

A Novel Improved Feature Extraction Technique for Ship-radiated Noise Based on Improved Intrinsic Time-Scale Decomposition and Multiscale Dispersion Entropy [†]

Zhaoxi Li ^{1,*}, Yaan Li ^{1,*}, Kai Zhang ^{2,*} and Jianli Guo ³

¹ School of Marine Science and Technology, Northwestern Polytechnical University, Xi'an 710072, China

² Department of Computer and Information of Science and Engineering, University of Florida, Gainesville, FL 32611, USA

³ School of Mathematics and Computer Science, Shaanxi University of Technology, Hanzhong 723001, China; gk2814@163.com

* Correspondence: lizhaoxi@mail.nwpu.edu.cn (Z.L.); liyaan@nwpu.edu.cn (Y.L.); zhangkai6@ufl.edu (K.Z.); Tel.: +86-29-8849-5817 (Y.L.)

[†] Presented at the 5th International Electronic Conference on Entropy and Its Applications, 18–30 November 2019; Available online: <https://ecea-5.sciforum.net/>.

Published: 17 November 2019

Abstract: Entropy feature analysis is an important tool for the classification and identification of different types of ships. In order to improve the limitations of traditional feature extraction of ship-radiation noise in complex marine environments, we proposed a novel feature extraction method for ship-radiated noise based on improved intrinsic time-scale decomposition (IITD) and multiscale dispersion entropy (MDE). The proposed feature extraction technique is named IITD-MDE. IITD, as an improved algorithm, has more reliable performance than intrinsic time-scale decomposition (ITD). Firstly, five types of ship-radiated noise signals are decomposed into a series of intrinsic scale component (ISCs) by IITD. Then, we select the ISC with the main information through correlation analysis, and calculate the MDE value as a feature vector. Finally, the feature vector is input into the support vector machine (SVM) classifier to analyze and get classification. The experimental results demonstrate that the recognition rate of the proposed technique reaches 86% accuracy. Therefore, compared with the other feature extraction methods, the proposed method is able to classify the different types of ships effectively.

Keywords: ship-radiated noise; dispersion entropy (DE); multiscale dispersion entropy (MDE); intrinsic time-scale decomposition (ITD); improved intrinsic time-scale decomposition (IITD); intrinsic scale component (ISC); feature extraction

1. Introduction

Ship-radiated noise signal has always been the active research in the field of underwater acoustic signal processing. It contains a lot of information about ship characteristics and is one of the important signs of ship performance [1–4]. In reference [5], the intrinsic time-scale decomposition (ITD) method has obvious advantages in terms of computational efficiency and processing edge effects. However, the definition of the baseline of the ITD method [6] is based on linear transformation of the signal itself, which may cause glitches and distortion of the proper rotation components obtained by the decomposition. Based on this, we used the akima interpolation [7] to improve the ITD method, and then the improved intrinsic time-scale decomposition (IITD) algorithm is proposed. In this

paper, IITD is employed for ship-radiated noise signal decomposition to extract effective intrinsic scale components (ISCs) from ship-radiated noise signals.

In order to quantify the ship-radiated noise feature information extracted by IITD, we use the multiscale dispersion entropy (MDE) method. The MDE value indicates the complexity of the signal. In reference [5], the fluctuation-based dispersion entropy (FDE) methods [8] are single-scale based, and they fail to account for the interrelationship of entropy and temporal scales. The coarse-graining process has better stability in feature extraction and it can be combined with arbitrary entropy estimators for multiscale analysis. Regarding this advantage, a MDE procedure was put forward to estimate the complexity of the original time series over a range of scales [9].

For resolving these problems, we introduces a novel feature extraction technique for ship-radiated noise based on IITD and MDE, named IITD-MDE. The proposed technique not only retains the advantages of existing techniques but also overcomes the disadvantages of ITD and FDE.

2. Results and Discussion

2.1. Theory of IITD

Because the ITD method uses a linear transformation method to obtain a baseline signal, it caused the waveform to appear with glitches and distortion. Therefore, in order to overcome this shortcoming, we propose an IITD method that replaces the linear transformation in the ITD method with akima interpolation. Although akima interpolation is used, it is different from the envelop mean based on local extrema in empirical mode decomposition (EMD), because IITD only requires one akima interpolation per decomposition.

2.1.1. Baseline Fitting Method

The comparison of the interpolation methods are shown in Figure 1. The proposed method, combined with akima interpolation, can effectively avoid the overshoot and maintain the advantages of cubic spline interpolation. As shown in Figure 1c, this method has a better fitting effect, avoids the phenomenon of “overshoot”, and has better smoothness.

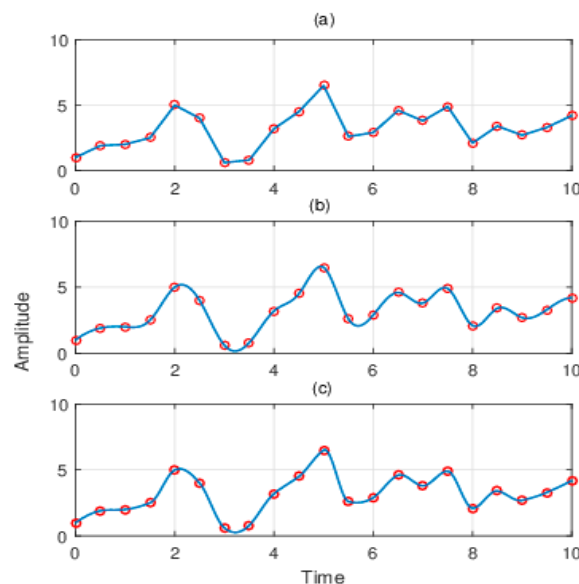


Figure 1. The comparison of the interpolation methods: (a) linear interpolation, (b) cubic spline interpolation, and (c) akima interpolation.

2.1.2. Intrinsic Scale Component (ISC)

In the ITD method, the proper rotation component (PRC) of signal decomposition should satisfy the baseline signal control points $L_{k+1}=0$. Based on this, we define the ISC of the physical meaning of instantaneous frequency and satisfy the conditions as follows:

- (1) Any two adjacent maxima and minima are monotonic in the whole data segment.
- (2) Let $X_k, k=1,2,\dots,M$ denote the extreme points of the whole data segment at time points $\tau_k, k=1,2,\dots,M$, the line connected by any two adjacent maxima points (τ_k, X_k) and minima points (τ_{k+2}, X_{k+2}) , the function value of extreme points (τ_{k+1}, X_{k+1}) at the corresponding time τ_{k+1} is $A_{k+1} = X_k + \left(\frac{\tau_{k+1} - \tau_k}{\tau_{k+2} - \tau_k} \right) (X_{k+2} - X_k)$, and its ratio to X_{k+1} remains the same. These are satisfied as follows: $\alpha \left[X_k + \left(\frac{\tau_{k+1} - \tau_k}{\tau_{k+2} - \tau_k} \right) (X_{k+2} - X_k) \right] + (1-\alpha)X_{k+1} = 0$ and $\frac{A_2}{X_2} = \dots = \frac{A_6}{X_6} = \dots = \mu$, where $\alpha \in (0,1)$ is typically selected as $\alpha = 1/2$. ISC satisfies the conditions, as shown in Figure 2.

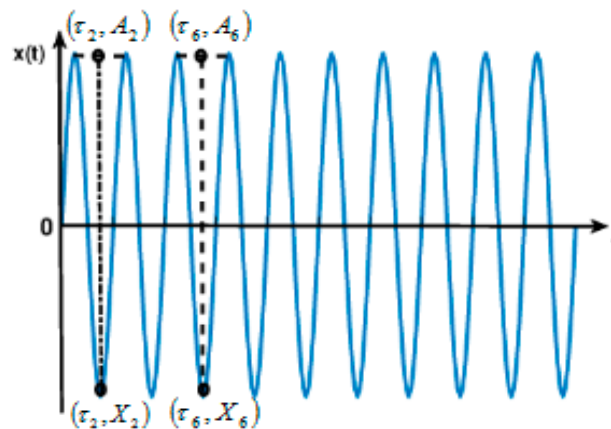


Figure 2. Intrinsic scale component (ISC) satisfies the conditions.

So, the IITD algorithm can be described as $X_t = \sum_{n=1}^n ISC_n + r_n(t)$, where ISC_n is the n th intrinsic scale component (ISC) and $r_n(t)$ is a monotonic trend signal.

2.2. Comparison between ITD and IITD

We apply ITD and IITD to simulation signals. The simulation signals are separately decomposed by ITD and IITD, and the results of the decomposed signals are shown in Figure 3. As seen in Figure 3, the PRC2 of ITD decomposition has obvious deformation and end effect, and the results of decomposition by the IITD method are smoother. In addition, it can be seen from the monotonic trend of signal r that the fitting error of ITD decomposition is also relatively large. Based on the above comparison, the original signal can be decomposed more accurately using the IITD method, which benefits from the akima interpolation. At the same time, it can overcome the waveform distortion caused by the ITD method using linear transform to calculate the baseline signal.

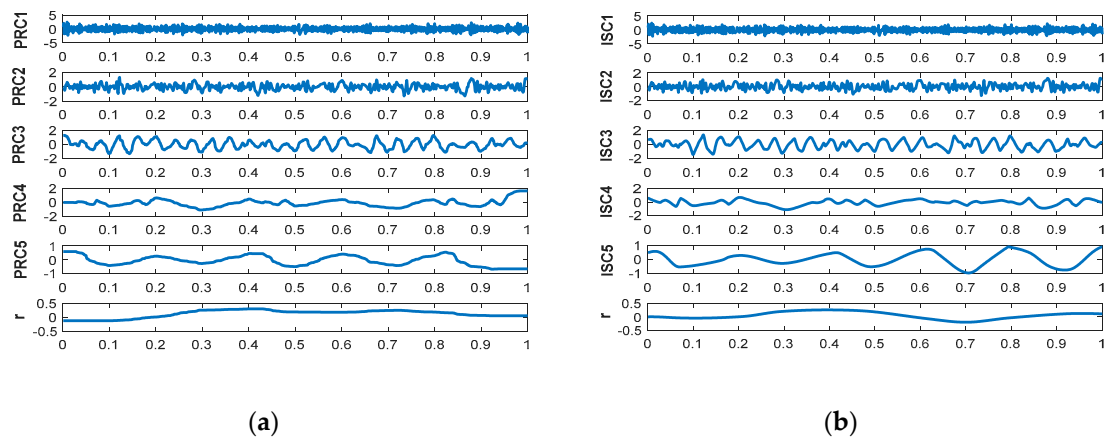


Figure 3. Results of signal obtained by (a) intrinsic time-scale decomposition (ITD) and (b) improved intrinsic time-scale decomposition (IITD).

2.3. Theory of Multiscale Dispersion Entropy

In order to overcome the incomplete problem of extracting the complexity of the signal in single-scale, we propose the MDE method. The coarse-grained process has better stability and the advantage of feature extraction and error calculation of the signal. Figure 4 shows the coarse-grained process.

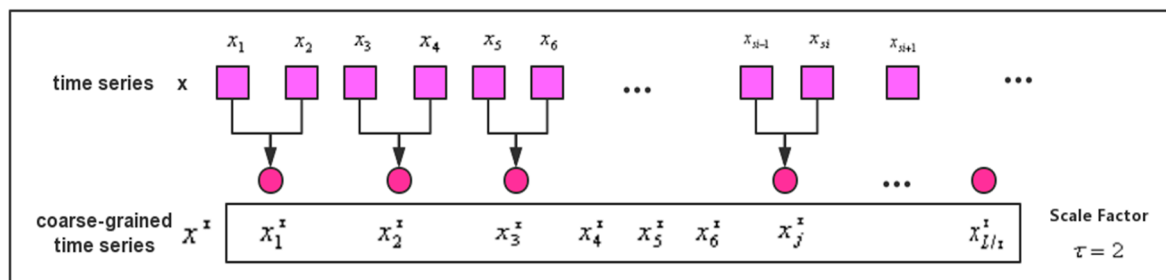


Figure 4. Coarse-grained process.

Under each scale factor, the dispersion entropy of each coarse-grained signal can be calculated by $MDE(x, m, c, d, \tau) = DE(x^{(\tau)}, m, c, d)$.

2.4. Experimental Verification and Analysis

In order to demonstrate the effectiveness of the feature extraction method based on IITD and MDE, all data we used are actual ship-radiated noise signals under the same conditions. Five different types of ship-radiated noise signals were selected as sample data, namely ferry ship, cruise ship, passenger ship, submarine, and ocean liner. For convenience, we respectively name the five ship-radiated noise signals as Ship-A, Ship-B, Ship-C, Ship-D, and Ship-E. The sample rate of Ship-A, Ship-B, and Ship-D are 44.1 kHz. The sample rate of Ship-C and Ship-E are 52,734 Hz. The time domain waveforms are shown in Figure 5.

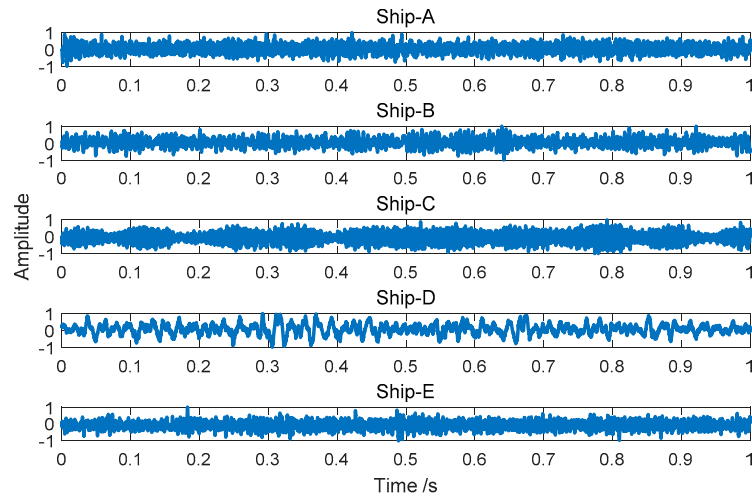


Figure 5. The time-domain waveform of five types of ship-radiated noise signals.

To verify the effectiveness of the proposed feature extraction method, the scale factor of each type of ship-radiated noise signals are selected as 1~20. The IITD-MDE distribution of the five types of ship-radiated noise signals are shown in Figure 6a; the abscissa represents the scale factor and the ordinate represents the feature vector MDE. The results demonstrate that the IITD-MDE value is at the same level for the same ships, but there is an obvious difference for different types of ships. The mean and standard deviation of this method are shown in Figure 7a. The ITD-MDE method results are depicted in Figure 6b. The means and standard deviations of this method are shown in Figure 7b. In order to compare the ITD-MDE method, the experiments were carried out under the same conditions. The results demonstrate that the overall entropy values are lower than the proposed method. It can be concluded that the mean and standard deviations of the proposed feature extraction method are different, while others are close to each other, and the ranges of fluctuations are severely overlapping and non-separable. It indicates that the proposed feature extraction is reliable and is better at distinguishing ship-radiated noise signals.

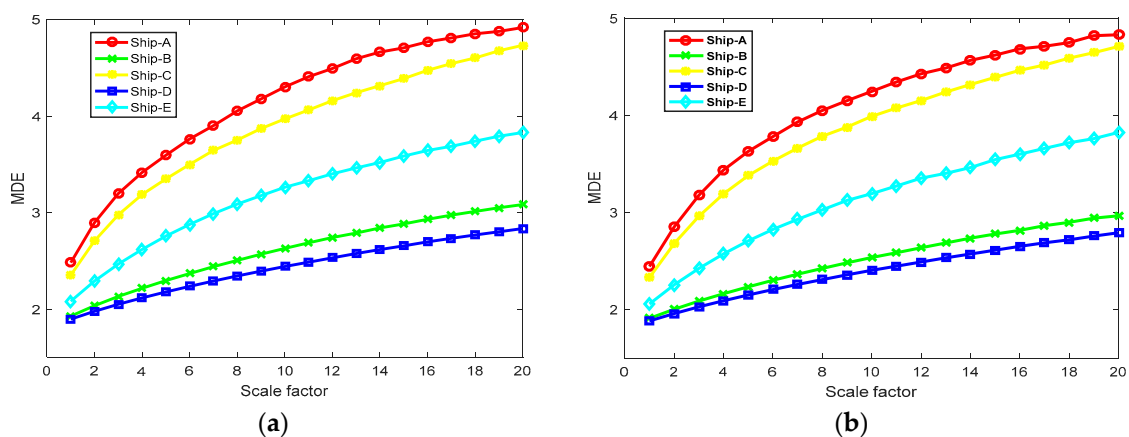


Figure 6. The results of the feature extraction method: (a) IITD-MDE, (b) ITD-MDE.

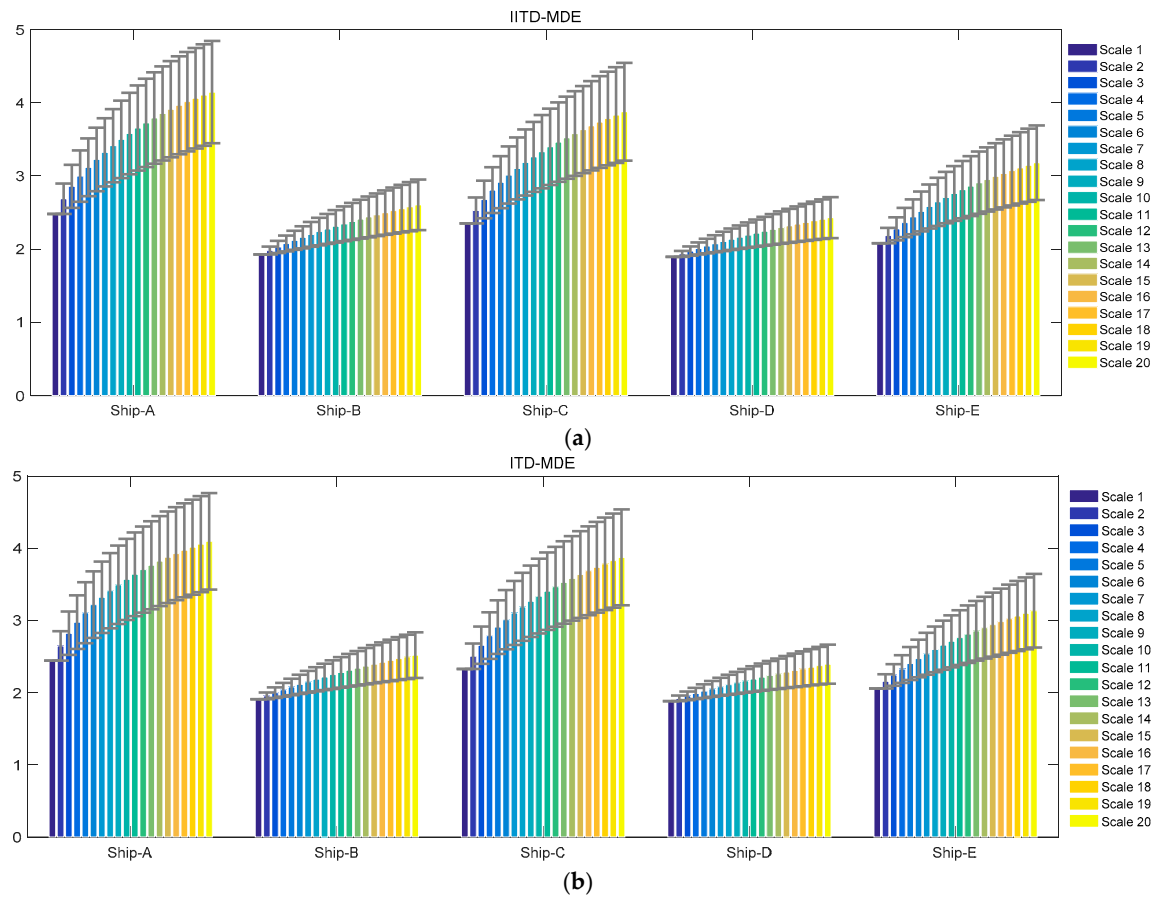


Figure 7. Error bar graph of these method: (a) improved intrinsic time-scale decomposition-multiscale dispersion entropy (IITD-MDE), (b) intrinsic time-scale decomposition-multiscale dispersion entropy (ITD-MDE).

To implement the automatic identification of ship-radiated noise, the extracted features were inputs into the support vector machine (SVM) [10] for training and testing. For each type of ship-radiated noise, 10 samples were used as the training set and the remaining 10 samples were used as the test set. To compare classification accuracy, the ITD-MDE method was also used to classify ship-radiated noise. The outputs of the SVM using these two methods as the feature extractor are shown in Figure 8, and the recognition accuracies are listed in Table 1. Compared with the ITD-MDE methods, the classification accuracy of the proposed method reaches 86%. The results indicate that the proposed method can better classify the five types of ship-radiated noise.

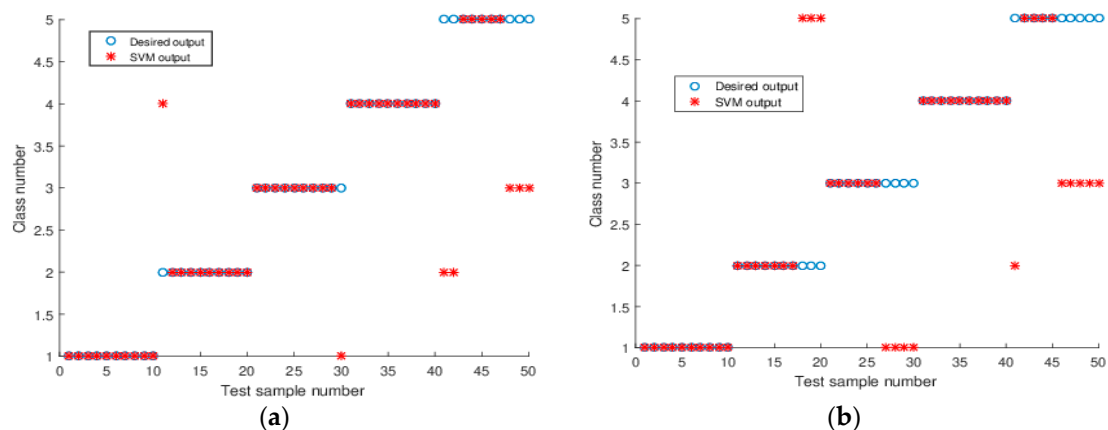


Figure 8. Support vector machine (SVM) classification results of different methods: (a) the proposed method, (b) the ITD-MDE method.

Table 1. SVM classification results of different methods.

Methods	Accuracy Rate
The proposed method	86%
The ITD-MDE method	74%

3. Conclusions

To improve the recognition accuracy of ship-radiated noise signals, a novel feature extraction method based on IITD and MDE was proposed. The main contribution of this paper are highlighted as follows:

- (1) An improved ITD algorithm for ship-radiated noise signal was put forward for the first time in this paper.
- (2) A novel feature extraction algorithm was proposed using IITD and MDE for ship-radiated noise signals in the field of underwater acoustic signal processing.
- (3) We compared IITD with ITD in the simulation experiments. It was found that IITD overcomes the defect of waveform distortion caused by the ITD method using linear transform to calculate the baseline signal. So, the IITD algorithm is better at extracting the baseline signal.
- (4) We conducted simulation experiments to demonstrate that MDE has the advantage of dispersion entropy (DE), which results in more robust results when dealing with noisy signals. Therefore, we applied the MDE method to the underwater acoustic signal processing.
- (5) When compared with other extract feature methods, IITD-MDE is more precise and comprehensive when extracting the characteristics of ship-radiated noise signals. The classification recognition rate for five types of ship-radiated noise signals was 86%.

Author Contributions: Z.L. designed the project and wrote the manuscript; Y.L., K.Z., and J.G. helped to revise the manuscript. All co-authors reviewed and approved the final manuscript. All authors have read and agreed to the published version of the manuscript.

Funding: The authors gratefully acknowledge the support received from the National Natural Science Foundation of China (No. 11874302, No. 11574250, and No. 51179157).

Conflicts of Interest: The authors declare no conflict of interest.

References

1. Wang, S.; Zeng, X. Robust underwater noise targets classification using auditory inspired time-frequency analysis. *Appl. Acoust.* **2014**, *78*, 68.
2. Wu, Z.; Huang, N.E. A study of the characteristics of white noise using the empirical mode decomposition method. *Proc. R. Soc. A Math. Phys. Eng. Sci.* **2004**, *460*, 1597–1611.
3. Li, Y.; Li, Y.; Chen, X.; Yu, J. Feature extraction of ship-radiated noise based on VMD and center frequency. *J. Vib. Shock* **2018**, *37*, 213–218.
4. Yang, H.; Li, Y.; Li, G. Energy analysis of ship-radiated noise based on ensemble empirical mode decomposition. *J. Vib. Shock* **2015**, *34*, 55.
5. Li, Z.; Li, Y.; Zhang, K. A Feature Extraction Method of Ship-Radiated Noise Based on Fluctuation-Based Dispersion Entropy and Intrinsic Time-Scale Decomposition. *Entropy* **2019**, *21*, 693.
6. Frei, M.G.; Osorio, I. Intrinsic time-scale decomposition: Time–frequency–energy analysis and real-time filtering of non-stationary signals. *Proc. R. Soc. A Math. Phys. Eng. Sci.* **2007**, *463*, 321–342.
7. Bica, A. M.; Degeratu, M.; Demian, L.; Paul, E. Optimal Alternative to the Akima’s Method of Smooth Interpolation Applied in Diabetology. *Surv. Math. Appl.* **2006**, *1*, 41–49.
8. Rostaghi, M.; Azami, H. Dispersion Entropy: A Measure for Time Series Analysis. *IEEE Signal Process. Lett.* **2016**, *23*, 610–614.

9. Azami, H.; Escudero, J. Coarse-Graining Approaches in Univariate Multiscale Sample and Dispersion Entropy. *Entropy* **2018**, *20*, 138.
10. Dagher, I.; Azar, F. Improving the SVM gender classification accuracy using clustering and incremental learning. *Expert Syst.* **2019**, *36*, e12372.



© 2019 by the authors. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (<http://creativecommons.org/licenses/by/4.0/>).