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# An entropy clustering method for blades biofouling detection of marine current turbine under variable marine current speeds

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**Abstract**—Marine current turbine (MCT) attracts extensive attention as a renewable energy power generation equipment. However, accurate and reliable blades biofouling detection for MCT remains a significant challenge, especially under variable marine current speed. This paper proposes an entropy clustering method to improve the detection accuracy of blades biofouling for MCT under variable marine current speed. Firstly, the stator current signal is decomposed based on variational mode decomposition (VMD) to enlarge the feature of blades biofouling. Secondly, to eliminate the influence of swell effect, fluctuating features caused by swell effect are divided into each subspace based on the proposed entropy clustering method. At the last stage, principal component analysis models (PCA) are established in each feature subspace to detect blades biofouling. To verify the effectiveness of the proposed method, experiments are carried out on a 230W MCT platform. The results show that the proposed method has satisfactory performance for blades biofouling detection under variable marine current speed.

**Keywords**—Marine current turbine, Blades biofouling detection, variable marine current speed, Entropy clustering method, Principal component analysis

## I. INTRODUCTION

Tidal energy is sustainable and has advantages of clean, reliable, high energy density, and predictable [1]. Marine current turbine (MCT) has attracted more and more attentions. However, MCT commonly works in harsh surroundings, such as humidity, corrosion and heavy salt spray. Sediment and organisms are easily attached to blades [2], which decrease the working efficiency of MCT, and destroy components of the system in severe cases. In addition, with the influence of variable marine current speed due to the swell effect [3], the rotor speed of MCT may oscillate continuously under classical MPPT strategy [4]. It further causes the irregular fluctuating amplitude and the frequencies feature of blades biofouling on stator current [5], which increases the difficulty of blades biofouling detection, even leads to misdetection when the trained detection model is applied to variable marine current speed. Therefore, it is necessary to consider the difficulties of blades biofouling detection caused by variable marine current speed in practical applications.

At present, many fault detection methods for MCT have been proposed. Xie et al. [6] reviewed different blades biofouling detection methods for MCT in terms of sensor-based and sensorless-based methods. In [7], vibration sensors are installed to obtain vibration signals for detecting the faults. In [8], underwater cameras are installed to obtain image signals for detect blade imbalance fault of MCT. However, these sensors need to be impervious and robust to environmental interference. Some research are carried out by using current and voltage signals. Empirical Mode Decomposition (EMD) and variational mode decomposition (VMD) are used to detect blades biofouling in [9,10]. However, there are still some problems such as the end effect and the modal confusion. Xie et al. [11] proposed a blades biofouling detection method based on principal components analysis (PCA) and frequency sequences subtraction (FSS). This method improves the accuracy of detection but traditional confidence limit is not applicable under variable marine current speed. All methods mentioned above have made significant contributions to blades biofouling detection under steady marine current speed, but the statistical features of blades biofouling are fluctuated due to swell effect, which lead to misdetection when the blades biofouling detection method under steady marine current speed directly applied to variable marine current speed.

Therefore, this paper analyzes the stator current signal and proposes an entropy clustering (EC) method is proposed to divide fluctuating features for MCT under variable marine current speed. Specifically, the main contributions of this paper are as follows:

- 1) To eliminate the influence of swell effect, fluctuating features are divided into subspaces, and blades biofouling were detected in each feature subspace.
- 2) An entropy clustering method is proposed to divide fluctuating features. This method selects central sample of each subspace by mutual information entropy, which have satisfactory performance.
- 3) The experimental data under the varying marine current speed condition are collected from a 230W marine current turbine prototype to verify the effectiveness of the proposed method.

The rest of this paper is organized as follows. The problem of blades biofouling detection under variable marine current speed is described in Section 2. The proposed method is described in Section 3. A case study is implemented in Section 4. The conclusion is summarized in Section 5.

## II. PROBLEM DESCRIPTION

### A. Effect of blades biofouling for stator current signal

MCT captures part of tidal energy and convert it into output mechanical torque to drive PMSG for generating electrical power [12]. The stator current under healthy state can be expressed as:

$$i_s(t) = A_i \sin(\sigma\omega_r t + \varphi) \quad (1)$$

where  $A_i$  denotes the amplitude of stator current,  $\varphi$  denotes the initial phase,  $\sigma$  denotes the number of pole pairs,  $\omega_r$  denotes the shaft rotation angular speed of MCT, and  $f_r = \omega_r/2\pi$  denotes the shaft rotating frequency.

The torque of MCT is distorted under the blades biofouling state, it can be equivalent to attaching a virtual mass  $m$  to one of the blades. As shown in Fig. 1, buoyancy  $F_b$  and gravity  $mg$  of the mass produce an additional torque. The rotating speed of bearing changes with torque, the shaft rotation angular speed with blades biofouling can be expressed as [11]:

$$\omega_n = \omega_r - \varepsilon \cos(\omega_r t + \varphi) \quad (2)$$

where  $\varepsilon$  denotes the coefficient of blades biofouling:

$$\varepsilon = \frac{(mg - F_b)r_u}{J\omega_r} \quad (3)$$

where  $J$  is the moment of inertia,  $r_u$  denotes the distance between the mass and the centroid of the shaft. The stator current of MCT under blades biofouling state can be expressed as follows [2]:

$$\begin{aligned} i_b(t) &= A_b \sin \left[ \int \sigma\omega_n d\tau \right] \\ &= A_b \sin \left[ \sigma\omega_r t - \frac{\sigma\varepsilon}{\omega_r} \sin(\omega_r t + \varphi) \right] \end{aligned} \quad (4)$$

where  $A_b$  denotes the amplitude of stator current under blades biofouling state.

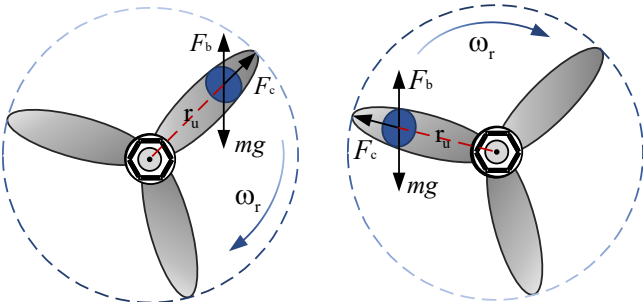


Fig. 1. Equivalent diagram of blades biofouling

The instant frequency of stator current under blades biofouling state can be expressed as follows:

$$f(t) = \frac{1}{2\pi} \frac{\partial}{\partial t} \left[ \int \sigma\omega_n d\tau \right] = \sigma f_r - \frac{\sigma\varepsilon}{2\pi} \cos(2\pi f_r t + \varphi) \quad (5)$$

According to Eq (5), an excitation of the same frequency as  $f_r$  are contained in stator current signal under blades biofouling state [13], which is different from the stator current signal under healthy state. Therefore, the shaft rotation frequency  $f_r$  can be used as the blades biofouling feature of MCT under steady marine current speed.

### B. Effect of swell effect for stator current signal

MCT operates on the seabed, and its operating conditions are largely affected by the variable marine current speed. To simulate the operation of MCT on the seabed, Zhou et al. [7] calculated the total current velocity through the combination of predictable tidal speed  $V_{\text{tide}}$  and swell effect  $V_{\text{swell}}$  as shown in Fig 2. The predictable tidal speed  $V_{\text{tide}}$  is a constant, and the swell effect  $V_{\text{swell}}$  contains more than one frequency component, which makes the marine current speed changes variably.

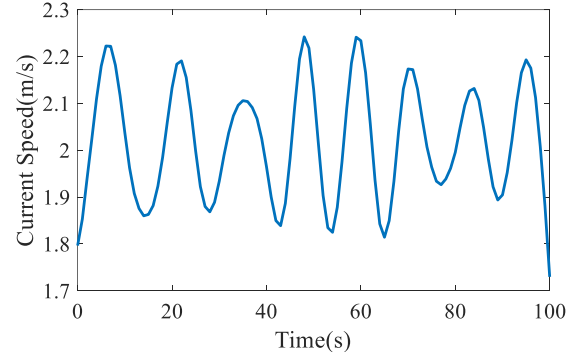


Fig. 2. The simulated waveform of the total current velocity

It can be seen that the swell effect causes oscillations of marine current speed within a given depth, and the marine current speed affects the shaft rotating speed of MCT [7]. In this situation, the shaft rotating speed as follows:

$$\omega_{rv} = \frac{\lambda V_{\text{current}}}{R} = \frac{\lambda(V_{\text{tide}} + V_{\text{swell}})}{R} = \omega_r + \sum_i \omega_{vi} \quad (6)$$

where  $R$  is the blade radius of MCT,  $\lambda$  is the blade tip speed ratio,  $\omega_{vi}$  is the shaft rotating speed fluctuating caused by the  $i$ th component of swell effect  $V_{\text{swell}}$ .

It can be seen that the varying marine current speed leads to fluctuations of shaft rotating speed. According to Eq. (4), the stator current under variable marine current speed of MCT with blades biofouling can be expressed as:

$$i_{rv}(t) = A_b \sin \left[ \sigma\omega_{rv} t - \frac{\sigma\varepsilon}{\omega_{rv}} \sin(\omega_{rv} t + \varphi) \right] \quad (7)$$

The instant frequency of stator current with blades biofouling under variable marine current speed can be expressed as:

$$f_{rv}(t) = \sigma(f_r + \sum_i f_{vi}) - \frac{\sigma\varepsilon}{2\pi} \cos(2\pi(f_r + \sum_i f_{vi})t + \varphi) \quad (8)$$

where  $f_{rv}$  is the instant frequency of stator current under variable current speed, and  $f_{vi}$  is instant frequency fluctuating caused by the  $i$ th component of swell effect.

To sum up, the blades biofouling frequency feature of MCT under steady marine current speed is  $f_r$ , but under variable marine current speed is  $f_r + \sum_i f_{vi}$ . There are variable frequency fluctuations  $\sum_i f_{vi}$  under variable marine current speed, which increases the difficulty of blades biofouling detection.

### III. THE PROPOSED BLADES BIOFOULING DETECTION METHOD

The proposed method is composed of three parts: (1) To enlarge the feature of blades biofouling, the stator current signal is decomposed based on Hilbert transform (HT) and VMD. (2) To eliminate effects of variable marine current speed, the fluctuating features are divided based on the proposed entropy clustering method. (3) PCA models are established in each subspace to detect blades biofouling. Details are elaborated in the following paragraphs.

#### A. Stator current pre-processing based on HT and VMD

The stator current in one phase of the generator under variable marine current speed collected from MCT is  $i_r(t)$ , and the instantaneous frequency  $f_{rv}(t)$  of  $i_r(t)$  can be obtained by HT [14]. Then, the instantaneous frequency  $f_{rv}(t)$  is decomposed into intrinsic mode functions (IMFs) denoted as  $u_q(t)$  ( $q=1,2,\dots,K_K$ ) with the number  $K_K$  based on VMD. They can be expressed as:

$$u_q(t) = A_q(t) \cos(\omega_q(t)) \quad (9)$$

where  $u_q(t)$  denotes the  $q$ th IMF,  $A_q(t)$  denotes the instantaneous amplitude of the  $q$ th IMF,  $\omega_q(t)$  denotes the instantaneous frequency of the  $q$ th IMF. And then, the IMF <sub>$r$</sub>  contained blades biofouling feature is selected by the maximum correlation coefficient [15] between IMFs and instantaneous frequency  $f_{rv}(t)$ .

#### B. Fluctuating features division based on the proposed entropy clustering method

The IMF <sub>$r$</sub>  obtained after VMD decomposition is windowed to obtain a sample matrix  $\mathbf{f}=[f_1, f_2, \dots, f_{K_f}]$ , and  $K_f$  is the number of samples. To ensure the frequency information is not lost, the length of the window is chosen to be 3000 in this paper, that is, samples contain 3000 sampling points. The number of feature subspaces  $K_1$  ( $K_1=1,2,3,\dots$ ) and  $K_1$  central samples are randomly selected as the initial central samples of each feature subspace. And then, divide all samples into their subspace according to the principle that the distance between each sample and the randomly selected central sample of the subspace is minimum:

$$\gamma^{(i)} = \arg \min \|f_j - v_i\|^2 \quad (i=1,2,\dots,K_1, j=1,2,\dots,K_f) \quad (10)$$

where,  $\gamma^{(i)}$  is the sample matrix of the  $i$ th feature subspace and  $v_i$  is the central sample of the  $i$ th feature subspace, the feature subspace  $\gamma = [\gamma^{(1)} \ \dots \ \gamma^{(K_1)}]$  can be formed.

Then, the central samples of each subspace are selected based on Mutual Information Entropy (MIE). Denote  $\gamma_a^{(i)}$  and  $\gamma_b^{(i)}$  ( $a,b=1,2,\dots,K_i$ ) are independent samples of subspace  $\gamma^{(i)}$ ,  $K_i$  is the number of samples of subspace  $\gamma^{(i)}$ . The mutual information entropy (MIE) [16,17] between samples  $\gamma_a^{(i)}$  and  $\gamma_b^{(i)}$  can be expressed as follows:

$$I(\gamma_a^{(i)}, \gamma_b^{(i)}) = \sum_{\gamma_a^{(i)} \in \gamma^{(i)}} \sum_{\gamma_b^{(i)} \in \gamma^{(i)}} p(\gamma_a^{(i)}, \gamma_b^{(i)}) \log_2 \left( \frac{p(\gamma_a^{(i)}, \gamma_b^{(i)})}{p(\gamma_a^{(i)})P(\gamma_b^{(i)})} \right) \quad (12)$$

where  $p(\gamma_a^{(i)}, \gamma_b^{(i)})$  represents the joint distribution probability,  $p(\gamma_a^{(i)})$  denote the probability of the sample  $\gamma_a^{(i)}$  to be the subspace centroid, and  $p(\gamma_b^{(i)})$  denote the probability of the sample  $\gamma_b^{(i)}$  to be the subspace centroid.

The MIE of each sample can be expressed by summing, which expressed as follows:

$$I(\gamma_a^{(i)}) = \sum_{b=1}^{K_i-1} I(\gamma_a^{(i)}, \gamma_b^{(i)}), (a \neq b) \quad (13)$$

And then, the selected centroid of subspace  $\gamma^{(i)}$  can be expressed as:

$$v_{\text{MIE}}^{(i)} = \gamma^{(i)} \left[ \min I(\gamma_a^{(i)}) \right] \quad (14)$$

where  $v_{\text{MIE}}^{(i)}$  denotes the central sample of subspace  $\gamma^{(i)}$  selected by MIE.

Iterate the above process to the minimum value of the objective function (Eq.(10)). The blades biofouling feature subspace  $\gamma_{\text{MIE}} = [\gamma_{\text{MIE}}^{(1)} \ \dots \ \gamma_{\text{MIE}}^{(K_1)}]$  can be obtained, when the value of the objective function is extremely small. Then, the number of subspaces  $K$  is determined by the index of  $S\_Dbw$  [18]:

$$S\_Dbw_{K_1} = Scat_{K_1} + Dens\_bw_{K_1} \quad (15)$$

where  $Scat_{K_1}$  and  $Dens\_bw_{K_1}$  are the compactness within the working condition and the density between working conditions. In this way, the optimal number of subspaces  $K$  can be obtained. The blades biofouling features of MCT can be divided into  $K$  subspaces  $\gamma_{\text{MIE}} = [\gamma_{\text{MIE}}^{(1)} \ \dots \ \gamma_{\text{MIE}}^{(K)}]$ .

#### C. Blades biofouling detection based on PCA

Correspondingly, the IMF <sub>$r$</sub>  containing fault features are divided into each subspace through the proposed entropy clustering method. And then, PCA models [19] are established in each subspace to realize the detection of blades biofouling

by using frequency domain signals. The  $T^2$  statistics and  $SPE$  statistics of the  $l$ th feature subspace are expressed as follows:

$$T_l^2 = \mathbf{f}_{\text{MIE}}^{(l)T} \mathbf{W}_l \mathbf{\Lambda}^{-1} \mathbf{W}_l^T \mathbf{f}_{\text{MIE}}^{(l)} \leq T_{al}^2 \quad (16)$$

$$SPE_l = \mathbf{f}_{\text{MIE}}^{(l)T} (1 - \mathbf{W}_l \mathbf{W}_l^T)^T (1 - \mathbf{W}_l \mathbf{W}_l^T) \mathbf{f}_{\text{MIE}}^{(l)} \leq \delta_{al}^2 \quad (17)$$

where  $\mathbf{f}_{\text{MIE}}^{(l)}$  is the frequency domain matrix of the feature matrix  $\mathbf{r}_{\text{MIE}}^{(l)}$  in the  $l$ th subspace and  $l=1,2,\dots,K$ ,  $\mathbf{W}_l$  is the projection matrix under the  $l$ th subspace,  $T_l^2$  and  $SPE_l$  are the statistics of the  $l$ th subspace,  $T_{al}^2$  and  $\delta_{al}^2$  are the confidence limit of  $T^2$  statistic and  $SPE$  statistic in the  $l$ th subspace, respectively. If the statistics exceeds their confidence limit, we assume that the MCT blade is biofouling and imbalanced.

#### D. Implementation procedures of the blades biofouling detection method

For blades biofouling detection using stator current signal of MCT under variable marine current speed, a specific method is proposed. The flow chart of the blades biofouling detection method is shown in Fig. 3.

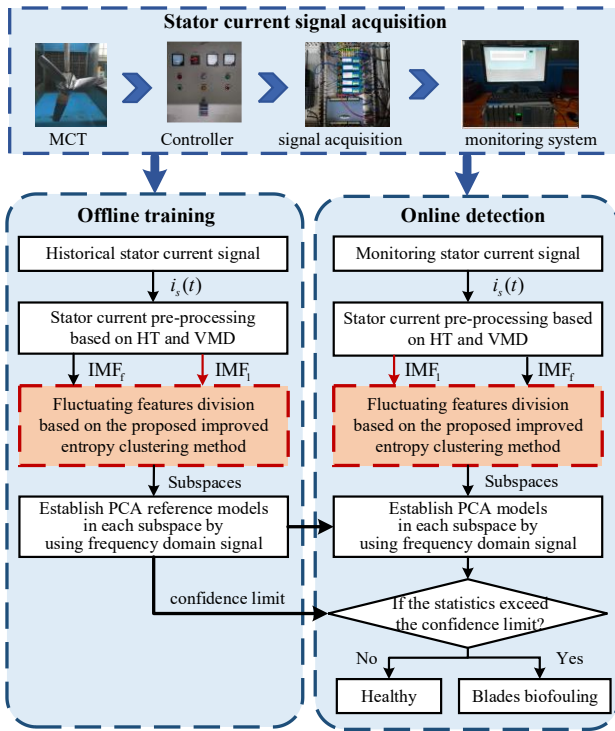


Fig. 3. The flow chart of the blades biofouling detection method

The stator current signal under variable marine current speed is collected from the MCT experiment platform. And the proposed method contains 3 steps as follows:

Step1: To enlarge the feature of blades biofouling, the stator current signal is preprocessed based on HT and VMD.

Step2: The fluctuating features of  $\text{IMF}_1$  and  $\text{IMF}_f$  are divided in  $K$  subspaces based on the proposed entropy clustering method. The proposed entropy clustering method selects central samples of each subspace based on mutual

information entropy and the number of subspaces is determined by the index of  $S_{Dbw}$ .

Step3: Establish PCA models in each subspace to detect blades biofouling for MCT by using frequency domain feature of  $\text{IMF}_f$ . As eq.(16) and eq.(17), if the statistics exceed the corresponding confidence limit, it indicates that the biofouling of blades for MCT has been detected.

## IV. EXPERIMENTS ANALYSIS

### A. Experiment platform

To verify the effectiveness of the proposed method, the stator current signal was collected on a 230W direct-drive permanent magnet synchronous MCT experimental platform. As shown in Fig. 4, the experimental platform contains four parts: turbine, direct-drive permanent magnet synchronous generator, data acquisition and states monitoring system, with the water pump system to control the water flow speed and for emulating swell effect. The sampling frequency of the data acquisition and states monitoring system is 1kHz, and the specific parameters of the experimental system are described in [11].

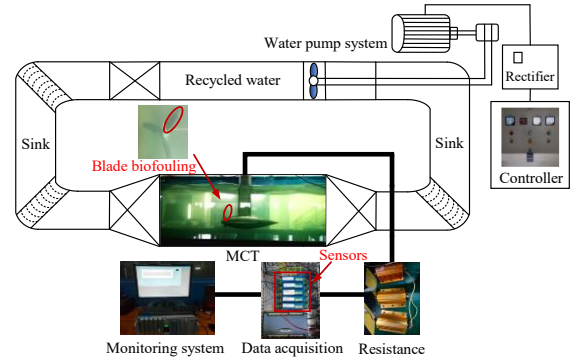


Fig. 4. The structure of the experimental platform

In the experiment, the blades biofouling is emulated by winding ropes with 80g at the root of the blade. As shown in the Fig. 9, Fig. 9 (a) is the MCT in healthy state, and Fig. 9 (b) is the MCT in the simulated blades biofouling state.

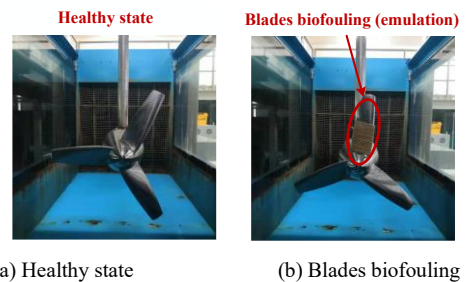


Fig. 5. Simulated blades biofouling of MCT in experiment

### B. Experimental results and analysis

To verify the effectiveness and the applicability of the proposed method, this paper randomly selects stator current signal under variable current speed (Shaft rotation speed is 15.9, 16.8 and 17.8 rpm). The collected stator current signal is preprocessed based on Hilbert transform and VMD to enlarge the feature of blades biofouling and improve the accuracy of blades biofouling detection. The stator current signal under healthy state and blades biofouling state is transformed to the time-frequency domain, time-frequency signal under healthy state shown in Fig. 6. And then, the instantaneous frequency

signal is decomposed into 5 components (IMF1, IMF2, ..., IMF5) by VMD, as shown in Fig. 7.

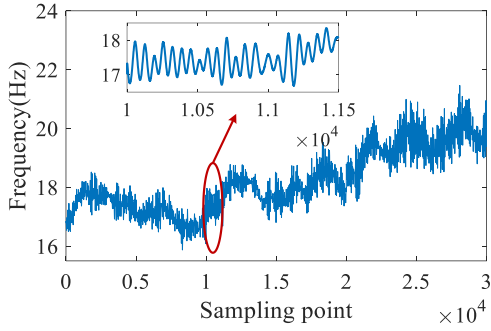


Fig. 6. The instantaneous frequency signal

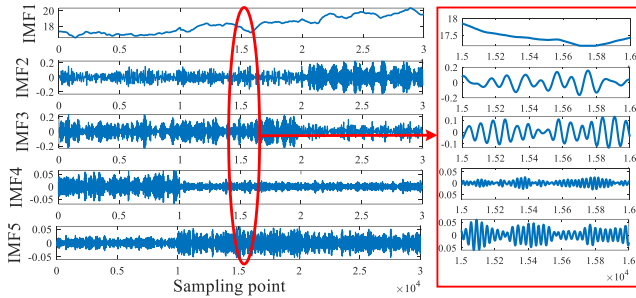


Fig. 7. The decomposed signal based on VMD

The IMF1 obtained by VMD decomposition is windowed to obtain sample matrix, the length of the window is chosen to be 3000 in this paper, that is, samples contain 3000 sampling points. Then all samples are divided into each subspace based on the proposed entropy clustering method. The centroids of each subspace are selected based on MIE, which is shown in Fig. 8. And the values of the  $S\_Dbw$  with different number of subspaces are shown in Table I. The index of  $S\_Dbw$  is the smallest one, when the number of subspaces is 3.

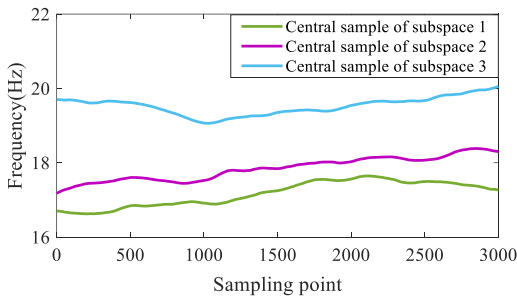


Fig. 8. The central samples of 3 feature subspace

TABLE I. THE INDEX OF DIFFERENT NUMBER OF SUBSPACES

The number of feature subspaces	The index of $S\_Dbw$
2	1.3372
3	<b>1.1759</b>
4	Null
5	Null

The fluctuating features division results are obtained and the visualization is shown in Fig. 9.

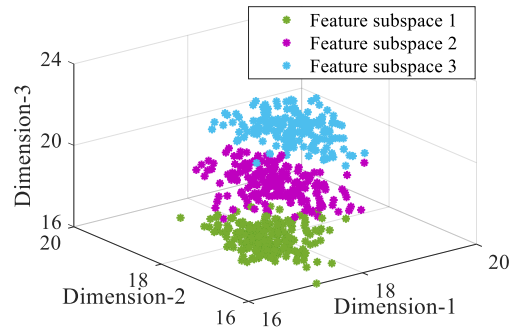


Fig. 9. The visualization of 3 feature subspace division

After fluctuating features division, PCA models are established in subspace 1-3 to detect blades biofouling. Fig. 10 shows the detection results in subspace 1-3. The training set of each PCA model is 100 healthy samples, and in test set, the samples 1-100 are under healthy state and the samples 101-200 are under blades biofouling state. This method makes the confidence limit and statistic correspond entirely in each feature subspace, and dramatically improves the accuracy of blades biofouling detection under variable marine current speed.

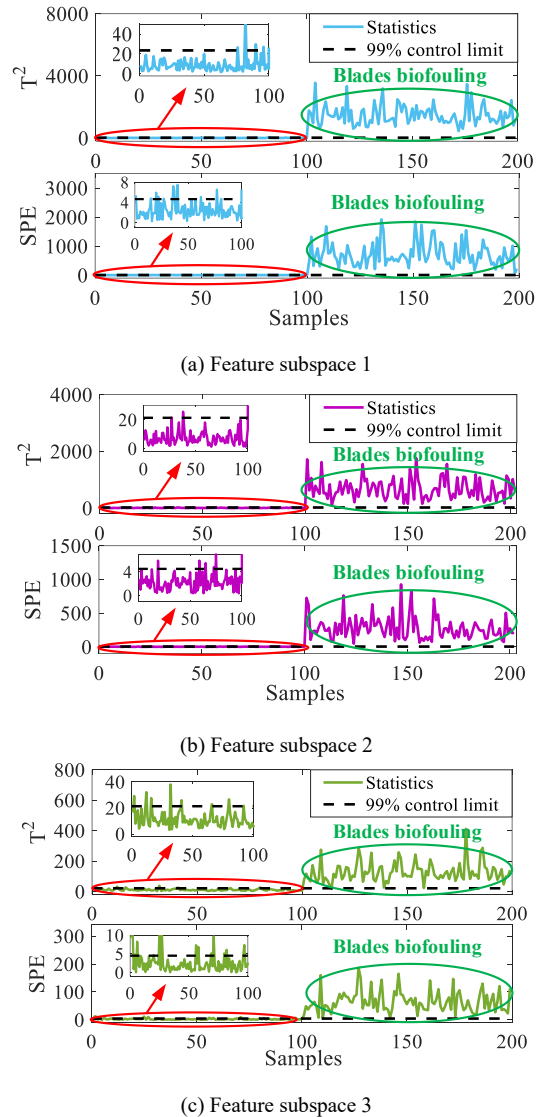


Fig. 10. Blades biofouling detection results of each feature subspace

Table II shows the accuracy of blades biofouling detection based on different methods. The accuracy of blades biofouling detection by using the proposed entropy clustering (EC) method is 96.70%. The accuracy of blades biofouling detection by using PCA without feature division is 62.31%. The detection based on the PCA method without dividing features is unsatisfactory when the MCT works under variable marine current speed. The blades biofouling detection by using the combination of PCA with KNN and K-means method for fluctuating feature division still need to be improved in detection accuracy and efficiency. Compared to the methods based on KNN and K-means, the accuracy of the proposed method has been improved by 9.64% and 13.45%, respectively. In addition, the proposed method has greatly reduced the false alarm rate and missed alarm rate, and it takes less time.

TABLE II. THE ACCURACY OF BLADES BIOFOULING DETECTION UNDER VARIABLE MARINE CURRENT SPEED

Method	Detection accuracy	Missed alarm rate	False alarm rate	Computational time
VMD+PCA	62.31%	0%	75.38%	2.0279s
VMD+KNN+PCA	87.06%	17.14%	8.74%	6.7152s
VMD+K-means+PCA	83.25%	0.67%	32.83%	2.1329s
VMD+EC+PCA	<b>96.70%</b>	<b>0.70%</b>	<b>5.90%</b>	<b>3.1952s</b>

## V. CONCLUSIONS

To solve the problem that blades biofouling is difficult to be detected under variable marine current speed due to the fluctuating blades biofouling features. This paper proposes an entropy clustering method to divide fluctuating features. The advantages of the proposed method as follows:

(1) The proposed method detect blades biofouling by using stator current signal of MCT without additional sensors, which has satisfactory performance on stability.

(2) The proposed entropy clustering method selects central sample of each feature subspace by mutual information entropy, which demonstrates satisfactory performance.

(3) It has solid universal applicability in fluctuating features division and blades biofouling detection under variable marine current speed, it can be applied to other fault diagnosis fields with fluctuating features.

An experiment has been performed on an 230W MCT experimental platform to verify the effectiveness of the proposed method. The experimental results show that the proposed method achieved satisfactory performance for blades biofouling detection of MCT under variable marine current speed.

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