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Feature extraction method of ship-radiated noise based on dispersion entropy: A review

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There is abundant ship information in ship-radiated noise, which is helpful for ship target recognition, classification and tracking. However, owing to the increasing complexity of the marine environment, it makes difficult to extract S-RN features. Dispersion entropy has been proven to be an excellent method to extract the features of S-RN by analyzing the complexity of S-RN, and has been widely used in feature extraction of S-RN. This paper summarizes the research progress of DE in the feature extraction of S-RN in recent years, and provides a comprehensive reference for researchers related to this topic. First, DE and its improved algorithm are described. Then the traditional and DE-based S-RN feature extraction methods are summarized, and the application of DE in S-RN feature extraction methods is concluded from two aspects: methods that apply DE algorithms only and methods that combine DE with mode decomposition algorithms. Finally, the research prospects of DE and the summary of this paper are given.

KEYWORDS

ship-radiated noise, feature extraction, dispersion entropy, mode decomposition, entropy

1 Introduction

In the ocean, sound waves are an effective way to transmit information over long distances. Ship-radiated noise (S-RN) is a good marine sound source, which is of great significance to ship navigation safety and marine exploration [1, 2]. However, the ocean is always accompanied by a large amount of environmental noise, which is a huge interference to the reception and recognition of S-RN. How to effectively extract the features of S-RN has become a hot issue [3, 4].

The traditional feature extraction method for S-RN mainly has two types: 1) feature extraction method based on spectrum analysis. The S-RN is analyzed by the spectrum, and the line spectrum feature and shape feature of power spectrum in S-RN are extracted [5]. 2) Feature extraction method based on time-frequency domain analysis. The features of the S-RN are extracted by Fourier transform [6], wavelet transform [7] and Hilbert-Huang transform [8], and so on. Although these methods achieved some results, the identification of S-RN in practical applications still cannot meet the expected requirements.

Recently, some nonlinear dynamical methods have achieved better results in feature extraction, such as Lempel-Ziv complexity (LZC) [9], fractal dimension [10], entropy [11]. LZC has been successfully applied to feature extraction of S-RN, such as permutation LZC (PLZC) [12], dispersion LZC (DLZC) [13, 14] and DE-based LZC (DELZC) [15], but it has high requirements for the length of time series, and its over-dependence on pattern conversion also limits the ability of LZC to characterize signals. Compared with LZC, the fractal dimension is suitable for processing various types of nonlinear and nonstationary signals like S-RN [16], but this excellent effect costs a lot of time; in addition, there are only a few types of fractal dimensions, such as box dimension [9, 17], so the application of fractal method to extract discriminant features has not been thoroughly studied. Last but not least, for entropy, the development in feature extraction of S-RN is more comprehensive and faster than LZC and fractal dimension, and recently proposed entropy in common use are PE [18–20], DE [21–23] and slope entropy [24–26]. However, the PE cannot reflect the amplitude change information of S-RN, and slope entropy is seriously affected by threshold setting, and the characteristic value is sufficiently enough. DE is the most widely used in S-RN feature extraction because of the absence of these defects. In general, compared with other entropies, LZC and fractal dimension, DE has higher computational efficiency and deeper stability, and there are richer research results of DE in feature extraction of S-RN.

The DE-based method has been widely used in feature extraction of S-RN and has shown superior performance. In this paper, we will give a comprehensive review of the DE-based methods and divide them into two types: methods that apply DE algorithms only [27, 28] and methods that combine DE with mode decomposition algorithms [23, 29]; then we introduce two aspects of DE in and its application for S-RN. The rest of this review is structured as follows. Section 2 introduces the DE and its improved algorithm. Section 3 describes the traditional S-RN feature extraction methods and the S-RN feature extraction method based on DE, and summarizes the relevant applications. The prospects of DE in the feature extraction method for S-RN are presented in Section 4. Section 5 gives the conclusion of this review.

2 Theory of dispersion entropy

2.1 DE algorithm

DE [30] is one of the important indexes to evaluate the complexity of time series, which considers the relationship between amplitudes, and has strong robustness and fast operability. The specific calculation steps are as follows:

Step 1: For a given time series $X = \{x(j), j = 1, 2, ..., N\}$, it is mapped to series $Y = \{y(j), j = 1, 2, ..., N\}$ by the normal cumulative distribution function (NCDF), and the element $y(j)$ is obtained as follows:

$$y(j) = \frac{1}{\sigma\sqrt{2\pi}}\int_{-\infty}^{x(j)} e^{\frac{-(t-\mu)^2}{2\sigma^2}} dt, j = 1, 2, \cdots, N \quad (1)$$

where μ and σ represent the mean and standard deviation of sequence X respectively, and each element $y(j) \epsilon\ (0, 1)$.

Step 2: The series Y is converted to a new series $Z^c = \{z_j^c, j = 1, 2, ..., N\}$, and the conversion formula is as follows:

$$z_j^c = R(c \cdot y(j) + 0.5) \quad (2)$$

where z_j^c is an integer within $[1, 2, ..., c]$, R a is rounding function and c indicates the category.

Step 3: The sequence Z^c is transformed into $l = N - (m-1)d$ components $z_i^{m,c}$, each component is defined as:

$$z_i^{m,c} = \{z_i^c, z_{i+d}^c, ..., z_{i+(m-1)d}^c\}, i = 1, 2, ..., N - (m-1)d \quad (3)$$

where m is the embedding dimension, and d represents a time delay.

Step 4: Each component is labeled as a dispersion pattern $\pi_{v_0 v_1 v_{m-1}}$ with $z_i^c = v_0, z_{i+d}^c = v_1, \cdots, z_{i+(m-1)d}^c = v_{m-1}$. According to step 2, each element in the component has c values, therefore, there are c^m dispersion patterns corresponding to $z_i^{m,c}$ in total. The probability of each dispersion pattern can be expressed as:

$$p(\pi_{v_0 v_1 v_{m-1}}) = \frac{Num(\pi_{v_0 v_1 v_{m-1}})}{N - (m-1)d} \quad (4)$$

where $Num(\pi_{v_0 v_1 v_{m-1}})$ indicates the number of dispersion patterns $\pi_{v_0 v_1 v_{m-1}}$ of series X.

Step 6: The value of DE can be calculated according to the formula of Shannon entropy:

$$DE(X, m, c, d) = -\sum_{\pi=1}^{c^m} p(\pi_{v_0 v_1 v_{m-1}}) \cdot ln(p(\pi_{v_0 v_1 v_{m-1}})) \quad (5)$$

and the normalized DE (NDE) can be defined as:

$$NDE(X, m, c, d) = \frac{DE(X, m, c, d)}{\ln c^m} \quad (6)$$

2.2 Improved DE algorithm

Since DE has excellent ability to represent signal complexity, many scholars have improved DE to improve the performance of DE, such as reverse DE (RDE), multiscale DE (MDE), and so on. According to the different ways of DE improvement, the improved dispersion entropy is mainly divided into two categories: 1) the improvement of DE steps; and 2) the preprocessing of DE.

To enhance the capacity of DE to characterize the complexity of signals, some scholars are committed to optimizing the calculation steps of DE, and various upgraded versions of DE have been advanced. Azami et al. [31] developed the fluctuation-based DE (FDE) by considering the fluctuation of signals, which provides a powerful tool for analyzing fluctuating signals. Li et al. [21] introduced distance information to DE, the reverse DE (RDE) is raised and demonstrates high stability when analyzing various sensor signals. To address the problem that DE is insensitive to information perception between adjacent elements of time series [32], proposed the fine-sorted DE (FSDE) by adding an additional factor to fine sort the normalized elements. Inspired by FDE and RDE, Jiao et al. [22] combined the advantages of FDE and RDE to propose fluctuation-based reverse DE (FRDE), and this operation further improved the stability and separability of DE. In 2021, the weighted multivariate DE (WMDE) was proposed [33] by integrating multivariate analysis and weighted calculation, which is more sensitive to signal changes and stable. In view of the problem of DE instability due to amplitude variation, Rostagh et al. [34] introduced a fuzzy membership function into DE and developed fuzzy DE (FuzzDE), which improves the performance of DE in detecting frequency changes and periodic changes. Influenced by fractional order calculation [35,36] proposed fractional extended DE (FrEDE) and fractional order fuzzy DE (FuzzDEα) respectively. In addition, Wang et al. [11] advanced a normalized cumulative residual function (NCRF) to magnify the difference between dispersion patterns, and give the give the definition of cumulative residual symbolic DE (CRSDE), which

TABLE 1 The overview of improved DE algorithms based on DE steps.

References	Improved DE	Improvement	Main advantages
[30]	FDE	Fluctuation information	Broadly used for the characterization of real signals
[20]	RDE	Distance information	High distinguishing ability for sensor signals
[31]	FSDE	Fine-sorted dispersion pattern	Provide a powerful aid to feature extraction for fault diagnosis
[21]	FRDE	Distance information and fluctuation information	Facilitates the distinction of ship signals and gear fault signals
[32]	WMDE	Weight information	Reveal the ordinal structure of stock market indices
[33]	FuzzDE	Fuzzy membership functions	Better performance in distinguishing various signlas
[34]	FrEDE	Fractional calculus	Accurately distinguish different faulty states
[35]	FuzzDEα	Fractional order calculation	Detect dynamics changes of signals sensitively
[49]	CRSDE	Normalized cumulative residual function	Excellent performance in detecting dynamics of sleep stages

realizes the representation of more effective pattern information. In summary, these improved algorithms can represent more abundant feature information and have higher anti-noise ability. The overview of improved DE algorithms based on DE steps are shown in Table 1.

Several improved DE algorithms have been proposed by preprocessing the signals to enhance the performance of DE. Zhang et al. [37] proposed MDE by introducing coarse-graining on the basis of DE to retain information on the potential characteristics of faults at different scales. Azami et al. [38] and Li et al. [27] also introduced coarse graining to RDE and FDE, and proposed multiscale FDE (MRDE) and multiscale FDE (MFDE), respectively, which describe the complexity of signals from different scales. In addition [39,40] introduced hierarchical information and proposed hierarchical DE (HDE) and hierarchical FDE (HFDE) respectively to characterize the complexity of all band signals. Xing et al. [41] combined the concepts of hierarchy and multiscale to propose the hierarchical multiscale RDE (HMRDE), which reflects the effective information of the bearing signal from both hierarchical and scaling perspectives. To represent the comprehensive information on signals, Azami et al. [42] proposed refined composite MDE (RCMDE), which is a refined composite multiscale processing based on DE. The proposed RCMDE not only solves the single-scale problem of DE, but also improves the stability of traditional coarse graining. Inspired by RCMDE, some scholars immediately proposed refined composite MFDE (RCMFDE) [43], refined composite RDE (RCMRDE) [44], and refined composite multiscale FRDE (RCMFRDE) [28], respectively. Referring to the experience that fine composite processing can effectively represent signal complexity, some scholars introduced multivariate theory based on refined composite multiscale processing, and proposed refined composite multiscale multivariate MDE (RCMMDE) [45] and refined composite multiscale multivariate FDE (RCMMFDE) [46], which have low sensitivity to signal length and high noise resistance. As the advantages of fine composite multiscale processing and hierarchical analysis have been recognized, refined composite HFDE (RCHFDE) [47] and hierarchical refined composite MFDE (HRCMFDE) [48] have been proposed respectively, which solve the problem of high frequency signal loss in coarse-graining process. Last but not least, some scholars have also proposed some other improved algorithms, such as time-shift multiscale cumulative residual symbolic (DE) TCRSDE [49], refined time-shift multiscale normalised DE (RTSMNDE) [11], time-shift MDE (TSMDE) [50], and generalized RCMFDE (GRCMFDE) [51], which all further improve the performance of dispersion entropy. The overview of improved DE algorithms based on preprocessing is listed in Table 2.

Whether the improvement of the DE step or the preprocessing of the DE further improves the performance of the scattering entropy and effectively represents the complexity of the signal. In order to show the development of DE more intuitively, we employ the Figure 1 to show all the improved DE algorithms.

3 Feature extraction methods for S-RN

The feature extraction of S-RN has been a difficult problem in the field of underwater acoustic signal processing due to the complexity of marine environmental noise. To solve this challenge, some S-RN feature extraction methods have been developed, mainly including two types: 1) traditional methods, such as those based on spectrum analysis, or time-frequency domain analysis; and 2) nonlinear dynamic methods, such as those based on fractal, Lempel-Ziv complexity (LZC), or entropy. The overall framework of feature extraction method for S-RN is displayed in Figure 2.

Traditional feature extraction methods have certain limitations when analyzing non-stationary S-RN, and the feature extraction results cannot well reflect the true characteristics of the target signal. While Entropy, LZC and fractal dimension are the mainstream nonlinear dynamic indexes applied to feature extraction of S-RN. However, LZC is limited by the length of time series and binary conversion, and it often needs to be combined with entropy theory to meet the demand of feature extraction, current research includes PLZC, DLZC, and DELZC, which have shown excellent performance in feature extraction. Although the fractal dimension can effectively analyze nonlinear signals such as S-RN, it will consume consumes considerable time, and the feature based on fractal dimension are not sufficiently stable. With the development of entropy theory, the ability of entropy to represent signals has also been improved, which can show more feature information of S-RN. From recent research, it can be seen that PE, DE, and slope entropy are the three main entropies used in feature extraction of S-RN, these

TABLE 2 The overview of improved DE algorithms based on preprocessing.

References	Improved DE	Improvement	Main advantages
[36]	MDE	Coarse-graining	Retain information on the potential characteristics of faults at different scales
[37]	MFDE	Coarse-graining	Further understand the dynamics of neurological disease records
[25]	MRDE	Coarse-graining	Describe the complexity of ship signals from different scales
[38]	HDE	Hierarchical information	Characterize the complexity of all band fault signals
[39]	HFDE	Hierarchical information	Compensate for the shortcomings of MFDE in ignoring high frequency component information
[40]	HMRDE	Hierarchical coarse-graining	Effectively reflect the difference characteristics in different frequency domains
[41]	RCMDE	Refined composite coarse-graining	Fully min the information of biomedical signals
[42]	RCMRDE	Refined composite coarse-graining	Min the comprehensive information on rolling bearing failures
[43]	RCMFDE	Refined composite coarse-graining	Further enhance the stability of MFDE
[26]	RCMFRDE	Refined composite coarse-graining	Reduce damage caused by misidentification of ships
[44]	RCMMDE	Refined composite multivariate coarse-graining	Has certain advantages in robustness compare to MDE
[45]	RCMMFDE	Refined composite multivariate coarse-graining	Low sensitivity to signal length and high noise resistance
[46]	RCHFDE	Refined composite hierarchical	Has the better stability and robustness than HFDE
[47]	HRCMFDE	Hierarchical Refined composite coarse-graining	Solve the problem of high frequency signal loss in coarse grain process
[48]	TCRSDE	Time-shift coarse-graining	Obtain comprehensive Neurodynamics characteristics
[49]	RTSMNDE	Refined time-shif coarse-graining normalised	Diagnose the locations and degrees of rolling bearing failures effectively
[50]	TSMDE	Time-shift coarse-graining	Achieve outstanding diagnosis performance for rolling bearing
[51]	GRCMFDE	Generalized refined composite coarse-graining	Provide a highly separable feature for diagnosing the fault of rolling bearings

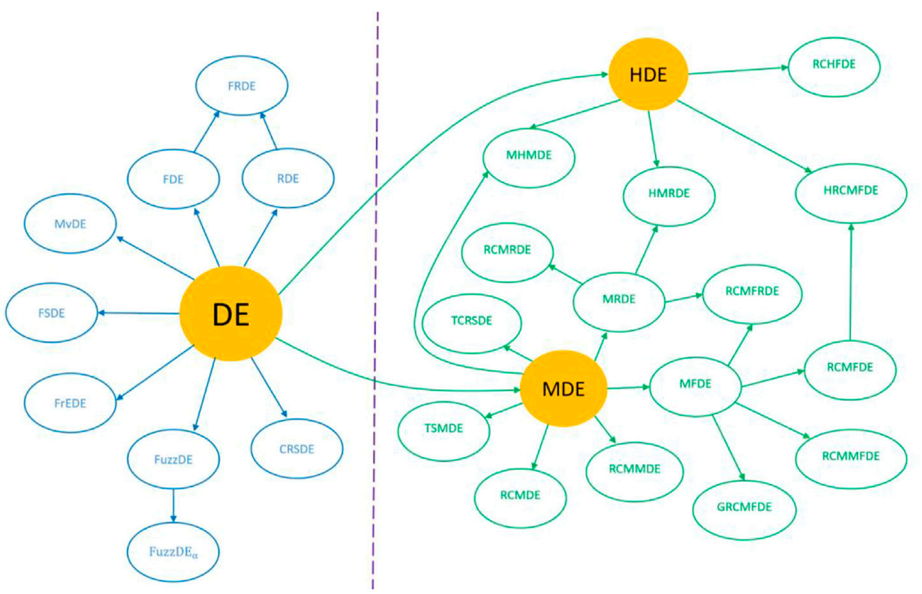

FIGURE 1
Improved DE algorithms.

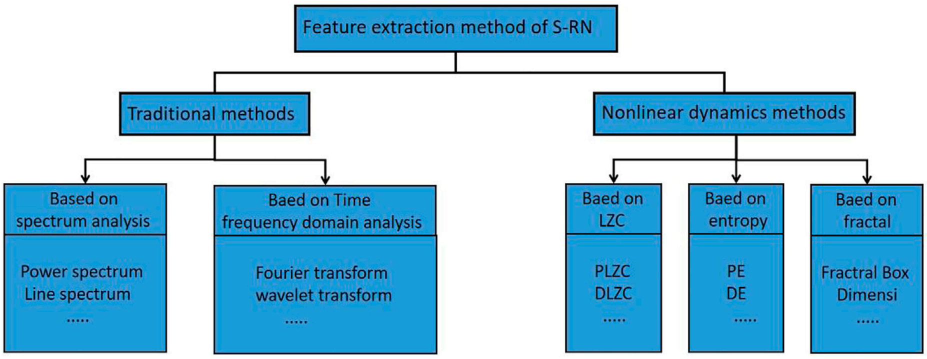

FIGURE 2
Overall framework of feature extraction method for S-RN.

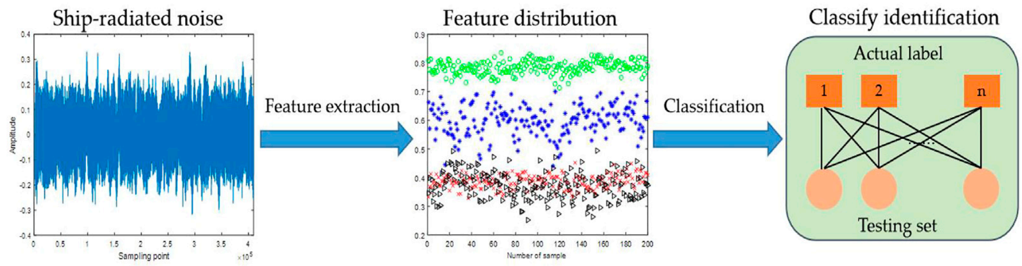

FIGURE 3
The main steps of feature extraction for S-RN using only DE.

entropies get rid of over-dependence on time series length and are more computationally efficient. Among them, DE is particularly convenient and effective, because it overcomes the defect that PE ignores amplitude information and is not limited by threshold parameters like slope entropy. Therefore, we review and summarize the DE-based feature extraction methods in this section.

In this section, the references on feature extraction of S-RN based on DE are listed and summarized as the following two subsections: methods that apply DE algorithms only, and methods that combine DE with mode decomposition algorithms, including empirical wavelet transform (EWT), intrinsic time-scale decomposition (ITD), and variational mode decomposition (VMD). Table 1 provides a brief summary of research articles on applications of DE combined mode decomposition in feature extraction of S-RN, which were published after 2015 to cover the latest contributions since the existing review.

3.1 Feature extraction using only DE algorithm

Due to the high computational efficiency, strong robustness and separability of DE, it has been introduced into the field of feature extraction of S-RN. The main steps of feature extraction for S-RN using only DE are illustrated in Figure 3.

Due to the high computational efficiency, strong robustness and separability of DE, it has been introduced into the field of feature extraction of S-RN in recent years. Li et al. [21] first defined the concept of RDE and take it as a new feature of S-RN, the utilization of RDE realized the accurate classification of three ship signals. In 2020, Li et al. [27] successively proposed MRDE-based feature extraction method and feature extraction method based on MRDE combined with the gray correlation degree (GRD) [52], the studies indicated that MRDE performs better than MDE, MPE and other entropy indexes in characterizing ship feature. In addition, RCMDE-KNN-based classification method of S-RN was raised [53], this method enhances the stability and anti-noise ability of the extracted ship features, and the recognition rate for four types of ships reaches 100%. Jiao et al. [22] presented FRDE and applied it to feature extraction of S-RN, the experimental results show that FRDE feature extraction is more prominent than PE and DE. Based on FRDE and RCMDE [28], proposed a novel feature extraction method of S-RN based on RCMFRDE, the experiments show that the excellent performance for feature extraction and classification of S-RN. Xiao [54] introduced hierarchical DE (HDE) into the underwater acoustic field for the first time, which mines the information hidden in the high frequency band of ship radiated noise. Table 3 reveals the applications of DE in feature extraction of S-RN, in which Rr means recognition rate, MRDE + GRD means MRDE and GRD.

TABLE 3 Applications of DE in feature extraction of S-RN.

References	Method	Database	Metric	Main conclusion
[20]	RDE	Unkonwn	99% Rr	Provide an effective complexity metric to analyze S-RN
[25]	MRDE	National Park Service	100% Rr	Accurate recognition of four types of S-RN is realized from different scales
[52]	MRDE + GRD	National Park Service	97.75% Rr	Effectiveness and practicability for feature extraction of S-RN
[53]	RCMDE	National Park Service	100% Rr	More suitable and stable for feature extraction of S-RN
[21]	FRDE	National Park Service	99.11% Rr	The most outstanding recognition effect in four S-RN
[26]	RCMFRDE	Unkonwn	100% Rt	Improve the feature extraction and classification performance of S-RN
[54]	HDE	Unkonwn	100% Rr	Show the different frequency bands feature of signals S-RN

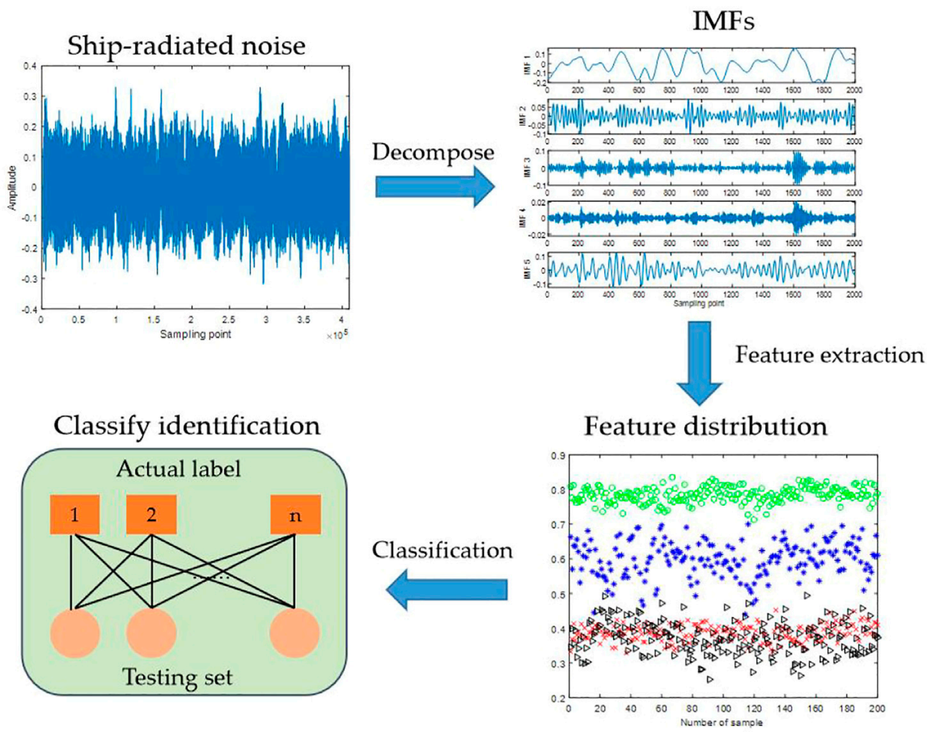

FIGURE 4
The main steps of ship-radiation noise method using DE and mode decomposition.

3.2 Feature extraction combining DE with mode decomposition algorithms

The feature extraction methods based on mode decomposition and DE have been widely used in the underwater acoustic field and show excellent performance. Figure 4 displays the main steps of S-RN feature method using DE and mode decomposition.

In recent years, some scholars have proposed many S-RN feature extraction methods based on DE and mode decomposition and achieve better results. Li et al. [29] combined ITD with FDE, and proposed a new S-RN feature extraction method, which achieves more than 95% classification accuracy for ten types of S-RN, realizing effective recognition of S-RN [55]. Improved the ITD and proposed a S-RN feature extraction method combining improved ITD (IITD) with MDE, which further enhanced the effect of feature extraction. Yang et al. [23] presented a novel a S-RN feature extraction technology using VMD and FDE, and the results presented that the presented technique has better separation effect and higher discrimination. Li et al [56]. Applied extreme-point symmetric mode decomposition (ESMD) to decompose the S-RN, extracted the DE of intrinsic mode functions (IMFs), and effectively distinguished different types of S-RN. [57] developed a S-RN feature extraction method based on EWT and RDE, and the results reveled that EWT not only has better decomposition performance than empirical mode decomposition (EMD), ensemble empirical mode decomposition (EEMD), and VMD, but also RDE has better separability than PE, RPE and DE; in addition, the recognition rate of the proposed method is higher than 95% for four kinds of

TABLE 4 Applications of DE combined mode decomposition in feature extraction of S-RN.

References	Method	Database	Metric	Main conclusion
[27]	ITD + FDE	Unkonwn	95.8% Rr	Effectively achieve the classification of S-RN
[55]	Improved ITD + MDE	Unkonwn	86% Rr	Provide a new scheme for accurate identification of different types of ship signals
[28]	VMD + FDE	Unkonwn	97.5% Rr	More precise for S-RN feature extraction
[56]	ESMD + DE	Unkonwn	99.5% Rr	Assist the feature extraction and classification recognition for S-RN
[57]	EWT + RDE	National Park Service	99.5% Rr	Improve the S-RN separability and stability
[58]	CEEMDASN + RCMFDE	National Park Service	98.5%Rr	Effectively solves the problem of information loss in feature extraction of ship signals
[59]	VMD + MDE	Unkonwn	100% Rr	Extract the line spectrum frequency feature of S-RN
[60]	VMD + WFDE	National Park Service	>90% Rr	Accurately and efficiently extract the features of ship signals

S-RN. Yang et al. [58] put forward a S-RN feature method based on complete ensemble empirical mode decomposition with adaptive selective noise (CEEMDANSN) and RCMFDE, which effectively solves the problem of information loss in feature extraction of ship signals. Li et al. [59] and Liu et al [60] used VMD to decompose the S-RN, and extracted the MDE and WFDE of IMFs respectively, which effectively extract the features of S-RN, and the recognition rate is higher than 90%. Table 4 exhibits the applications of DE combined mode decomposition in feature extraction of S-RN, in which Rr means recognition rate, ITD + FDE means ITD and FDE, VMD + FDE means VMD and FDE.

4 Prospects of DE in feature extraction method for S-RN

Based on the above research, we can find that traditional feature extraction methods for S-RN have great limitations, and cannot effectively reflect the real characteristics of S-RN; moreover, compared with other nonlinear dynamic indexes such as LZC and fractal dimension, DE can better represent the complexity of the signal, and effectively distinguish different types of S-RN. However, the feature extraction of S-RN has always been the focus of the research on the development of marine economy and coastal defense, and the huge development needs promote the output of more relevant research results. At present, it is hard to meet the growing demand by relying solely on DE-based indexes. So combining with multiple features and further upgrade DE with multiple improvement methods is an important development direction in the future.

(1) Combined with other categories of feature indicators.

Different types of features have their own advantages and disadvantages, they are applicable to different ship signals. Combining DE with other types of features for feature extraction, such as entropy index and LZC-based index, can make full use of the complementarity between different features. Therefore, DE combined with other class features is suitable for more complex environments and unknown ship signals, which can further improve the feature extraction performance and recognition effect of S-RN.

(2) Upgrade DE with multiple improvement methods.

Different improvements measures of DE have solved different problems encountered in signal analysis. For the complex and changeable S-RN, the improvement for a specific problem has difficulty reflecting the comprehensive characteristic information. For this reason, integration of multiple improvement methods, including different computational steps and ship signal preprocessing, will be one of the future focuses on upgrading the feature extraction method based on DE.

5 Conclusion

This paper is intended to review the application of DE in feature extraction of ship-radiated noise, and divides it into two categories: Only DE theory and the combination of DE and mode decomposition algorithm. The main conclusions of the review are as follows

(1) Both DE and its improved version improve the feature extraction effect of S-RN from different aspects, and previous studies also show that the feature extraction method based on DE is superior to other entropy measures.
(2) The mode decomposition algorithm is used in feature extraction to reduce the aliasing effect between feature information, combined with DE theory, the anti-noise and stability of the extracted S-RN features are further improved.
(3) Through the review and analysis of the previous DE in the feature extraction of S-RN, the shortcomings and improvements of the current method are illuminated, and the future prospects and work directions are summarized.

Author contributions

The conception, and writing of this review are all completed by GJ.

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.

Publisher's note

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