A NEW LOW SNR UNDERWATER ACOUSTIC SIGNAL CLASSIFICATION METHOD BASED ON INTRINSIC MODAL FEATURES MAINTAINING DIMENSIONALITY REDUCTION

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ABSTRACT

The classification of low signal-to-noise ratio (SNR) underwater acoustic signals in complex acoustic environments and increasingly small target radiation noise is a hot research topic. . This paper proposes a new method for signal processing—low SNR underwater acoustic signal classification method (LSUASC)—based on intrinsic modal features maintaining dimensionality reduction. Using the LSUASC method, the underwater acoustic signal was first transformed with the Hilbert-Huang Transform (HHT) and the intrinsic mode was extracted. the intrinsic mode was then transformed into a corresponding Mel-frequency cepstrum coefficient (MFCC) to form a multidimensional feature vector of the low SNR acoustic signal. Next, a semi-supervised fuzzy rough Laplacian Eigenmap (SSFRLE) method was proposed to perform manifold dimension reduction (local sparse and discrete features of underwater acoustic signals can be maintained in the dimension reduction process) and principal component analysis (PCA) was adopted in the process of dimension reduction to define the reduced dimension adaptively. Finally, Fuzzy C-Means (FCMs), which are able to classify data with weak features was adopted to cluster the signal features after dimensionality reduction. The experimental results presented here show that the LSUASC method is able to classify low SNR underwater acoustic signals with high accuracy.

Keywords: Acoustic,Low SNR,Signal classification,Feature maintain,Dimension reduction

INTRODUCTION

Underwater acoustic signal processing is widely used in marine exploration to map the topography and geomorphology of the seafloor, monitor biological factors, and search and rescue operations at sea. Computer processing of underwater acoustic signals is continuously advancing, and acoustic signal classification and recognition are of great theoretical significance and application value [8, 18, 20], and the requirements for signal classification and recognition are increasing [7]. Due to the complex background noise in marine environments and the improvement of acoustic stealth technology, underwater acoustic signals comprise a complicated physical process. With the decrease of target radiation noise, the SNR of underwater military targets (such as torpedoes, mines, submarines, etc.) is decreasing, which presents new challenges for research into the classification and recognition of acoustic signals underwater. Therefore, as a precondition of acoustic signal analysis and underwater target detection and recognition, the classification of low SNR underwater acoustic signals in complex acoustic environments along with decreasing target radiation noise has become a hot topic in acoustic signal processing [4, 16].

Traditional classification methods of acoustic signals have serious limitations. When we analysed data produced by nonlinear and nonstationary processes, we hoped to obtain frequency information and detailed information about signal features and characteristics. The time-frequency analysis method represented by the early short time Fourier transform (STFT) and the Wigner-Ville distribution obviously lack this ability to produce frequency data and greater detail [7, 19]. Although the appearance of the Wavelet Transform (WT) [1] was once favoured by scientists, it is essentially a window-adjustable Fourier transform and thus subject to the limitations of the Fourier transform. Huang et al. [10] proposed the HHT, a new adaptive time-frequency analysis method especially suited for analysis and processing of nonlinear and nonstationary signals, described by the National Aeronautics and Space Administration (NASA) as the most important research discovery in the field of applied mathematics in the last 200 years. At present, some scholars apply HHT and EMD(empirical mode decompositon) to acoustic signal processing [9, 12]. The classification of underwater acoustic signals requires the extraction of the feature parameters of the original signal so as to achieve fast, accurate, and stable decisions on signal classification. The feature parameters currently used are: (1) the time domain waveform feature parameter and (2) the spectral analysis feature parameter, including such widely used methods as the line spectral feature, LOFAR spectrum diagram, DEMON spectrogram, stealth features, high-order spectra, and so on [5, 14]; (3) the time-frequency analysis feature parameter; (4) the nonlinear feature parameter, which is the reflection of attractor topological structures in the reconstructed phase space of the target noise signal; and (5) the auditory feature parameter extraction including the auditory cepstrum coefficient (ACC), the MFCC, the linear prediction cepstrum coefficient (LPCC), and so on [2, 21, 22]. Extraction of these feature parameters is a method for the classification and recognition of underwater acoustic signals according to the mechanism of human hearing based on bionics, which is one of the main research directions in the processing of underwater acoustic signals. In the classification and recognition of underwater acoustic signals, common classification methods are: support vector machine (SVM), back propagation neural network (BPNN), k-nearest neighbor (KNN), FCM [3, 11, 13 ,15 ,17]. However, with low SNR underwater acoustic signals, it is a challenge to develop the classification method for a signal class that is nonlinear, non-Gaussian and nonstationary.

This paper presents the challenges to accurate classification of low SNR underwater acoustic signals and proposes a new method (LSUASC) based on intrinsic modal features maintaining dimensionality reduction. The method makes two main contributions. First, HHT is adopted in this method because it is suitable for processing nonlinear nonstationary signals, and EMD is used to extract the intrinsic mode because it is able to make full use of the local sparse and discrete features of the signals. The ability to represent the features of underwater noise excitation sources, underwater

acoustic channels, and auditory laws, MFCCs are used as the feature vector set of low SNR underwater acoustic signal classification and recognition. Manifold dimension reduction feature maintenance is used to reduce the dimensionality of the feature vector set, and FCM is used to identify the weak fuzzy feature data so as to evaluate and classify low SNR signals. Based on the dimensionality reduction problem of the feature vector set in low SNR underwater acoustic signal classification, a new semi-supervised local feature maintenance manifold dimension reduction method SSFRLE is proposed in which sparse, discrete, fuzzy, and weak local features can be maintained effectively. In addition, in dimension reduction processing, PCA is used to define the reduced dimensionality adaptively. With the innovative points, the LSUASC was formed. The experimental results show that this method is feasible with high classification accuracy.

The rest of the paper is structured as follows: Section 2 describes related works. Section 3 introduces the HHT of low SNR underwater acoustic signals. Section 4 introduces the extracted MFCCs of underwater acoustic signals. Section 5 describes the semi-supervised local feature maintenance manifold dimension reduction method. Section 6 introduces the FCM-based signal classification method. Section 7 presents the experiment and results of our study. Finally, Section 8 presents the conclusions.

RELATED WORKS

Acoustics researchers have given the classification and recognition of underwater acoustic signals their attention and studied the matter from different angles, classification of underwater noise targets has applications in many fields. For long-range detection, background noise in the environment decreases recognition accuracy [20]. the classification of underwater acoustic signals have been summarized, and the classification of underwater acoustic sensor signals with low SNR has become a hot research topic in underwater signal processing and a key issue to be solved [4].

Because underwater acoustic signals are nonlinear, non-Gaussian, and nonstationary, and target features are discrete, sparse, fuzzy, and weak, HHT was used to classify and recognise acoustic signals because HHT is especially suited for analysis and processing of nonlinear and nonstationary signals. Wang et al. [20] presented a time-frequency analysis method that combined Bark-wavelet analysis and HHT. Using this combination of methods, instantaneous frequencies and amplitudes were extracted with the help of HHT [20]. Song et al. [16] presented an automatic identification algorithm for the Yangtze finless porpoise based on an HHT and a BP artificial neural network [16].

The new Ensemble Empirical Mode Decomposition (EEMD) method was used with HHT to analyse underwater target signals [9]. Using EEMD and HHT, certain features can be extracted and applied in the classification, including (1) the central frequency of the strongest intrinsic mode function,

(2) the energy difference between high and low frequencies, and (3) the instantaneous energy variation range. Li et al. [12] demonstrated the difference in properties between the Hilbert spectrums of a target echo and reverberation. Because the Hilbert marginal spectrum can reduce reverberation, the HHT is an effective method for extracting the features of underwater targets.

Used in the classification and recognition of underwater acoustic signals according to the mechanism of human hearing based on bionics, MFCCs represent one of the main research directions in the processing of underwater acoustic signals. Chinchu and Supriya [2] constructed a real time underwater target recognition system in which MFCCs were used for feature extraction, the SVM method was employed as the classification algorithm and the entire system was implemented using Labview. Wang et al. [21] presented a feature extraction algorithm which focused on the MFCC feature coefficients of underwater targets and the radiated noise of different marine life (whales, sea lions, dolphins), divers, boats, and ships were studied, demonstrating that MFCCs can be effective in feature extraction and recognition. Zhang et al. [22] showed that the features of MFCCs, first-order differential MFCCs, and second-order differential MFCCs can be effectively used to recognise different underwater targets, and the recognition rate can be improved by combining features.

In recent years, manifold learning has been introduced to feature extraction of acoustic targets and dimensionality reduction. Liu et al. [13] studied the low dimensional manifold in the frequency domain of acoustic signals based on the classical algorithm of manifold learning, and found that manifold learning can be used to identify intrinsic features and increase the accuracy and robustness of a low altitude passive acoustic target recognition system. Sun et al. [17] proposed a novel method termed 'Robust sEmi-supervised multi-lAbel DimEnsion Reduction' (READER) . The READER method finds a feature subspace to keep original neighbor distances close and embed labels into a low-dimensional latent space so as to realise the dimensionality reduction of feature maintenance.

In the classification and recognition of underwater acoustic signals, the common classification methods are SVM, BP neural network, KNN, FCM . The SVM method was used as a classifier in Wang and Zeng [20]. In Song et al. [16], the BP artificial neural network was trained in 11 dimensions and a signal feature vector based on HHT was extracted. In Sherin and Supriya [15] , SVM was used as a classifier to distinguish the acoustic signatures of four different target types. Li et al. [11] used a wavelet packets-fractal and SVM for underwater target recognition.

From these related works, we drew the following conclusions: (1) there is little research on the classification and recognition of low SNR underwater acoustic signals. The classification and recognition methods thus far proposed are mainly for underwater acoustic signals with distinct features and high SNR. As for low SNR signals in which nonlinearity, non-Gaussianity, and nonstationary conditions are prominent and the target features are discrete, sparse, fuzzy, and weak, there is a lack of effective classification and recognition methods. (2) Regarding the problem of feature vector set dimensionality reduction in classification, the question of how to maintain sparse and discrete target features requires special research. (3) An effective low SNR underwater acoustic signal classification and recognition system has yet to be developed.

HILBERT-HUANG TRANSFORM OF LOW SNR UNDERWATER ACOUSTIC SIGNALS

The HHT) was proposed by Huang et al. [10] to solve the Hilbert Transform of nonlinear and nonstationary signals. Based on the uniqueness of the instantaneous frequency required by the Hilbert Transform, it is able to directly obtain instantaneous frequencies of physical significance from the derivative of the phase by reconstructing the signal space. After many experiments, the upper envelopes (u(t)) and lower envelopes (l(t)) of the original signals were fitted to the maximum point set and the minimum point set of the signal by cubic spline interpolation, and the envelope averaging ml(t) was ml(t) = (u(t) + l(t))/2. next, the original signal is used to reduce the average envelope. By sheltering the intrinsic mode, the original signal is decomposed into several intrinsic modes, while the instantaneous frequency of the intrinsic modes remains the same, and so the original signal is decomposed.

The main part of HHT is the EMD algorithm, the principle of which is to select the intrinsic mode [10]. The decision conditions are as follows:

a). The average value of the upper and lower envelopes of the signal tends to be 0 (generally, the difference between the average and 0 is less than 0.1).

b). The difference between the number of extreme value points in the original signal (including the number of maximum and minimum value points) and the number of joint points in the original signal (when y = 0) should not be greater than 1 . The EMD algorithm is as shown in Figure 1.
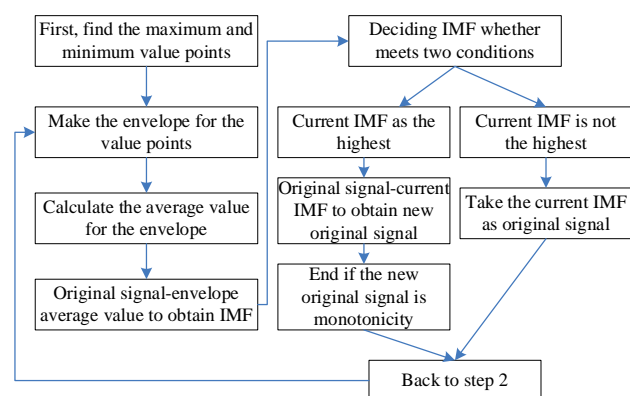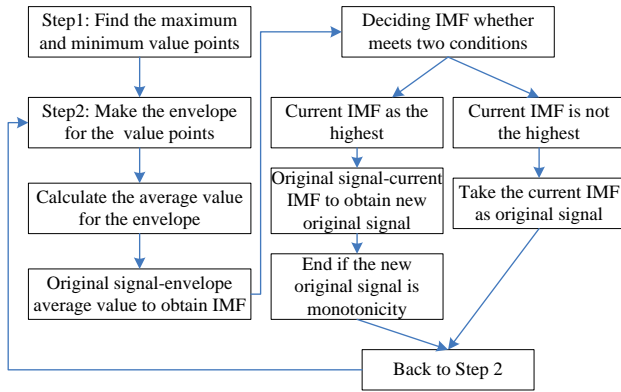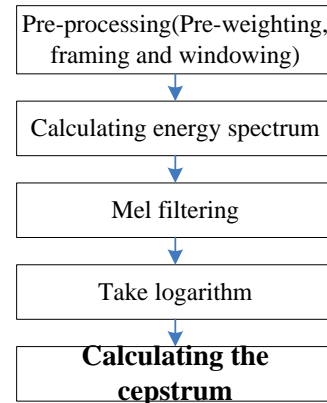
Fig. 1 EMD Algorithm Process

Fig. 2 Extraction Process of MFCCs

Underwater acoustic signals with low SNR have fuzzy, sparse, discrete, and weak features, and their nonlinearity, non-Gaussianity, and nonstationarity are prominent; as such, HHT is able to extract the intrinsic modes formed by the intrinsic mode function (IMF) of underwater acoustic signals with low SNR and provide input data for accurate classification.

MEL-FREQUENCY CEPSTRUM COEFFICIENTS OF UNDERWATER ACOUSTIC SIGNALS

After the HHT of low SNR underwater acoustic signals, a Mel-frequency cepstrum transformation is performed on the extracted intrinsic mode and its MFCCs are extracted. The multiple-dimension MFCCs are used as decisive features for classification. The Mel-frequency cepstrum is intended to simulate the principle of human hearing based on bionics, then curve the spectrum to construct the Mel-frequency cepstrum and achieve the function of human hearing. The difference between the cepstrum and Mel-frequency cepstrum is that the frequency band division of the Mel-frequency cepstrum is based on the Mel-scale, which is closer to the human auditory system than the linear division band used in the common cepstrum; moreover, the frequency curve better represents the human auditory features. The extraction process of MFCCs is shown in Figure 2.
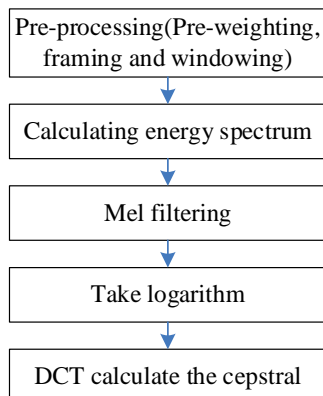
In the process of extracting MFCCs, the input signal is first pre-processed (pre-weighting, framing, and windowing), then fast Fourier is performed on the basis of the windowing function. Next, the norm length and logarithm of the transformed results are taken, and the discrete cosine transform (DCT) is adopted to obtain MFCCs, in which the Mel-frequency spectrum is used to replace the frequency spectrum in performing the transformation, while all the transformations are conducted with the transform method of the cepstrum. Therefore, the features obtained are not only stable in the frequency spectrum, but also agree with the the principle of human hearing . The specific process includes the following five steps:

Step 1. Pre-processing. Pre-weighting, framing, and windowing are done to steady underwater acoustic signals within a suitable sampling length; in fact, underwater acoustic signals have a time-changing characteristic which can be regarded as sound signals to be analysed and processed.

Step 2. Calculating the energy spectrum. The fast Fourier transform (*fft*) is adopted in the preprocessed signals to obtain a square amplitude energy spectrum:

$$p(f) = |X(f)|^2 = |fft(x(n))|^2 \qquad \textbf{(1)}$$

Step 3. Mel filtering. The energy spectrum $p(f)$ is filtered using the Mel filter. The frequency f of the Mel filter group is <u>greater than</u> 0 up to f_s (f_s is the sampling frequency):

$$E(m) = \sum_{k=0}^{N-1} \left(p(f) \cdot H_m(f) \right) \qquad \textbf{(2)}$$

where N is the total number of framing signals and m is the number of filters.

Step 4. . The logarithm. The logarithm of the obtained filter energy spectrum is taken. The nonlinearity of the underwater acoustic signal is then calculated with this logarithm:

$$E'(m) = \lg \sum_{k=0}^{N-1} \left(p(f) \cdot H_m(f) \right) \qquad \textbf{(3)}$$

Step 5. Calculating the cepstrum. The DCT is adopted for the obtained logarithm energy spectrum in order to obtain the MFCCs:

$$C(n) = \sum_{k=0}^{M} E'(m) \cos\left(\frac{\pi(k - 0.5)n}{M}\right) \tag{4}$$

where $n = 1, 2, \ldots, p$, and p is the order of magnitude of MFCCs. After adopting the MFCC transform in the intrinsic mode of underwater acoustic signals, the multiple feature vector set of low SNR signal classification is obtained and in which the relevance between intrinsic modes is maintained, making it conducive to reducing the dimensionality of low SNR underwater acoustic signals.

SEMI-SUPERVISED LOCAL FEATURE MAINTAINING MANIFOLD DIMENSION REDUCTION

For the extracted MFCC feature vector set of underwater acoustic signals, the semi-supervised local feature maintaining manifold dimension reduction method SSFRLE is proposed to reduce the dimensionality of the feature vector set of MFCCs, and the reduced dimensionality is decided by PCA adaptively.

The main process of SSFRLE is to construct the feature significance of a data set with fuzzy similarity, then comprehend all the information and make use of the data with feature significance to construct a similarity matrix. After that, neighbouring rough fuzzy sets are constructed on the basis of the fuzzy similarity matrix to define the membership degree of each kind of sample. Tthe membership degree, nuclear distance, and classification information are combined in order to construct the weight value as follows:

a) $W_{ij}^N = 1$, if x_i and x_j have the same classification, and $x_i \in N_k(x_j)$ or $x_j \in N_k(x_i)$;

b) $W_{ij}^N = \mu_{NX_i}(x_j) e^{-d_{ij}^2(x_i, x_j)/\beta}$, if there is one has been not labelled

in x_i and x_j and $x_i \in N_k(x_j)$ or $x_j \in N_k(x_i)$; and

c) $W_{ij}^N = 0$, for all others.

On this basis, the following optimisation problem is constructed:

$$\min(1 - \gamma)\sum_{i,j}^{n} W_{ij}^N \|y_i - y_j\|^2 + \gamma\sum_{i=1}^{n}\sum_{t=1}^{f} W_i^C \|y_i - c_t\|^2 \tag{5}$$

where γ is a real parameter and $\gamma \in [0,1]$. In order to weight the effect of the distance between adjacent samples and the distance between sample and center class on function value, it is organised as follows:

$$(1 - \gamma)\sum_{i,j=1}^{n} W_{ij}^N \|y_i - y_j\|^2 + \gamma\sum_{i=1}^{n}\sum_{t=1}^{f} W_{it}^C \|y_i - c_t\|^2$$

$$= (1 - \gamma)\sum_{i,j=1}^{n} W_{ij}^N (y_i - y_j)(y_i - y_j)^T + \gamma\sum_{i=1}^{n}\sum_{t=1}^{f} W_{it}^C \|y_i - c_t\|^2$$

$$= \sum_{i=1}^{n}\sum_{j=1}^{n} 2(1 - \gamma)W_{ij}^N y_i y_i^T + \sum_{i=1}^{n}\sum_{t=1}^{f} \gamma W_{it}^C y_i y_i^T + \sum_{i=1}^{n}\sum_{t=1}^{f} \gamma W_{it}^C c_t c_t^T$$

$$- \left(\sum_{i=1}^{n}\sum_{j=1}^{n} 2(1 - \gamma)W_{ij}^N y_i y_j^T + \sum_{i=1}^{n}\sum_{t=1}^{f} \gamma W_{it}^C (y_i c_t^T + c_t y_i^T)\right) \tag{6}$$

$$= \left(\sum_{i=1}^{n}\sum_{j=1}^{n} 2(1 - \gamma)W_{ij}^N y_i y_i^T + \sum_{i=1}^{n}\sum_{t=1}^{f} \gamma W_{it}^C y_i y_i^T + \sum_{i=1}^{n}\sum_{t=1}^{f} \gamma W_{it}^C c_t c_t^T\right.$$

$$+ \sum_{t=1}^{f} c_t c_t^T\right) - \left(\sum_{i=1}^{n}\sum_{j=1}^{n} 2(1 - \gamma)W_{ij}^N y_i y_j^T + \sum_{i=1}^{n}\sum_{t=1}^{f} \gamma W_{it}^C (y_i c_t^T + c_t y_i^T) + \sum_{t=1}^{f} c_t c_t^T\right)$$

$$= tr(Z^T DZ) - tr(Z^T WZ)$$

$$= tr(Z^T LZ).$$

where $c_1, c_2, \cdots, c_f \in R^d$ is the class centre of data set X in low dimension space used to make the following:

$$Z = \begin{pmatrix} c_1 \\ \vdots \\ c_f \\ y_1 \\ \vdots \\ y_n \end{pmatrix} = \begin{pmatrix} c_{11} & c_{12} & \cdots & c_{1d} \\ \vdots & \vdots & & \vdots \\ c_{f1} & c_{f2} & \cdots & c_{fd} \\ y_{11} & y_{12} & \cdots & y_{1d} \\ \vdots & \vdots & & \vdots \\ y_{n1} & y_{n2} & \cdots & y_{nd} \end{pmatrix} = \begin{bmatrix} z^1 z^2 \cdots z^d \end{bmatrix}. \tag{7}$$

$$W = \begin{pmatrix} I & \gamma(W^C)^T \\ \gamma W^C & 2(1 - \gamma)W^N \end{pmatrix}, D_{ii} = \sum_j W_{ij}.$$

$$W = \begin{pmatrix} I & \gamma(W^C)^T \\ \gamma W^C & 2(1 - \gamma)W^N \end{pmatrix}, D_{ii} = \sum_j W_{ij}. \tag{8}$$

where D is a diagonal matrix of $(f + n) \times (f + n)$ and L=D-W is a semi-defined Laplace matrix of $(f + n) \times (f + n)$.

To ensure that there are solutions to the optimisation problems, add two constraint conditions:

$$tr(Z^T DZ) = 1, Z^T D_1 = 0 \tag{9}$$

The optimisation problem is obtained with the Lagrange multiplier method:

$$F(Z) = tr(Z^T LZ) - \lambda\left[tr(Z^T DZ) - 1\right] = tr[Z^T(L - \lambda D)Z] + \lambda \tag{10}$$

derivative of F is calculated as:

$$\frac{\partial F(Z)}{\partial Z} = \frac{\partial \left[tr\left(Z^T \left(L - \lambda D \right) Z \right) + \lambda \right]}{\partial Z}$$

$$= \frac{\partial \left[tr\left(Z^T \left(L - \lambda D \right) Z \right) \right]}{\partial Z}$$

$$\qquad (11)$$

$$= \frac{\partial \left[tr\left(Z Z^T \left(L - \lambda D \right) \right) \right]}{\partial Z}$$

$$= \left(L - \lambda D \right)^T Z + \left(L - \lambda D \right) Z$$

making $\frac{\partial F(Z)}{\partial Z} = 0$ and $\left(L - \lambda D \right)^T Z = \left(L - \lambda D \right) Z = 0$

because $L - \lambda D$ is a symmetrical matrix. Therefore, the optimisation problem can be transformed into the generalised given values problem as:

$$LZ = \lambda DZ \qquad (12)$$

The column vectors $z^1, z^2, \cdots, z^d$ can be obtained to give the corresponding feature vector of the previous d minimum nonnegative eigenvalues $0 \neq \lambda_1 \leq \lambda_2 \leq \cdots \lambda_d$, the previous f lines of the matrix $\left[z^1 z^2 \cdots z^d \right]$ are the class centre of data set X in low dimensional space, and the latter n lines of the matrix $\left[z^1 z^2 \cdots z^d \right]$ represent data set X in low dimensional space.

The SSFRLE method is adopted to perform manifold dimensionality reduction on the MFCC intrinsic mode of underwater acoustic signals. In this process, PCA is used to define the reduced dimensionality adaptively. For data in different hydrophones, high feature value can be maintained effectively when the dimensionality of the data is reduced, helping to enhance classification accuracy. The FCM method is used for classification when the feature vector of the acoustic signal is maintained by dimensionality reduction.

FUZZY C-MEANS-BASED SIGNAL CLASSIFICATION METHOD OF UNDERWATER ACOUSTIC SIGNALS

Although the MFCCs of underwater acoustic signals are able to maintain sparse and discrete features of target noise after dimensionality reduction, these features are still weak and fuzzy. To this end, FCM can be used to classify these feature vectors with improved accuracy. The FCM method is an unsupervised dynamic clustering method which requires the stipulation that there are certain classes of data sets and C classes. For each class of data, the membership degree of each class can form a fuzzy classification matrix, the requirements for which are as follows:

$$\sum_{i=1}^{c} \mu_{ik} = 1 \qquad (13)$$

$$0 < \sum_{k=1}^{n} \mu_{ik} < n \qquad (14)$$

where μ_{ik} is the membership degree of kth data in ith class; therefore, Eq. (13) represents a membership degree sum for each data point of 1, and Eq. (14) implies that there is at least one and at most n points in each class.

The energy function can be defined according to distance based on membership degree as in shown in Eq. (15):

$$J(U, v) = \sum_{k=1}^{n} \sum_{i=1}^{c} \mu_{ik}^m d_{ik}^2 \, (m > 1) \qquad (15)$$

where the distance between the kth point, and the class centre of the ith class is defined as the Euclidean distance (v_{ij} is the jth dimension of the ith cluster centre):

$$d_{ik} = \left[\sum_{j=1}^{m} \left(x_{kj} - v_{ij} \right)^2 \right]^{1/2} \qquad (16)$$

Minimise formula (15) with a gradient descent:

$$v_{ij} = \frac{\sum_{k=1}^{n} \mu_{ij}^m x_{ij}}{\sum_{k=1}^{n} \mu_{ij}^m} \qquad (17)$$

Equation (17) is now the optimal expression of the cluster centre, and the iterative method is used to update the cluster centre . By clustering the features maintained by underwater acoustic signals after dimensionality reduction using FCM, each kind of signal can be classified with high degree of accuracy from data classes with different features.

EXPERIMENT AND ANALYSIS

To verify the classification performance of the LSUASC method for underwater acoustic signals with low SNR, experiments were carried out. The experimental data was obtained in the anechoic tank at Harbin Engineering University, then the LSUASC method and common methods were adopted to analyse the data.

EXPERIMENTAL DATA COLLECTION

The experimental data was collected in the anechoic tank at Harbin Engineering University. The sound absorption rubbers were in the tank , and the sands were layered at the bottom, and the sound absorption wedges were placed on the surface of the water, so the sound absorption coefficient was about

0.99, and acoustic reflections were effectively eliminated. Underwater acoustic signals with low SNR were simulated. The related equipment and layout are shown in Figure 3:
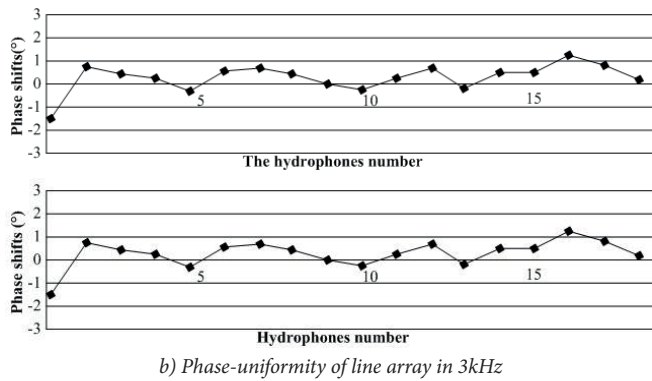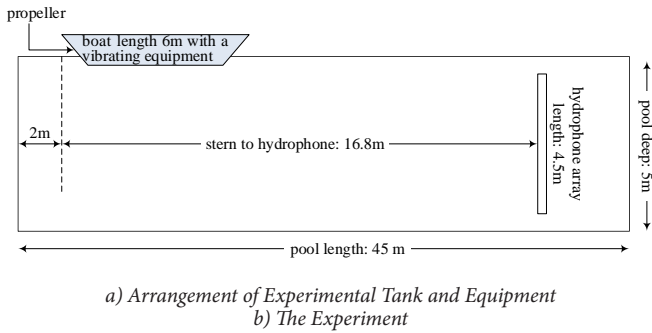

a) Arrangement of Experimental Tank and Equipment
b) The Experiment

b) Phase-uniformity of line array in 3kHz

Fig. 3. Experimental Equipment Layout (a)
and Phase-uniformity of Line Array (b)

In Figure 2, the acoustic sensor consists of 18 bottom-ranked hydrophones. No. 1 hydrophone is 0.5 m from the bottom of the pool and each subsequent hydrophone is spaced at a distance of 0.25 m, making a total length of 4.5 m. Each hydrophone corresponds to the same coded channel (signal), and the phase shifts for all 18 hydrophones were tested and adjusted and controlled within 1.5°. The phase-uniformity of line array at 3 kHz is shown in Figure 3c. The vessel was fixed along the centre line of the pool (Fig. 3b) over the hydrophones with vibrating equipment inside to simulate low SNR noise. The data was recorded in accordance with the station and group as shown in Table 1.

Tab. 1. Data Collection Table

	Station 1	Station 2	Station 3	Station 4	Station 5
Group 1	Background-pure	Background Stall-0	Background Stall-20	Background Stall-50	Background Stall-80
Group 2	Vibe-equipment working	Stall-0 and working	Stall-20 and working	Stall-50 and working	Stall-80 and working

In Table 1, 'Background Stall-0' is the stalled vessel at 0% power but running (i.e., engine idles, but propeller does not turn), 'Background Stall-20' is the vessel at 20% power and stalled but working, and 'Stall-0 and working' is the vessel at 0% power and stalled, but working along with the vibrating

equipment. During the experiments, 10 min of acoustic signals were collected in different groups at different stations, with a sampling frequency of 25.8 kHz. Because the sound of the vessel (Stations 2 to 5 in Group 1) was greater than the noise of the vibrating equipment, the stations in Group 1 were used as the background noise. The vessel noise in Group 1 was also high, so the noise of the vessel and the vibrations were compared with that of Group 1, and an acoustic signal with low SNR was obtained in the laboratory. Acoustic signal classification with low SNR was obtained through an analysis of the data in Groups 1 and 2.

EXPERIMENTAL DATA ANALYSIS

In the classification experiment involving two groups of underwater acoustic signals in the same station (Groups 1 and 2), 100,000 sampling points were selected at different starting points for each hydrophone in the two data groups, then the LSUASC method was adopted for the classification of the data. First, the data from each hydrophone was transformed with HTT and the MFCC was extracted. For MFCC, the pre-weighting coefficient was 0.97. In the framing division, 1024 sampling points were used as a frame, and the overlapping area between the two frames had 256 sampling points. The Hamming window was used, and the order of the Mel filter was 18. The length of FFT was 1024, and the Hamming window was used too. Second, the classification feature vector was then formed with manifold dimensionality reduction, and classification accuracy was obtained with FCM. The classification experiments at each station were performed three times (Calculation 1, Calculation 2 and Calculation 3). The experimental results are shown in Figures 4–8. The hydrophone number is on the horizontal axis and the classification accuracy is on the vertical axis.
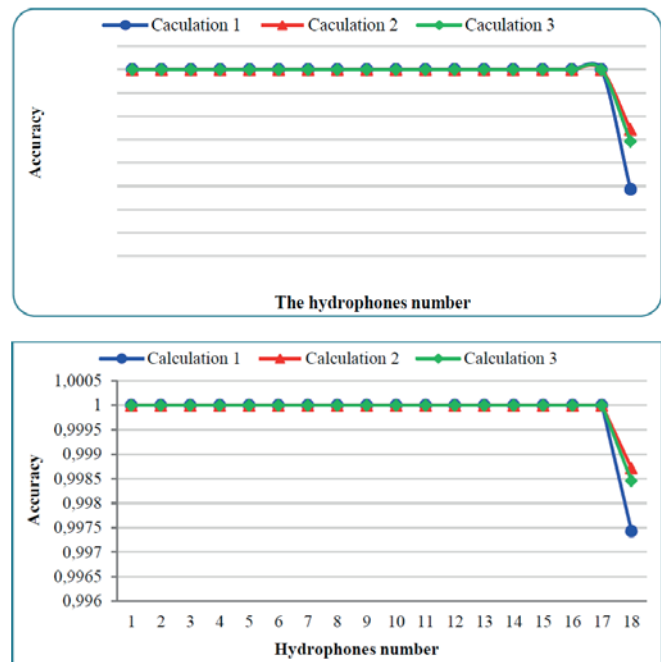

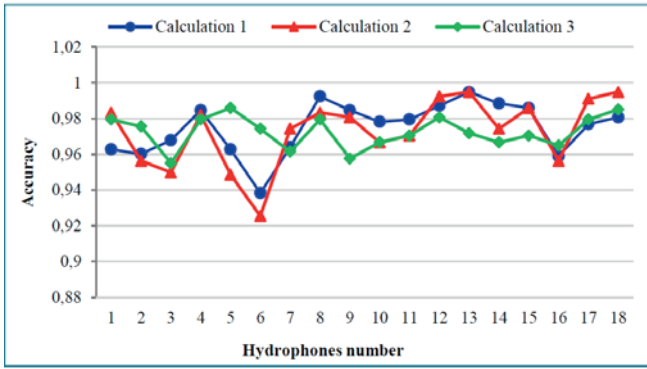*Fig. 4 Classification Accuracy of Two Data Groups under Station 1*

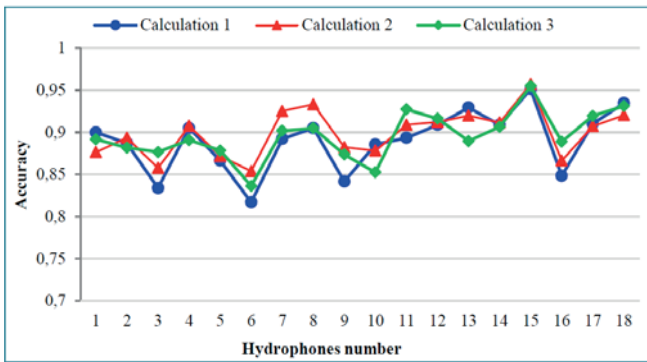*Fig. 5 Classification Accuracy of Two Data Groups under Station 2*

Fig. 6 Classification Accuracy of Two Data Groups under Station 3
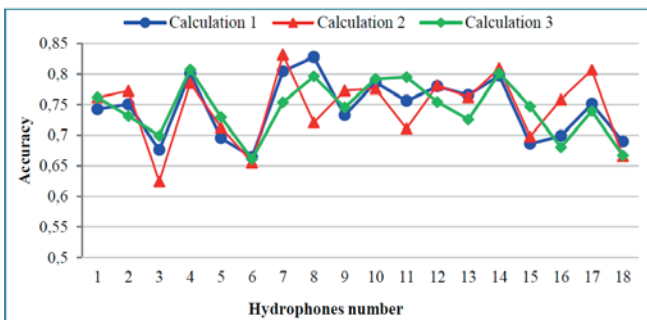

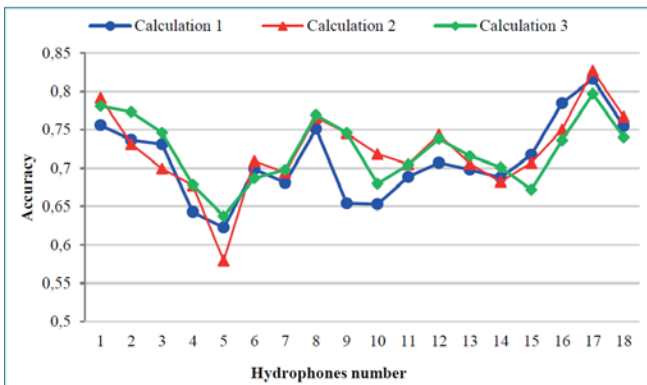*Fig. 7 Classification Accuracy of Two Data Groups under Station 4*

Fig. 8 Classification Accuracy of Two Data Groups under Station 5

The classification performance of the two data groups under Station 1 and Station 2 was good, while classification accuracy decreased as the SNR decreased. The mean values under Stations 3, 4, and 5 were 0.8948, 0.7444, and 0.7182, respectively. In order to enhance classification accuracy, the signals of the 18 hydrophones at Stations 3, 4, and 5 were combined (i.e., in the data selection process, the signals were not selected from a single hydrophone but from 18 hydrophones evenly and respectively by using the same time point). The classification experiment at each station was performed five times. The classification results are shown in Figure 9, plotted by classification number on the horizontal axis and accuracy on the vertical axis.
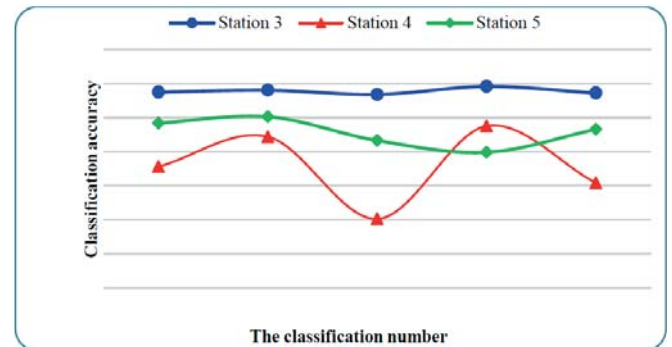

Fig. 9 Combined Classification Results of 18 Hydrophones under Three Stations

Compared with single hydrophone classification, the combined results of the signals in 18 hydrophones greatly enhanced the accuracy under stations 4 and 5 (Figs. 6–9). The average value under Station 3 increased from 0.8948 to 0.9977, that under Station 4 increased from 0.7444 to 0.9757, and that under Station 5 increased from 0.7181 to 0.9856. The percentage of increase in classification accuracy was 11.5, 31.1, and 37.2%, respectively. On this basis, we analysed the results. The EMD algorithm was adapted to select 10,000 sampling points in the 5th hydrophone corresponding to Group 2 Station 3, and the 12-dimension IMF was extracted (Figs. 10–12). It can be seen that the main feature of the acoustic signal focuses on the 1–4-dimension IMF and the signal feature decreases gradually in the 5–8-dimension IMF, while there is almost no signal feature in the 9–12-dimension IMF. If we want to classify the acoustic signal data in each hydrophone, each IMF in the energy set should be analysed individually; however, if we want a comprehensive analysis of the acoustic signal data from all 18 hydrophones, then the LSUASC method is not only able to overlay the feature value of the same IMF, but it also complements the feature values of different IMFs, even if the dimensionality has been reduced. As such, this method can greatly improve the comprehensive classification accuracy of acoustic sensor signals.
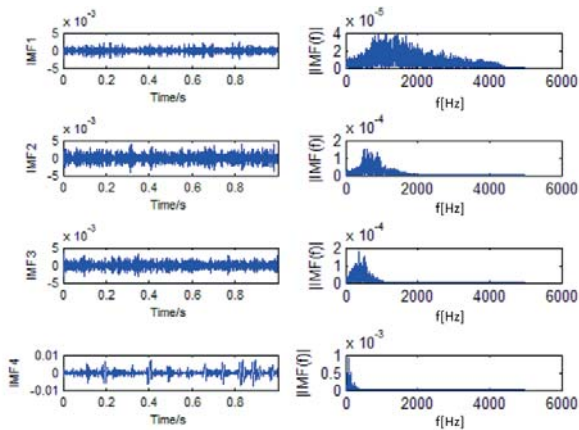
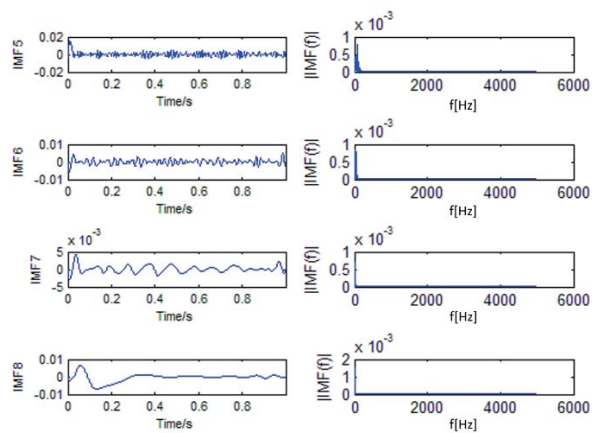*Fig. 10 1–4-dimension IMF and Corresponding Frequency Spectrums*

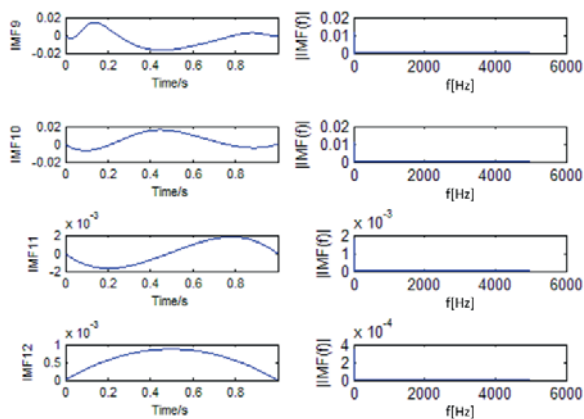*Fig. 11 5－8-dimension IMF and Corresponding Frequency Spectrums*

Fig. 12 9－12-dimension IMF and Corresponding Frequency Spectrums

After analysis of the experimental data, comparison experiments were performed using the same acoustic sensor signal with LSUASC, SVM of work [8] , and BP artificial neural network of work [18]. The experimental results are shown in Figure 13, plotted by station number on the horizontal axis and accuracy on the vertical axis.
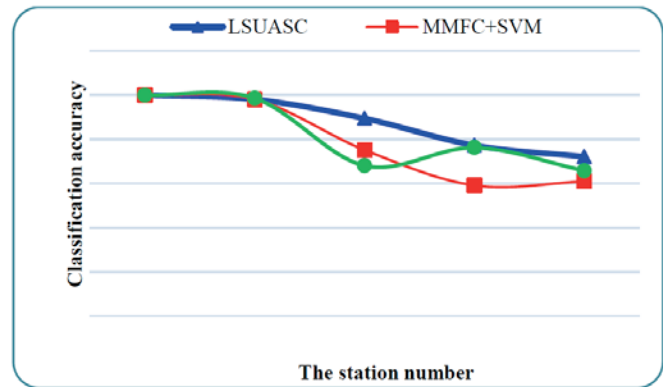

Fig. 13. Classification Accuracy of LSUASC, SVM, and BP nueral network methods

From the analysis of the results in Figures 9 and 13, and the comparison between LSUASC, SVM, and BP methods, we drew the following conclusions:

a) In Stations 1 and 2, the classification accuracy of all the methods tested were high, and there was little difference among them, mainly because the SNR of the acoustic signal was higher under two stations (Station 1: -1.86 dB and Station 2: -16.86 dB), and all these methods made accurate classifications according to the feature differences among the acoustic signals.

b) In Stations 3, 4, and 5, the classification accuracy of the LSUASC method was higher than that of SVM and BP methods for two reasons. On the one hand, in our experiment, a very small target noise was used in an environment with very high background noise, so the SNR of the acoustic signal was low (Station 3: -31.36 dB, Station 4: -41.24 dB, Station 5: -41.53 dB). On the other hand, the processed underwater acoustic signal was characterised by nonlinearity, non-Gaussianity, and nonstationarity; therefore, the LSUASC method was able to extract multiple intrinsic modes of acoustic signals with low SNR. In the process of dimension reduction, it was also able to maintain the sparse and discrete features of low SNR signals effectively, and the FCM method performed well in the classification of the fuzzy feature data set. As such, the performance of the LSUASC method was better than that of SVM and BP.

c) However, it should be mentioned that according to the experiment design , the classification performance of Station 4 should have surpassed that of Station 5, while in fact, the classification performance of Station 5 was better than that of Station 4 under the proposed method and all other methods alike. There may be two reasons for this. First, the SNR of the acoustic signals under these two stations was lower and the difference between them was not so great; and second, the sensitivity of the LSUASC method to acoustic sensor signals with low SNR was decreased.

RIVER EXPERIMENT

We conducted an experiment on the Songhua River to test the ability of the LSUASC method to classify low SNR underwater acoustic signals in a natural environment. In the experiment, two targets (a small boat and a big boat) were used to obtain underwater acoustic signals. We collected three kinds of underwater acoustic signals: (1) when the small boat sailed alone, (2) when the big boat sailed alone, and (3) when the two boats sailed side by side. The experimental equipment layout and station are shown in Figure 14 (with the two boats side by side). The classification results using LSUASC, SVM, and BP are shown in Table 2 and Figure 15.
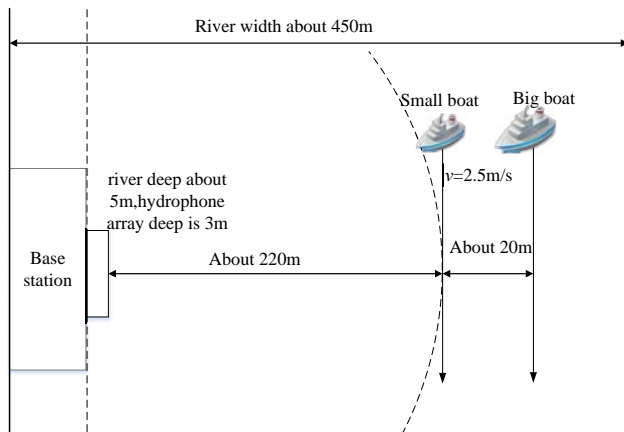
a) Experimental Equipment Layout and Station

b) Small Boat	*c) Big Boat*

Fig. 14. Diagram of Experimental Layout on the Songhua River (a) and Photos of Small (c) and Large (d) Boats used to Collect Underwater Acoustic Signals

Tab. 2. Classification Results as a Function of Signal Processing Method

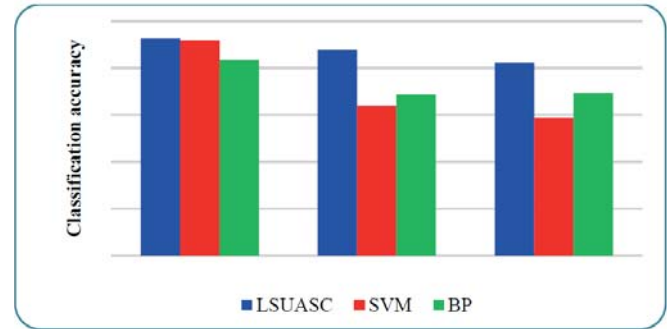|	LSUASC	SVM	BP
Small boat alone	0.9262	0.9165	0.8333
Big boat alone	0.8782	0.6391	0.6865
Two boats together	0.8239	0.5887	0.6931

Fig. 15. Classification Results from Experimental Data Collected on the Songhua River

From Table 2 and Figure 15, we can see that these methods show good results in the classification of the underwater acoustic signals collected by the small boat sailing alone. The highest classification result for the BP method reached 83.33%. However, for the classification results from the big boat sailing alone and the two boats sailing side by side, the target noise features were similar for both these scenarios (big boat alone and 2 boats side by side), we obtained low SNR signals. This is why the LSUASC method obtained better results than the other two methods. The results of the experiment conducted in a natural environment verified the conclusions of the pool experiment while demonstrating the practical use of the proposed LSUASC method.

CONCLUSIONS

As technology advances, target radiation noise will continue to decrease and the SNR of underwater military targets (such as torpedoes, mines, submarines, etc.) will consequently decrease as well, introducing new challenges for research into the classification and recognition of acoustic signals. For low SNR underwater acoustic signals, features such as nonlinearity, non-Gaussianity, and nonstationarity are more prominent, while the target features are discrete, sparse, fuzzy, and weak; therefore, classifying low SNR underwater acoustic signals is a great challenge.

This paper proposes a new method—LSUASC—based on intrinsic modal features maintaining dimensionality reduction. The HHT was adopted for this method by virtue of its suitability for processing nonlinear and nonstationary acoustic signals, and EMD was used to extract the intrinsic modes of the low SNR signals. In addition, MFCCs were used as the feature vector set for low SNR underwater acoustic signal classification and recognition by virtue of its ability to represent the features of underwater noise excitation sources, underwater acoustic channels, and the principle of hearing. The new SSFRLE method was also used to reduce the dimensionality of the feature vector set, and the FCM was used to recognise the weak fuzzy feature data so as to evaluate and classify the low SNR signals. The experiments show that the LSUASC method has higher classification accuracy and feasibility.

In future work, we will mainly focus on how to improve the classification efficiency and decrease the processing time of the LSUASC method. In addition, we hope to prove the feasibility of this method in experiments at sea. We will then adaptively improve LSUASC and SSFRLE in other feature vector sets such as LPCC, LOFAR, and DEMON for low SNR underwater acoustic signal classification.

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