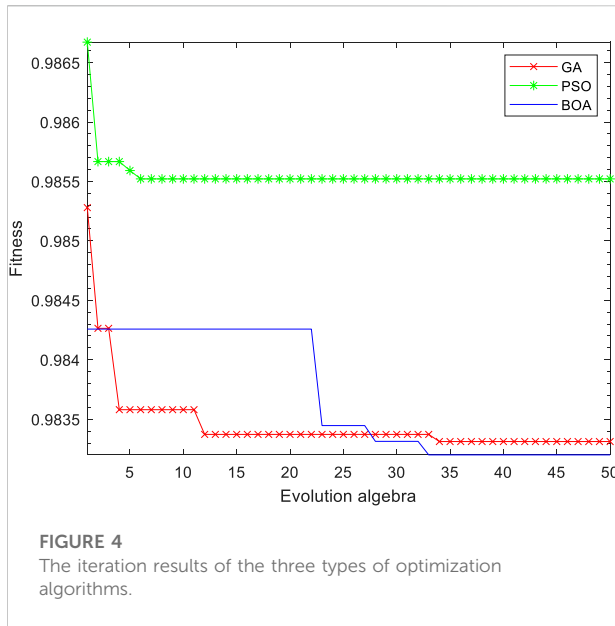
FIGURE 4
The iteration results of the three types of optimization algorithms.

TABLE 1 Optimization results of three types of optimization algorithms.

Optimal results	Optimization		
	GA	**PSO**	**BOA**
Iteration time	404.14s	324.98s	399.35s
Min envelope entropy	0.9842	0.9848	0.9832
$[K, \alpha]$	[8,1393]	[8,919]	[6,1541]

(3) Calculate the probability of each type, $P_1 = \frac{k_1}{k}$, $p_2 = \frac{k_2}{k} \ldots P_n = \frac{k_n}{k}$. On the basis of Shannon entropy, the definition formula of SE is as follows.

$$H_s(m) = -\sum_{j=1}^{n} P_j \ln P_j \qquad (3)$$

3 Feature extraction method

In this section, the BOA-VMD is proposed to select the best parameter combination of VMD, and combined with SE, we propose a feature extraction method based on BOA-VMD and SE to extract single, dual and three features of SRN.

The flow chart of the feature extraction method of SRN based on BOA-VMD and SE is shown in Figure 2. The specific implementation steps of the proposed feature extraction method for SRN are as follows:

(1) Different types of SRN signals are input and normalized.

(2) The SRN is decomposed by the BOA-VMD algorithm, and K IMF components are obtained.

(3) The SE of each decomposed IMF component is calculated.

(4) SE is taken as the feature value, the feature extraction experiments of single feature, dual feature and three feature are carried out respectively.

(5) The KNN classifier is introduced for classification of feature values.

(6) The recognition rate is obtained.

4 Simulation

Two parameters of VMD, namely the number of decompositions K and the penalty factor α, will affect its decomposition effect. In this section, a set of simulation signals are set up to optimize VMD parameters by BOA, GA and PSO, and the optimization results of the three optimization algorithms are compared and analyzed.

4.1 Simulation signal

To verify the optimization effect of the three optimization algorithms on VMD parameters, a set of simulation signals are set up for analysis, and the specific expressions are as follows:

$$X = x_1 + x_2 + x_3 \qquad (4)$$

$$\begin{cases} x_1 = 0.7 \sin(2\pi f_1 t) \\ x_2 = 0.5 \sin(2\pi f_2 t) \\ x_3 = 0.3 \sin(2\pi f_3 t) \end{cases} \qquad (5)$$

$$Y = X + f \qquad (6)$$

here, X is the original signal, which consists of three sinusoidal components with different amplitudes and center frequencies, x_1, x_2 and x_3. f_1, f_2, f_3 are the center frequencies of each sinusoidal component, $f_1 = 10$ Hz, $f_2 = 50$ Hz, $f_3 = 80$ Hz. f is Gaussian white noise, and Y is the noise-added signal with a signal-to-noise ratio of 6 dB after adding noise.

Figure 3 shows the waveform of the simulated signal. It can be seen from the figure that the time-domain waveform of the noise-added signal is complex, so signal decomposition is required.

4.2 Parameter optimization variational mode decomposition

In this section, BOA-VMD is used to optimize the modal component K and the penalty factor α. To verify the effect of the BOA-VMD algorithm, the optimization experiments of GA and PSO on VMD parameter selection are designed, so as to carry out comparison and analysis. For the convenience of comparison, the

FIGURE 5
The normalized four types of SRN: **(A)** SRN-I; **(B)** SRN-II; **(C)** SRN-III; **(D)** SRN-IV.
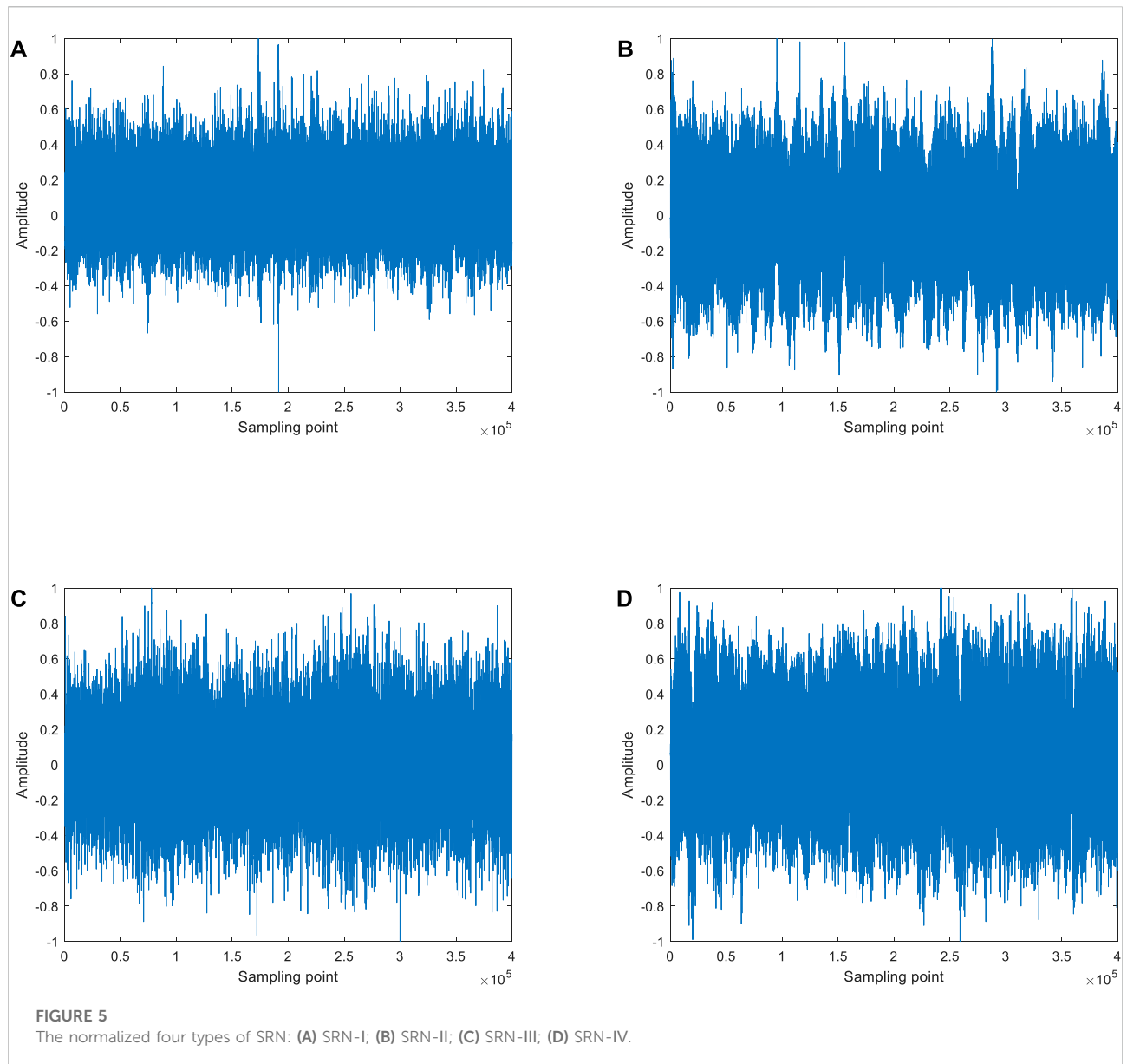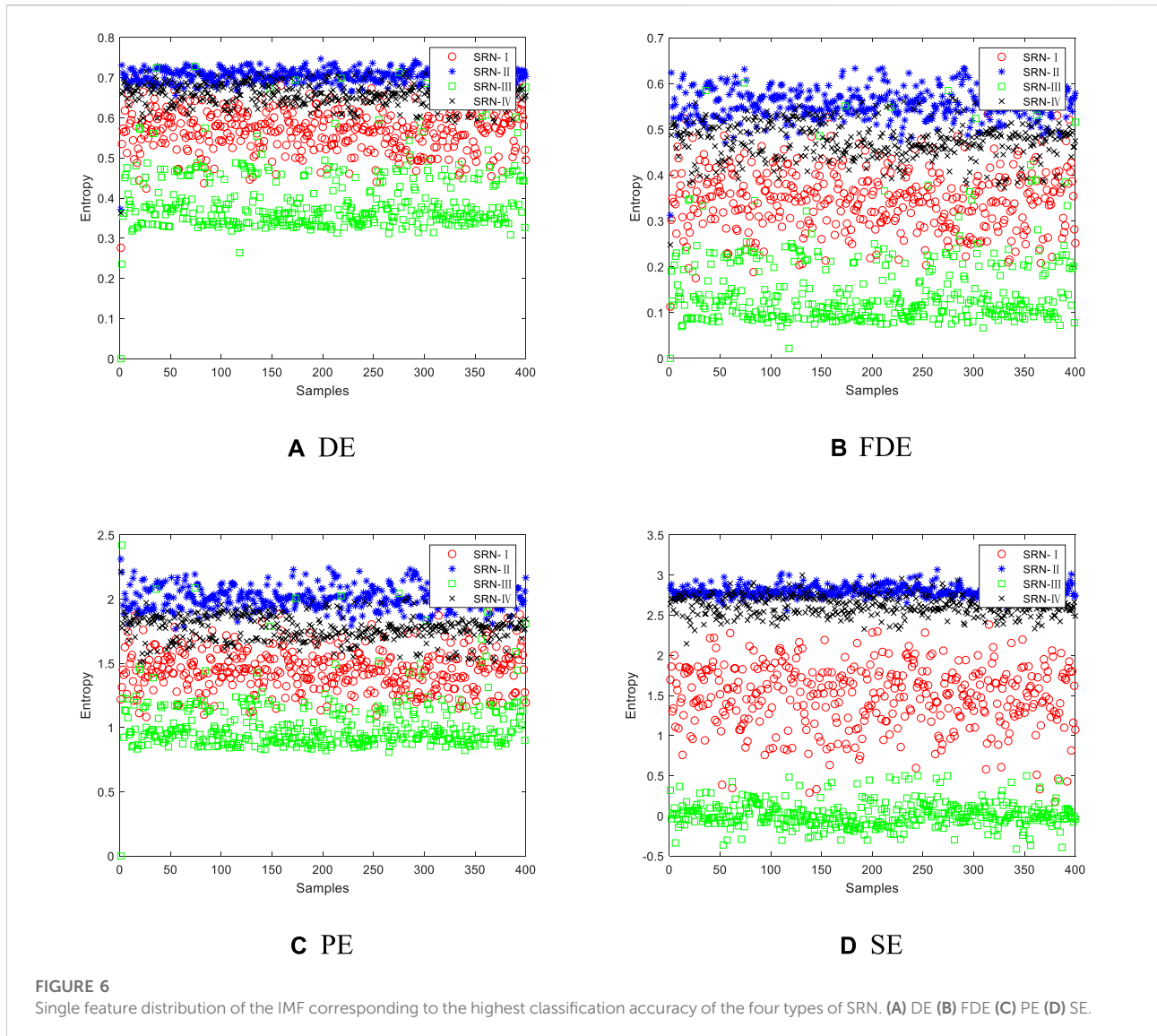
initial population of the three optimization algorithms is 10, and the number of iterations is 50.

After several optimizations for the three types of algorithms, the average value of the iteration time and the minimum envelope entropy value are obtained. The iteration results of the three types of optimization algorithms are shown in Figure 4.

From Figure 4, it can be concluded that GA and BOA begin to converge after about the 35th iteration, and PSO begins to converge after about the 6th iteration. The convergence speed of PSO is much faster than that of BOA and GA. BOA has the smallest fitness value, which is about 0.9820, while the minimum fitness value of PSO and GA is approximately 0.9850 and 0.9830, which are larger than BOA.

By calculating the iteration time and minimum envelope entropy of the three types of optimization algorithms for comparison, the optimization results of the three types of optimization algorithms are shown in Table 1.

As shown in Table 1, PSO has the least iteration time and GA has the most iteration time, that is, PAO has the fastest optimization speed. But in terms of optimization results, BOA has the smallest envelope entropy value, which is 0.9832. The minimum envelope entropy values of GA and PSO are bigger than BOA. The experimental results show that BOA's optimization speed is second only to that of PSO, and has the smallest envelope entropy value. Considering comprehensively, the parameter combination obtained by BOA search is the most reliable.

FIGURE 6
Single feature distribution of the IMF corresponding to the highest classification accuracy of the four types of SRN. **(A)** DE **(B)** FDE **(C)** PE **(D)** SE.

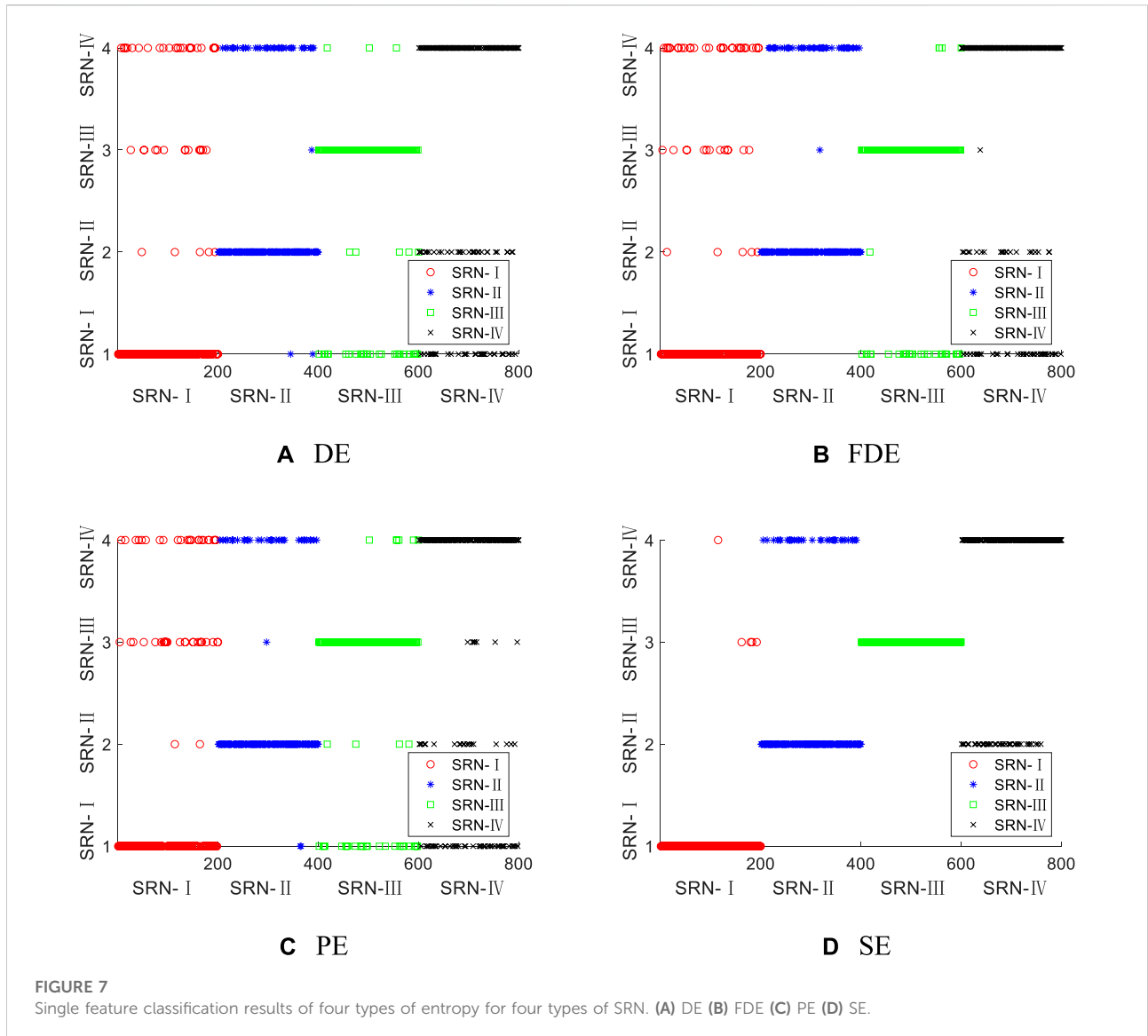# 5 Experiment on feature extraction of ship radiated noise

This section uses four types of SRN from the United States Park Service, which are ferries, freighters, cruise ships, and engine-driven ships [32]. The four types of SRN are coded as SRN-I, SRN-II, SRN-III, and SRN-IV. The data lengths of the four types of SRN are 1379568, 1641072, 5314800, and 446448, respectively. Each SRN sampling segment is [3001, 403000], containing 400,000 data points, and the sampling frequency is 44100Hz. The normalized four types of SRN are shown in Figure 5.

According to the BOA-VMD algorithm proposed in Section 3, the VMD decomposition results of four types of SRN are optimized. The optimal number of IMF K is 9, and the penalty factors α are 6165, 1000, 5746 and 4374, respectively.

5.1 Single feature extraction and classification

5.1.1 Single feature extraction

In this single feature extraction experiment, 400 samples are selected for each type of SRN with 3001 as the starting point, and each sample contains 1000 data points. In order to compare with SE, FDE, DE and PE of each IMF are calculated at the same time. All entropies have two parameters in common, the embedding dimension m is set to 4 and delay time τ is set to 1. There are two common parameters of DE and FDE, which are the number of categories c is set to 3, and the mapping method uses NCDF. SE has two thresholds that need to be set, where γ is set to 0.1666 and δ is set to 0.0222. Figure 6 shows the single feature distribution of the IMF corresponding to the highest classification accuracy of the four types of SRN.

FIGURE 7
Single feature classification results of four types of entropy for four types of SRN. **(A)** DE **(B)** FDE **(C)** PE **(D)** SE.

It can be gained from Figure 6 that the single feature distributions of the four types of SRN all fluctuate within a certain range, and the DE mixing of SRN-II and SRN-IV is the most serious; DE, FDE and PE of SRN-I and SRN-III have different degrees of aliasing, and only a few samples of their SE are aliased; the FDE of SRN-I and SRN-IV is the most aliased, and their SE has only very little eigenvalue mixing. Experiments show that SE is the best for feature extraction of the four types of SRN.

5.1.2 Single feature classification

A KNN classifier is added to perform single-feature classification of four types of SRN [33, 34]. For the four types of SRN, 400 samples are selected, the first 200 samples are taken as training samples, and the remaining 200 samples are used as

test samples for classification. Figure 7 shows the single feature classification results of four types of entropy for four types of SRN.

As shown in Figure 7, DE, FDE, PE and SE have different degrees of error in the classification of the four types of SRN samples; DE, FDE and PE have more classification errors for SRN-I, SRN-II and SRN-IV samples, but less for SRN-III samples; this indicates that DE, FED and PE have a stronger ability to identify SRN-III samples than the other three samples; compared with these three types of features, the SE has only four wrong classifications for SRN-I, and all the classifications for SRN-III are correct; this suggests that SE has the strongest recognition ability for SRN-III samples, but poor recognition ability for SRN-II and SRN-IV, which is stronger than the other three features. Experiments show that SE is better than DE, FDE and PE for
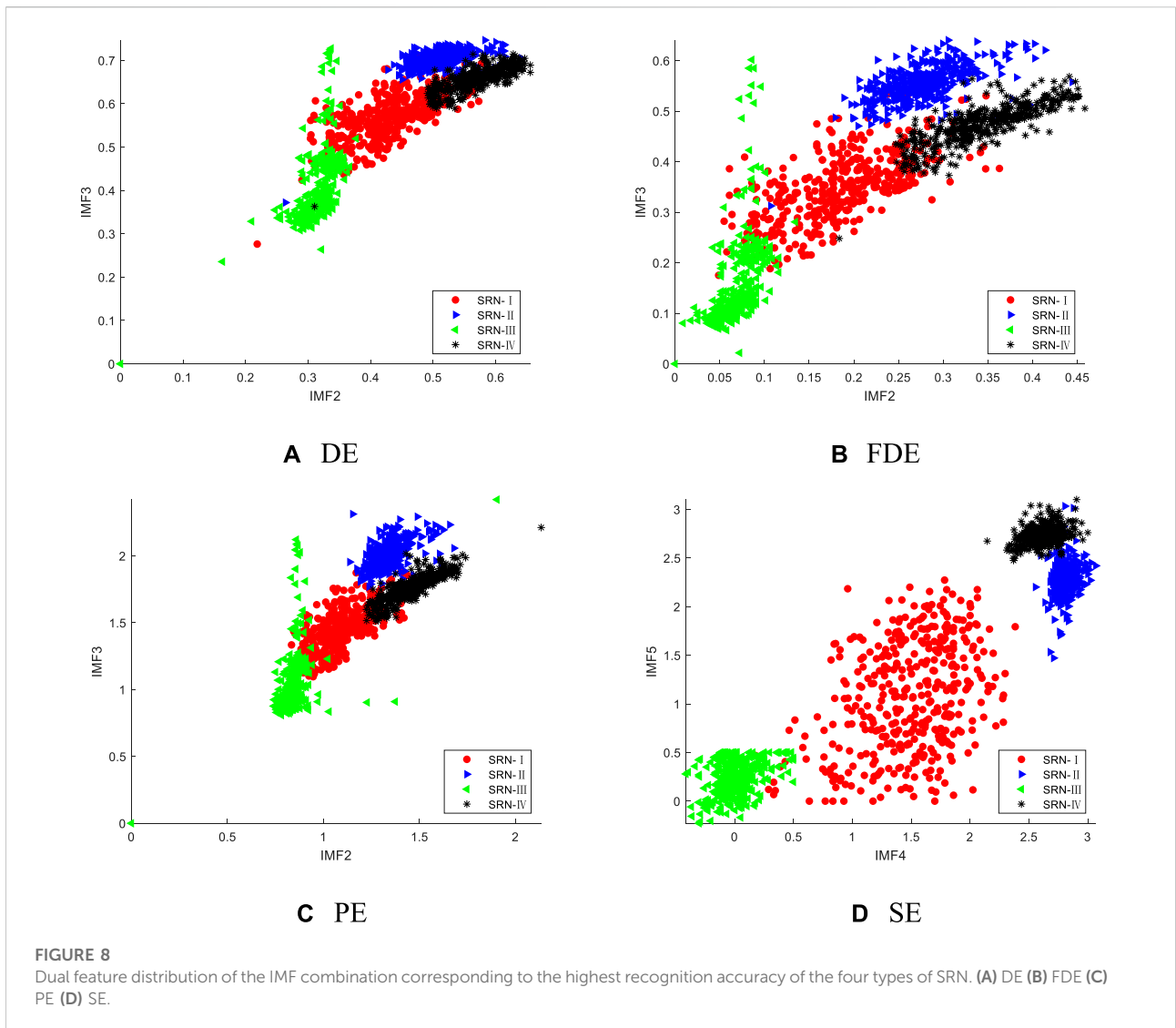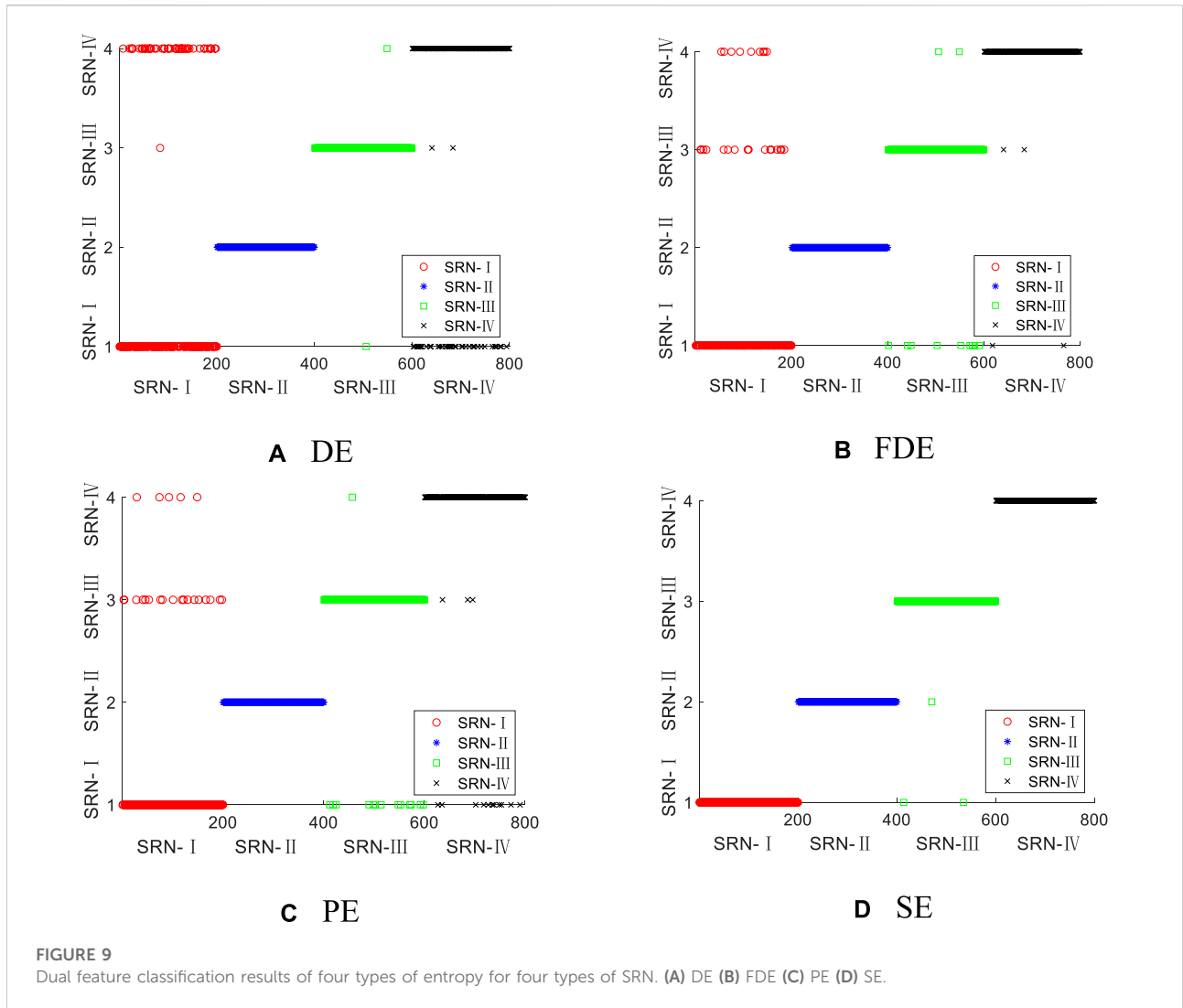
FIGURE 8
Dual feature distribution of the IMF combination corresponding to the highest recognition accuracy of the four types of SRN. **(A)** DE **(B)** FDE **(C)** PE **(D)** SE.

TABLE 2 The highest average recognition rate of four kinds of entropy under single-feature.

Entropy	Average recognition rate (%)
DE	76.88
FDE	76.75
PE	76.38
SE	90.38

the classification of the four types of SRN. The highest average recognition rate of the four types of entropy under single-feature is shown in Table 2.

According to Table 2 can be obtained that the highest recognition rate of SE is 90.38%. Among DE, FDE and PE, the highest recognition rate did not exceed 80%. The highest recognition rates corresponding to DE, FDE and PE are 13.5%, 13.63%, and 14% lower than the highest recognition rates for SE, respectively. The experimental results show that under single feature extraction, the average recognition rate of SE is the highest compared with the other three entropies.

However, under single feature extraction, there are still many samples of four types of entropy that are not correctly identified and classified, and only the highest recognition rates of SE reach more than 90%. To further improve the recognition rates, we adopt dual feature extraction, that is, identifying two IMF components at the same time.

FIGURE 9
Dual feature classification results of four types of entropy for four types of SRN. **(A)** DE **(B)** FDE **(C)** PE **(D)** SE.

5.2 Dual feature extraction and classification

5.2.1 Dual feature extraction

In the dual feature extraction experiment, all parameters used in the experiment are the same as the data listed in Section 5.1. According to the principle of permutation and combination, the IMF components are combined in pairs, and a group of IMF components with the highest recognition rate is selected for feature extraction. Figure 8 shows the dual feature distribution of the IMF combination corresponding to the highest recognition accuracy of the four types of SRN, where the abscissa and ordinate are the corresponding IMF components.

From Figure 8 we can obtain that, the mixing phenomenon of entropy value of the four types of SRN is significantly reduced under dual feature extraction; compared with the entropy values of the other three types of samples, the SRN-III samples have obvious differences; in DE, FDE and PE, the SRN-I sample is close to the

other three types of samples in terms of partial entropy, which may lead to errors in sample identification; the entropy values of the four types of samples in SE are significantly different, which is easier to distinguish in sample identification. Experiments show that, compared with the other three types of features, the SE has better separability for the four types of SRN samples.

5.2.2 Dual feature classification

In order to prove that the identification effect of simultaneously identifying the SE of two IMF components is better under dual feature extraction, KNN classifier is also adopted to perform dual feature extraction classification of four types of SRN. The selection of training samples and test samples is the same as in Section 5.1. The dual feature classification results of the four types of entropy for four types of SRN are shown in Figure 9.

It can be seen from Figure 9 that under the dual feature extraction, the four types of entropy have improved the classification accuracy for the four types of SRN samples, and
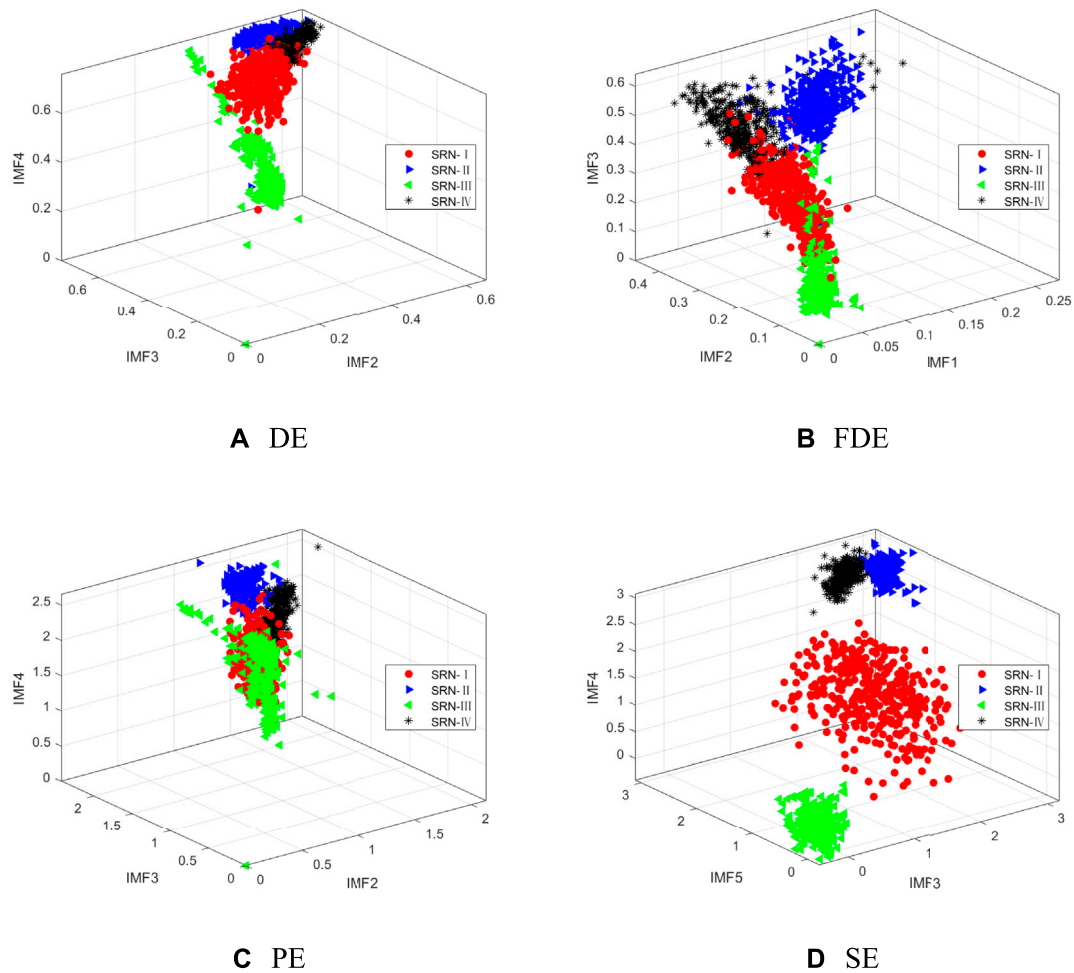
FIGURE 10
Three-feature distribution of the IMF combination corresponding to the highest recognition accuracy of the four types of SRN. **(A)** DE **(B)** FDE **(C)** PE **(D)** SE.

TABLE 3 The highest average recognition rates of the four entropies under dual features.

	DE	FDE	PE	SE
Selected IMF component	(2,3)	(2,3)	(2,5)	(3,4)
Average recognition rate (%)	97.50	95	93.63	99.63

the SE samples have the highest classification accuracy; the classification of SRN-II samples in DE, FDE and PE is completely correct, but some errors are found in SRN-I, SRN-III and SRN-IV samples; in SE, only three samples of SRN-III are classified incorrectly, and the other three SRN samples are classified correctly. Through program operation, the highest average recognition rates of the four entropies under dual features are shown in Table 3, where (2, 3) in the table

represents the selected modal components are IMF2 and IMF3, and so on.

As can be seen from the data in Table 3, the recognition rates of the four types of entropy for SRN all reach more than 90%. The SE has the highest recognition rate for the four types of SRN, up to 99.63%, which is 2.13%, 4.63%, and 6% higher than the recognition rates of DE, FDE and PE, respectively. This shows that the recognition effect of SE is the most significant.

FIGURE 11
Three-feature classification results of the four types of entropy for the four types of SRN. **(A)** DE **(B)** FDE **(C)** PE **(D)** SE.
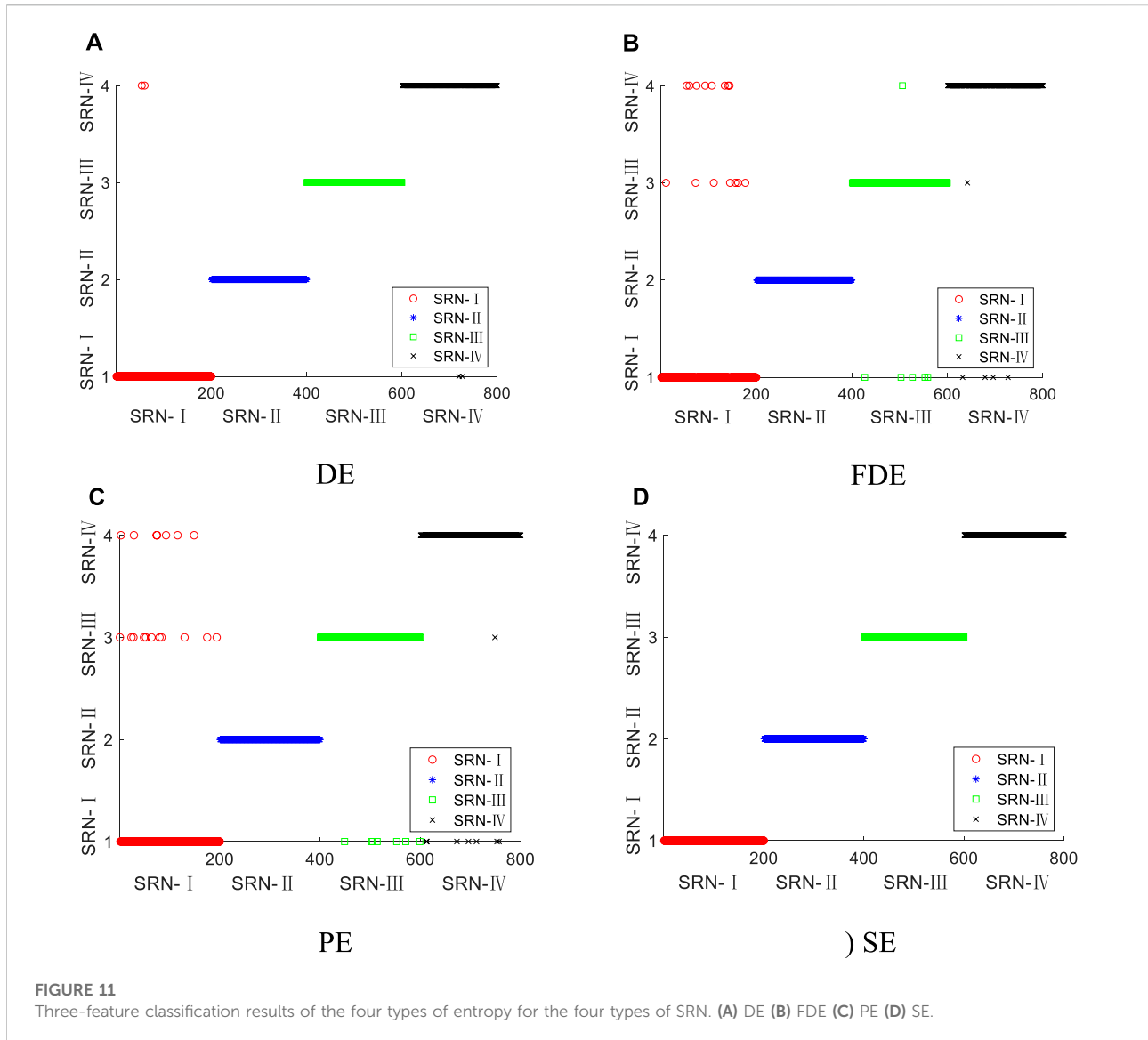
To sum up, under dual feature extraction, although there are still some sample errors in the classification for the four types of SRN samples by the four types of entropy, the average recognition rate is greatly improved compared with the single feature extraction. The highest average recognition rate under dual feature extraction is still SE, which is 9.25% higher than the average recognition rate of 90.38% under single feature extraction.

5.3 Three feature extraction and classification

5.3.1 Three feature extraction

In view of the fact that the recognition rate of four kinds of entropy in dual feature extraction is greatly improved compared

with single feature extraction, SE still has the highest recognition rate. Therefore, in order to further improve the recognition rate, this section classifies the four types of SRN by identifying the three IMF components. All parameters used in the experiment are the same as the data listed in Section 5.1. In the three-feature extraction experiment, according to the principle of permutation and combination, three IMF components are selected for combination, and a group of IMF components with the highest recognition rate is selected for feature extraction. Figure 10 shows the three-feature distribution of the IMF combination corresponding to the highest recognition accuracy of the four types of SRN, where the x, y, and z coordinates are the corresponding IMF components.

As shown in from Figure 10, under the three-features extraction, the SRN-I, SRN-II and SRN-IV samples in the DE and the FDE have

partial entropy distributions overlapping, the SRN-III sample has a small amount of entropy mixed with SRN- I distribution; the four types of SRN in the PE have partial entropy aliasing; in the SE, only a few samples of SRN-II and SRN-IV have close entropy values. Experiments show that under the three-feature extraction, for the four types of SRN samples, the difference in the entropy value of the SE is the most obvious, so it has better distinguishing ability than the other three types of features.

5.3.2 Three feature classification

In order to prove that the identification effect of SE is better under three-feature extraction, KNN classifier is also introduced to perform three-feature classification of four types of SRN. The selection of training samples and test samples is the same as that in Section 5.1. The three-feature classification results of the four types of entropy for the four types of SRN are shown in Figure 11.

It can be seen from Figure 11 that under the three-feature extraction, the classification and recognition ability of the four types of entropy is greatly improved; the DE classification of SRN-II and SRN-III samples is completely correct, and only a few samples have errors in the DE classification of SRN-I and SRN-IV; the FDE and PE are completely correct for the classification of SRN-II samples, but some samples are wrong for SRN-I, SRN-III and SRN-IV; the classification of the four types of SRN samples by the SE is all correct. Experiments show that, compared with DE, FDE and PE, SE has a better ability to distinguish four types of SRN.

Through program operation, the highest average recognition rates of the four types of entropy under three-feature are shown in Table 4, where (1, 2, 7) in the table represents the selected IMF components are IMF1, IMF2 and IMF7, and so on.

From the data in Table 4, we can get that under the three-feature extraction, the four types of entropy have more than 95% recognition rates for SRN samples. Among them, the SE has the highest recognition rate of 100%, which is much higher than the SE under the single feature, and is also higher than the SE under the dual feature.

To sum up, under three feature extraction, the four types of entropy can greatly improve the recognition rate for the four types of SRN samples, and the classification performance of the SE is better than other entropies.

6 Conclusion

In this paper, BOA algorithm is introduced to realize the optimization of VMD parameters selection, and then BOA-VMD

TABLE 4 The highest average recognition rates of four kinds of entropy under three-feature.

	DE	FDE	PE	SE
Selected IMF component	(2,3,4)	(1,2,3)	(2,3,4)	(2,4,5)
Average recognition rate (%)	99.50	96.75	95.88	100

algorithm is proposed. Combined with the SE, a feature extraction method of SRN based on BOA-VMD and SE is proposed. The feasibility of the method is verified by simulation experiments and features extraction experiments of four SRNs. The main conclusions reached are as follows:

(1) In order to achieve the optimal selection of VMD parameters, the BOA algorithm is adhibited to optimize the VMD, called BOA-VMD. Compared with GA and PSO, the algorithm is more accurate and reliable, and can realize adaptive decomposition of signals in simulation experiments.
(2) In order to improve the effect of feature extraction and classification of SRN, this paper proposes a feature extraction method based on BOA-VMD and SE. Under single feature, the method achieves a remarkable effect on feature extraction, and the average recognition rate of SE is 90.38%, which is much higher than DE, FDE and PE.
(3) Compared with single feature, dual features and three features further improve the recognition rate of SRN. Compared with the other three entropies, the feature extraction method based on BOA-VMD and SE can obtain the highest recognition rate under the same number of features, furthermore, the three-feature recognition rate has reached 100%.

Data availability statement

The original contributions presented in the study are included in the article/Supplementary Material; further inquiries can be directed to the corresponding author.

Author contributions

YY and GT designed research, performed research, and analyzed data, and GT wrote the paper.

Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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