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Multiscale Sample Entropy-based Analysis of Ship Radiated Noise Signal for Surface Ship Recognition

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Abstract: Recently many signal processing and pattern recognition schemes have been developed to process ship radiated noise signals to improve the detection and recognition accuracy of surface ships. In this paper, we propose a new target recognition scheme for surface ship recognition that the contributions concentrate on feature selection and object classification. In the recognition scheme, first multiscale sample entropy (Multi-SampEn) method is applied to extract the discriminating features from ship radiated noise signals which has good performance in analysis of discrete signal of complexity. Then, in order to alleviate the parameter selection problem and enhance the generalization performance in Multi-SampEn, the two multilinear subspace learning (MSL) methods, i.e., multilinear principal component analysis (MPCA) and uncorrelated multilinear discriminant analysis (UMLDA) are respectively adopted for feature extraction and dimensionality reduction. Finally using the extracted features as the inputs, we construct two individual support vector machines (SVM) classifiers with different penalty constants for different classes, resulting in MPCA-SVM and UMLDA-SVM for surface ship recognition. The performance of the proposed scheme is demonstrated on real data which was collected by a towed array sonar on East China Sea in 2013. Experimental results show that Multi-SampEn for the analysis of ship radiated noise signals outperforms the other methods.

Keywords: Ship radiated noise, multiscale sample entropy, feature extraction, multilinear subspace learning

1 Introduction

In the last twenty years, detection and recognition of underwater targets from acoustic signals had attracted much interest, which included discrimination between targets and non-targets and classification in different types of targets. However in the detection and recognition processes, several factors, i.e., non-repeatability, competing clutter caused by the biological sources, surface and bottom reverberation effects, and lack of prior knowledge about the shape and geometry of the targets, make the processes a very complex problem. Consequently, an efficient and robust detection and recognition scheme for automatic target recognition (ATR) is needed to solve this complex problem.

In the ATR, many signal processing schemes [1,2,3, 4,5,6,7] had been developed to extract signatures of underwater targets from acoustic signal. In [5], hidden Markov model-based (HMM) method was used for the representation of the multiaspect of underwater targets. The experiment results demonstrated that the adaptive sensing procedure yielded significant improvements in the performance of detection and recognition. Liu [6] respectively used wavelet transform to extract statistical features of ship radiated signals and person-by-person optimization (PBPO) approach to select the separability features of target. The selected features were efficient for different target classification. In [8], a wavelet packet-based classification scheme was developed to discriminate mine-like and non-mine-like objects from the acoustic backscattered signals. In this scheme, a fourth-order linear predictive coding (LPC) model was fitted to each sub-band signal and the coefficients were extracted as features. Using the extracted features as the inputs, some statistical classification methods, i.e., probabilistic neural networks (PNN) [9], back propagation neural network (BPNN) [8,10], and support vector machine (SVM) [11] were used as classifiers of ship radiated noise signals.

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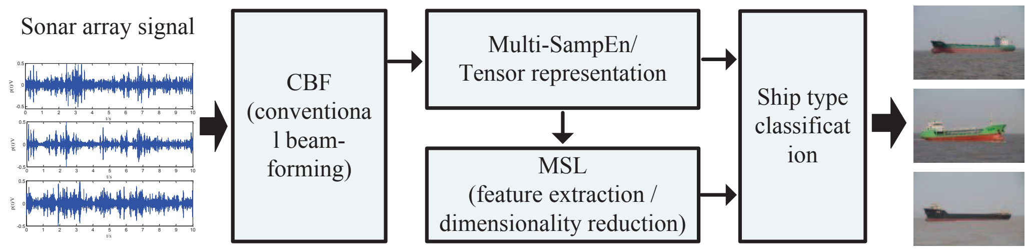

Fig. 1: The scheme of Multi-SampEn-based surface ship recognition.

Though many techniques of feature extraction and classification had been developed, features for classifier are remarkably overlapped due to the complicated mechanism of ship radiated noise [9]. Moreover referring [8,12] it showed that the classification performance would not be improved as more features were added. Consequently, in detection and recognition of underwater targets, many feature selection schemes [8,12,13,14,15] were adopted to choose the best set of features to represent the data. In [8], a statistical feature selection scheme was adopted to select an appropriate set of features as the inputs of a two-layer back propagation neural network. The classification results demonstrated the excellent discrimination performance of targets and non-targets. Tai et al. [12] designed a sophisticated filter method for feature selection, in which it combined several feature relevance measures to provide a more comprehensive assessment of the features. The selected features could be able to separate objects of different classes on real synthetic aperture sonar imagery data set.

It had been observed that excellent feature extraction and feature selection were indispensable for detection and recognition of underwater targets. Consequently, as described in Fig.1, in this paper we propose a Multi-SampEn-based ATR scheme for surface ship recognition, which mainly includes four steps: surface ship detection, feature extraction, feature selection and surface ship recognition. In first step, conventional beam-forming [16] is used on sonar array signal for detection of surface ships, which could enhance the signal-to-noise ratio (SNR) of ship radiated noise signals by phase compensation among the adjacent hydrophone. After the detection of surface ships, the combined array signals are forwarded to the subsequent steps. Then Multi-SampEn method [17,18] is used to quantify nonlinear dynamics of ship radiated noise signals which could not be disclosed by other conventional methods [1,2,3]. In Multi-SampEn method, sample entropy (SampEn) proposed by Richman and Moorman et al. [19,20] is excellent for the description of nonlinear characteristics of time series, so it could capture the important nonlinear features of ship radiated noise signals. Furthermore in view of ship radiated noise signals affected by some other factors (e.g., reverberation and source noise), it is desirable to extend the single-scale SampEn to a multiscale framework for more exact description. Compared with the traditional definition of SampEn, we could acquire more desirable complexity measures of ship radiated noise signals. In next step, multilinear subspace learning (MSL) method [21,22,23] is adopted for feature extraction and dimensionality reduction. Finally using the extracted features as the inputs, we construct an individual SVM classifier [24], resulting in Mutil-SampEn-SVM, to validate the effectiveness of the proposed scheme in surface ship recognition.

The remainder of the paper is organized as follows. Section 2 describes the Multi-SampEn method and the multilinear subspace learning (MSL) method, respectively. The data set of ship radiated noise signals is addressed in section 3. Section 4 provides the experimental results. Finally, Section 5 ends this paper with concluding comments.

2 Materials and methods

In the ocean environment, many factors caused by the organisms in the water column, bottom and surface reverberation of the sea and ocean noise etc., reduce the SNR of ship radiated noise signals, and increase the difficulty of underwater target recognition. Thus, in the underwater target recognition, the primary task is to process the data of ship radiated noise signals to isolate the noise and enhance the discrimination measurement. In this paper a Multi-SampEn method and MSL method are respectively introduced to exploit ship radiated noise signals for surface ship recognition.

2.1 Multiscale sample entropy (Multi-SampEn)

1) Sample entropy. In [19,20], Richman and Moorman et al. proposed a modification of approximate entropy (ApEn) algorithm named sample entropy (SampEn). SampEn is a measure of the complexity and predictability of a time series and thus can be used to describe the nonlinear characteristics of ship radiated noise signals.

Compared with ApEn algorithm there are two improvements in SampEn algorithm.

a. The value of SampEn is very robust against the values of the input parameters.

b. The probability measure is calculated directly as the logarithm of conditional probability instead of the ratio of the logarithmic sums, which could enhance the accuracy.

In the following content, we describe the procedure of the SampEn algorithm in more detail.

First, given N data points of original signal $x(i)$ $i = 1,2,\ldots N$, the new series $X_m(i)$ with the dimension m is then constructed by,

$$X_m(k) = [x(k), x(k+1), x(k+2), \ldots, x(k+m-1)], \quad (1)$$

where $k = 1,2,...N-m+1$.

Second, the quantity of constructed sequences could be calculated by,

$$B_i^m(r) = \frac{1}{N-m} num\{d[X(i),X(j)] < r\}, \quad i = 1,2,\ldots N-m+1, \quad (2)$$

where $d[X_m(i), X_m(j)]$ is the Euclidean Distance between the vectors with m dimensions, and r is the threshold. Referred to [19], the input parameters of m and r could be fixed.

Finally the regularity parameter of SampEn is defined as

$$SampEn(m,r) = \lim_{N\to\infty} \{-\ln[B^{m+1}(r)/B^m(r)]\}, \quad (3)$$

where $B^m(r) = (N-m+1)^{-1} \sum_{i=1}^{N-m+1} B_i^m(r)$.

2) Multiscale approach. In virtue of only supplying a single index concerning the general behavior of the time series by ApEn and SampEn, Costa et al. [25,26,27] introduced the so-called multiscale entropy approach to reveal the underlying dynamics of the generating system and quantify the regularity of time series. Compared with the traditional definition of entropy, it has the desirable property of yielding higher complexity and is a more meaningful measure of complexity by calculating entropy over multiple scales.

Then we briefly describe the multiscale approach. Based on N data points of original signal $x(i)$ $(i = 1,2,\ldots N)$ the consecutive coarse-grained time series could be constructed by,

$$y_j^{(\tau)} = \frac{1}{\tau} \sum_{i=(j-1)\tau+1}^{j\tau} x_i, 1 \le j \le \frac{N}{\tau}, \quad (4)$$

where τ is the scale factor. For scale 1, the coarse-grained time series is the original time series. Then we calculate the entropy for each one of the coarse-grained time series $\{y^{(\tau)}\}$. Then the new coarse-grained series $Y_m(i)$ with the dimension m is then constructed by,

$$Y_m(k) = [y^{(\tau)}(k), y^{(\tau)}(k+1), \ldots y^{(\tau)}(k+m-1)]. \quad (5)$$

Finally by computing the SampEn of each new coarse-grained series, we could obtain the Multi-SampEn-based tensor for the description of ship radiated noise signals.

2.2 Multilinear subspace learning for dimensionality reduction

Multilinear subspace learning (MSL) [23] is recently proposed for dimensionality reduction of multidimensional data directly from their tensorial representations. Compared with the traditional linear subspace learning, multilinear subspace learning is much simpler and more efficient in representation of data, and could save more information. In this section, we will introduce two multilinear subspace learning methods, i.e., multilinear principal component analysis (MPCA) and uncorrelated multilinear discriminant analysis (UMLDA).

1) Multilinear principal component analysis (MPCA). In [21], Lu and Plataniotis et al. proposed a MPCA framework for dimensionality reduction and feature extraction of tensor object. The core of MPCA is the determination of a multilinear projection for capturing most of the original tensorial input variations that the projected tensor objects are used for classification. Thus the MPCA could be used for dimensionality reduction on Multi-SampEn-based tensor.

Given a set of M tensor objects $\{x_1, x_2, \ldots x_M\}$ for training, where $x_m \in \mathrm{R}^{I_1 \times I_2 \times \cdots \times I_N}$ that the values are in tensor space $\mathrm{R}^{I_1} \otimes \mathrm{R}^{I_2} \ldots \otimes \mathrm{R}^{I_N}$, MPCA intends to define a multilinear transformation $\{\widetilde{\mathrm{U}}^{(n)} \in \mathrm{R}^{I_n \times P_n}, n = 1, \ldots, N\}$ to map the original tensor space $\mathrm{R}^{I_1} \otimes \mathrm{R}^{I_2} \ldots \otimes \mathrm{R}^{I_N}$ into a tensor subspace $\mathrm{R}^{P_1} \otimes \mathrm{R}^{P_2} \ldots \otimes \mathrm{R}^{P_N}$ $(P_n < I_n, n = 1,\ldots N)$. The projected tensor of original tensor x_m is,

$$y_m = x_m \times_1 \widetilde{\mathrm{U}}^{(n)^T} \times_2 \widetilde{\mathrm{U}}^{(n)^T} \ldots \times_N \widetilde{\mathrm{U}}^{(n)^T} \quad (6)$$

where $\{y_m \in \mathrm{R}^{P_1} \otimes \mathrm{R}^{P_2} \ldots \otimes \mathrm{R}^{P_N}\}$ and $m = 1, \ldots, M$.

In order to capture most of the variations observed in the original tensor objects, the total tensor scatter is adopted to measure the variations. In other words, by maximizing the total tensor scatter Ψ_y, the N projection matrices $\{\widetilde{\mathrm{U}}^{(n)} \in \mathrm{R}^{I_n \times P_n}, n = 1, \ldots, N\}$ are determined by

$$\{\widetilde{\mathrm{U}}^{(n)}, n = 1, \ldots, N\} = \arg \max_{\widetilde{\mathrm{U}}^{(1)}, \widetilde{\mathrm{U}}^{(2)}, \ldots, \widetilde{\mathrm{U}}^{(n)}} \Psi_y. \quad (7)$$

To solve (7), the MPCA utilizes an iterative procedure that the more details please refer to the pseudocode of MPCA algorithm in Fig.3 of [21].

2) Uncorrelated Multilinear Discriminant Analysis (UMLDA). UMLDA [22] was proposed by Lu et al. for feature extraction and dimensionality reduction. In UMLDA, it could extract uncorrelated discriminative features directly from tensorial data by solving a tensor-to-vector projection (TVP). Thus we could adopt

Table 1: Details of collection condition of ship radiated noise signals

Name of ship	Depth of sea (m)	Length of array (m)	Minimum distance between sonar and ship (m)	Sea condition
Mingying	38	10	450	2 level
Huadong	38	10	1008	2 level
Shunlong	38	10	270	2 level
Henghai	38	10	424	2 level
Buena Esperanza	38	10	686	2 level
Gangtong	38	10	437	2 level

UMLDA for feature extraction and dimensionality reduction on Multi-SampEn-based tensor.

Given a set of training tensor object samples $\{x_1, x_2, \ldots, x_M\}$, $x_m \in \mathrm{R}^{I_1 \times I_2 \times \ldots \times I_N}$, where M is the number of training samples and I_n is the n-mode dimension of the tensor, the objective of UMLDA is to find a TVP, which consist of a set of P elementary multilinear projections (EMP) $\{\mathrm{u}_p^{(n)} \in \mathrm{R}^{I_n \times 1}, n = 1, \ldots, N\}_{p=1}^{P}$. Thus the original tensor space $\mathrm{R}^{I_1} \bigotimes \mathrm{R}^{I_2} \ldots \bigotimes \mathrm{R}^{I_N}$ is mapped into a vector subspace $\mathrm{R}^P (P < \prod_{n=1}^{N} I_n)$ by,

$$y_m = x_m \times_{n=1}^{N} \{\mathrm{u}_p^{(n)^T}, n = 1, \ldots, N\}_{p=1}^{P}, m = 1, \ldots, M, \quad (8)$$

where y_m is the projected feature of the sample x_m and P is the number of projection vectors.

In UMLDA, in order to determine a set of P EMPs $\{\mathrm{u}_p^{(n)^T}, n = 1, \ldots, N\}_{p=1}^{P}$, it needs to maximize the scatter ratio while producing features with zero correlation. Thus, the objective function for the pth EMP is

$$\begin{aligned} &\{\mathrm{u}_p^{(n)^T}, n = 1, \ldots, N\} = \arg\max F_p^y \\ &\text{subject to } \frac{g_p^T g_q}{\|g_p\| \|g_q\|} = \delta_{pq}, p, q = 1, \ldots, P, \end{aligned} \quad (9)$$

where δ_{pq} is the Kronecker delta, g_p is the pth coordinate vector and F_p^y is the classical Fisher's discrimination criterion (FDC), i.e., scatter ratio in linear discriminant analysis (LDA) which is defined as,

$$F_p^y = S_{B_p}^y / S_{W_p}^y \quad (10)$$

where $S_{B_p}^y$ and $S_{W_p}^y$ are respectively the between-class scatter and the within-class scatter and are defined as,

$$S_{B_p}^y = \sum_{c=1}^{C} N_c (\bar{y}_{c_p} - \bar{y}_p)^2 \quad (11)$$

$$S_{W_p}^y = \sum_{m=1}^{M} (\bar{y}_{m_p} - \bar{y}_{c_{m_p}})^2 \quad (12)$$

where C is the number of classes, N_c is the number of samples for class c, c_m is the class label for the mth training sample, $\bar{y}_p = (1/M) \sum_m y_{m_p} = 0$ and $\bar{y}_{c_p} = (1/N_c) \sum_{m, c_m = c} y_{m_p}$. Then, referring to [28] the successive determination approach is adopted in UMLDA to solve this problem. More details of the implementation of UMLDA, please refer to the pseudocode in Fig.3 of [22].

3 Ship radiated noise signal data set

The performance of the proposed classification scheme is evaluated on real measured ship radiated noise signals which are collected by towed array sonar. The towed array sonar includes 6 hydrophones in which the interval of each hydrophone is 2 m and the sampling frequency is 27 kHz.

More specifically, in the classification experiments, we adopt ship radiated noise signals of six ships collected by towed array sonar on East China Sea in 2013. In the collection of ship radiated noise signals the towed array sonar is located and then respectively collect ship radiated noise signals of each ship which sails from far to near at low speed. The details of collection conditions are summarized in Table 1.

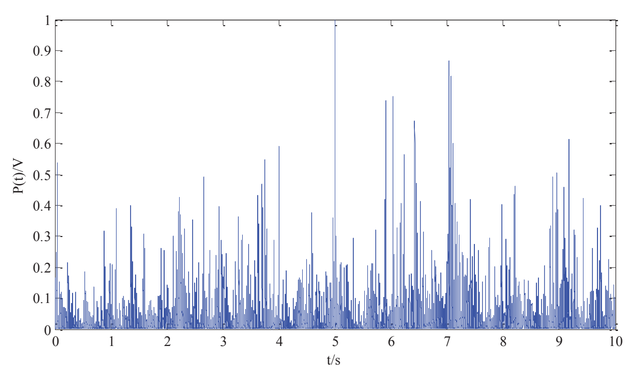

Fig. 2: Ship radiated noise signals after CBF.

Furthermore, in order to improve SNR of ship radiated noise signals a preprocessing step, i.e., conventional beam-forming (CBF) is adopted for the array signals. The ship radiated noise signals after CBF

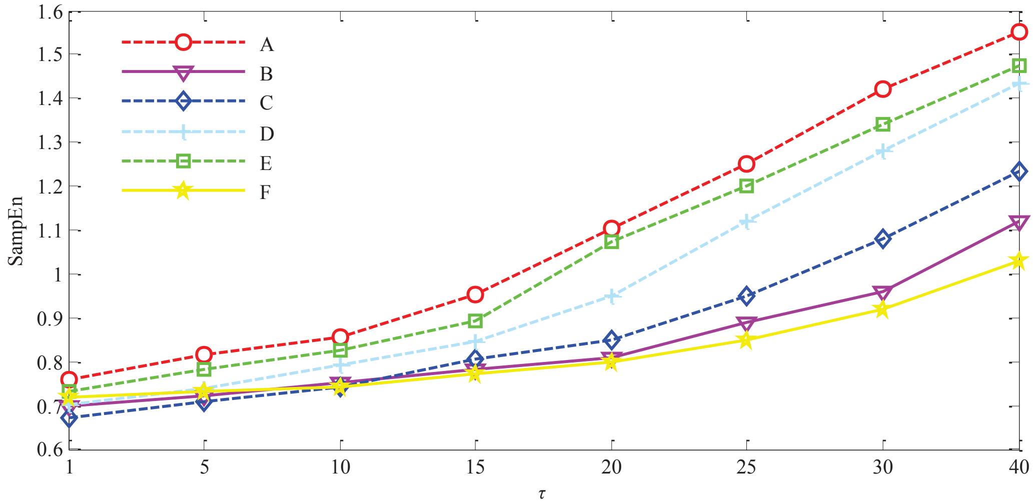

Fig. 3: The mean SampEn values of different kinds of surface ships with m = 2 and r = 0.2 at different scales.

Table 2: Details of data set of ship radiated noise signals

Name of ship	Code	Number of sample	Time of sampling (s)
Mingying	A	37	10
Huadong	B	57	10
Shunlong	C	59	10
Henghai	D	53	10
Buena Esperanza	E	25	10
Gangtong	F	49	10

are depicted in Fig.2 that will be used in subsequent feature extraction and classification. In the study, the long data record of ship radiated noise signals is broken into overlapped short segments. By randomly selecting a stable segment of 10s data, we construct a data set of ship radiated noise signals. Details of the data set are given in Table 2, from which a little of imbalance in different categories need to be noted.

4 Experiment results

In this section, Multi-SampEn was performed on constructed data set of ship radiated noise signals. In order to evaluate the performance of Multi-SampEn, two experiments were conducted. Specifically complexity analysis would generate multiple ”look” of the complexity of ship radiated noise signals. Classification experiment would present the performance of surface ship recognition.

4.1 The complexity analysis of ship radiated noise signals

In the complexity analysis, the SampEn values of ship radiated noise signals are calculated at different scales, i.e., $\tau = 1, 5, 10, 15, 20, 25, 30$, and 40 with m = 2 and r = 0.2, and thus a 8-dimensional feature vector of ship radiated noise signals is derived. As depicted in Fig.3, for scale one, the mean SampEn values of different kinds of surface ships are similar that are indistinguishable for each surface ship. However, in some other scales the separation among the mean SampEn values of different kinds of surface ships is distinguishable. Therefore, in this respect Multi-SampEn could achieve more meaningful measure of the complexity of ship radiated noise signals for surface ship recognition.

4.2 The classification experiment of ship radiated noise signals

In order to verify the effectiveness of Multi-SampEn in surface ship recognition, we constructed an individual SVM classifier, resulting in Mutil-SampEn-SVM which was trained by using the constructed data with the SampEn values of each coarse-grained time series. To the end, we tested the classification methods by classifying six kinds of surface ships. In the experiment, in order to efficiently achieve surface ship recognition the following two issues were needed to solve:

1) To investigate the dimensionality reduction on Multi-SampEn-based tensor;

2) To solve the problem of imbalance of samples in the surface ship recognition experiment.

In order to solve the two issues, MSL method and the classifier with different penalty constants method were respectively adopted.

Specifically, the SampEn values of ship radiated noise signals were calculated at different scales with different values of parameters, i.e., $\tau = 1, 5, 10, 15, 20, 25, 30$, m = 1, 2, 3, 4, 5, 6, 7, 8, 9, 10 and r = 0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9, 1, and then the calculated values of Multi-SampEn were represented as $7 \times 10 \times 10$ tensor. In view of alleviating the parameter selection problem and enhancing the generalization performance, in Multi-SampEn-based surface ship recognition the two multilinear subspace learning (MSL) methods, i.e., MPCA and UMLDA were respectively adopted for feature extraction and dimensionality reduction from the tensor. Using the extracted features as the inputs, we constructed two individual SVM classifiers resulting in MPCA-SVM and UMLDA-SVM. Finally we adopted the 10-fold cross-validation method to evaluate the accuracy of the proposed scheme, where the MPCA-SVM and UMLDA-SVM respectively achieved the classification accuracy of 68.21% and 69.64%, and the mean classification accuracy of 65.17% and 66.19%. As shown in Table 3, the classification accuracy and the mean classification accuracy of the proposed scheme were remarkably higher than the Mutil-SampEn-SVM with the optimal parameters. Besides in the proposed scheme it alleviated the parameter selection problem and enhanced the generalization performance in the surface ship recognition.

Table 3: The rusults of different classification methods

Method	Total Accuracy (%) /Mean Accuracy (%)
Mutil-SampEn-SVM (optimal parameters)	60.36/57.87
Mutil-SampEn-SVM (all parameters)	50.36/47.33
MPCA-SVM	68.21/65.17
UMLDA-SVM	**69.64/66.19**

In virtue of the imbalance of samples in SVM classifier, we adopted the different penalty constants for different classes in surface ship recognition [29]. As shown in Table 4, the mean classification accuracy of the proposed scheme obviously increased which showed the proposed scheme was more significant for surface ship recognition.

In order to provide a comprehensive evaluation, we compared the performance of the proposed scheme with SVM with other individual feature extractor, i.e., ApEn [30], and SampEn [31], thus we constructed two individual SVM classifiers, i.e., ApEn-SVM and SampEn-SVM. Then the 10-fold cross-validation method

Table 4: The rusults of different classification methods with different penalty constants

Method	Total Accuracy (%) /Mean Accuracy (%)
ApEn-SVM	42.14/41.67
SampEn-SVM	44.29/44.01
Mutil-SampEn-SVM (optimal parameters)	56.79/56.14
Mutil-SampEn-SVM (all parameters)	47.50/46.89
MPCA-SVM	67.14/66.67
UMLDA-SVM	**68.93/68.29**

was adopted to assess the classification accuracy. From Table 4, one could see that, the proposed scheme could obtain much higher classification accuracy and mean classification accuracy than any individual classifier, which verified that the Multi-SampEn was much more effective for the analysis of ship radiated noise signals in surface ship recognition.

Table 5: The confusion matrix of the UMLDA-SVM

		Predicted					
		A	**B**	**C**	**D**	**E**	**F**
Actual	**A**	25	5	3	3	0	1
	B	2	40	6	5	1	3
	C	2	5	43	6	1	2
	D	2	4	4	37	2	4
	E	1	2	3	1	16	2
	F	1	3	6	4	3	32

In Table 5 we listed the confusion matrices of the recognition results by the UMLDA-SVM. As show in Table 5, the UMLDA-SVM could achieve comparable classification accuracy for different ships.

5 Discussions and conclusions

In this paper, we adopt an effective nonlinear analysis method, i.e., Multi-SampEn, for the analysis of ship radiated noise signals in surface ship recognition. The method could measure the degree of complexity of ship radiated noise signals on different scales. Compared with other nonlinear analysis methods, e.g. ApEn, and SampEn, Multi-SampEn could achieve more valuable information from the hidden properties of ship radiated noise signals.

To evaluate the performance of Multi-SampEn, the complexity analysis and the classification experiments are respectively carried out on data set of ship radiated noise signals. In the complexity analysis, by the comparison of the mean value of Multi-SampEn, we find it could achieve more meaningful measure of complexity and yield consistent findings of ship radiated noise signals for different ships.

In the classification experiments, firstly the calculated Multi-SampEn values of ship radiated noise signals are represented as third-order tensor. Then in order to alleviate the parameter selection problem and enhance the generalization performance in Multi-SampEn, two MSL methods, i.e., MPCA and UMLDA are respectively adopted for feature extraction and dimensionality reduction from the tensor. Finally using the extracted features as the inputs, we construct two individual SVM classifiers with the different penalty constants for different classes, resulting in MPCA-SVM and UMLDA-SVM for surface ship recognition. Experimental results show that the proposed scheme respectively achieves the classification accuracy of 67.14% and 68.93%, and the mean classification accuracy of 66.67% and 68.29%. The performance of surface ship recognition outperforms the other methods.

For future work, we will further investigate proper nonlinear analysis methods and develop more effective classification methods for surface ship recognition.

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