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Anchor Fault Identification Method for High-Voltage DC Submarine Cable Based on VMD-Volterra-SVM

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Abstract: This article introduces a new method for identifying anchor damage faults in fiber composite submarine cables. The method combines the Volterra model of Variation Mode Decomposition (VMD) with singular value entropy to improve the accuracy of fault identification. First, the submarine cable vibration signal is decomposed into various Intrinsic Mode Functions (IMFs) using VMD. Then, a Volterra adaptive prediction model is established by reconstructing the phase space of each IMF, and the model parameters are used to form an initial feature vector matrix. Next, the feature vector matrix is subjected to singular value decomposition to extract the singular value entropy that reflects the fault characteristics of the submarine cable. Finally, singular value entropy is used as a feature value to input into the Support Vector Machine (SVM) for classification. Compared with Empirical Mode Decomposition (EMD) and Ensemble Empirical Mode Decomposition (EEMD), the proposed method achieves a higher fault identification accuracy and effectively identifies anchor damage faults in submarine cables. The results of this study demonstrate the feasibility and practicality of the proposed method.

Keywords: submarine cable; anchor damage; Volterra model; fault identification

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1. Introduction

Offshore and deep-sea wind power generation relies heavily on submarine cables for electricity transmission [1]. However, due to the complex marine environment, submarine cables are vulnerable to anchor damage, especially when ships illegally enter prohibited areas. Anchor damage can often cause insulation and armoring damage to submarine cables, and some damage may not become immediately apparent. However, over time, these damages can evolve into faults under the influence of seawater and electric fields, leading to serious consequences [2]. Therefore, the timely identification of submarine cable faults is of great significance for ensuring the safety of energy transmission.

In 2013, Zhang, X. et al., studied the damage to a 110 kV Cross-Linked Polyethylene (XLPE) optical fiber composite submarine power cable under the action of anchor smash [3]; in 2018, Wang, Y. et al., used distributed fiber-optic sensing technology for the anchor damage fault detection of a submarine cable and analyzed its fiber-optic vibration signal [4]; in 2020, Zhang, Z.P. et al., established a 500 kV optical fiber composite submarine power cable anchor smash finite element model and simplified the anchor into a trapezoidal body to study the stress and deformation of each structural layer during anchor smash [5]; and in 2021, Shang Q.F. et al., used finite element analysis to obtain the acceleration data of a submarine cable in the X, Y, and Z directions when it was subjected to anchor smash and studied the vibration characteristics of the submarine cable under the action of anchor smash [6]. For the study of feature extraction and fault identification of the submarine cable anchor damage vibration signal, in 2021, Zheng used ESMD (Extreme-Point Symmetric Mode Decomposition) to perform the modal decomposition of a submarine cable vibration signal, and extracted three features from it: energy, sheath degree, and the envelope entropy spectrum, and used SVM to classify the vibration signal of the submarine cable [7]. Although the ESMD algorithm is an improvement on the EMD algorithm, the high-frequency components of the decomposition are characterized by strong fluctuations and large absolute values, which still have some influence on the feature extraction. VMD, as a non-recursive signal processing method, can not only effectively suppress the modal mixing problem of EMD, but also transform the high-frequency components into simpler subsequences [8], thus ensuring the reliability of fault feature extraction. In the research of the fault diagnosis of nonlinear systems, the Volterra model is one of the most widely used models [9], and it is not only able to express the objective laws of dynamic systems but also has a high computational efficiency. Combining the singular value entropy with the Volterra model can facilitate the signal evaluation of singular value entropy [10] to achieve the accurate extraction of fault features. The SVM, with its short training time and high recognition accuracy, is widely used in the field of vibration signal recognition [11], and overcomes problems such as artificial neural networks relying on empirical selection.

Based on the above analysis, this paper proposes a submarine cable anchor damage fault recognition algorithm that integrates VMD, the Volterra model, and the SVM algorithm to extract the feature quantity of the submarine cable anchor damage fault. Specifically, this paper uses the VMD algorithm to decompose the vibration signal of the submarine cable, establishes a Volterra model for each order of the IMF component, and then builds a feature parameter matrix using the model prediction parameters. Then, the feature quantity is extracted by solving the singular value of the matrix, and the singular value entropy is used as the feature quantity and input into the SVM classifier to complete classification and recognition.

2. VMD-Volterra-SVM Algorithm

2.1. VMD Principle

VMD, as a frequency-domain decomposition method, is essentially a group of multiple adaptive Wiener filters with good noise robustness, which can effectively improve the endpoint effect and mode mixing phenomenon of EMD [12]. The constrained variational problem is obtained as follows [8]:

$$\begin{cases} \min\limits_{\{u_k\},\{\omega_k\}} \left\{ \sum\limits_{k=1}^{K} \left\| \partial_t \left[\left(\delta(t) + \frac{j}{\pi t} \right) * u_k(t) \right] e^{-j\omega_k t} \right\|^2 \right\} \\ s.t. \sum\limits_{k=1}^{K} u_k = x(t) \end{cases} \tag{1}$$

where $x(t)$ is the anchor smash vibration signal; $u_k(t)$ is the decomposed modal component of $x(t)$; K is the sum of all modal components of the decomposition; $\partial_t(\cdot)$ is the partial derivative for time t; $\delta(t)$ is the Dirac distribution; $*$ is the convolution operator; and ω_k is the center frequency corresponding to $u_k(t)$.

Subsequently, a quadratic penalty term and the Lagrange multiplier are simultaneously introduced to reconstruct the problem with constraints. The quadratic penalty term can improve the reconstruction accuracy, while the Lagrange multiplier can strictly enforce the reconstruction constraints. As a result, the reconstructed model is as follows:

$$\begin{aligned} L(\{u_k\},\{\omega_k\},\lambda) = \alpha \sum_{k=1}^{K} \left\| \partial_t \left[\left(\delta(t) + \frac{j}{\pi t} \right) * u_k(t) \right] e^{-j\omega_k t} \right\|^2 \\ + \left\| x(t) - \sum_{k=1}^{K} u_k(t) \right\|^2 + \left\langle \lambda(t), x(t) - \sum_{k=1}^{K} u_k(t) \right\rangle \end{aligned} \tag{2}$$

where $L(\cdot)$ is the Lagrange function, α is the quadratic penalty factor, and λ is the Lagrange multiplicative operator.

The optimal solution of Equation (2) is found using the frequency-domain iterative method and the modal components and central frequency are updated using the alternating direction multiplier method [13]. The iterative equation is as follows:

$$u_k^{(n+1)}(\omega) = \frac{x(\omega) - \sum\limits_{k=1}^{k-1} u_k^{(n+1)}(\omega) + \sum\limits_{k=k+1}^{K} u_k^{(n)}(\omega)}{1 + 2\alpha\left(\omega - \omega_k^{(n)}\right)^2} \tag{3}$$

$$\omega_k^{n+1} = \frac{\int_0^\infty \omega \left| u_k^{n+1}(\omega) \right|^2 d\omega}{\int_0^\infty \left| u_k^{n+1}(\omega) \right|^2 d\omega} \tag{4}$$

$$\lambda^{(n+1)}(\omega) = \lambda^{(n)}(\omega) + \tau\left(x(\omega) - \sum_{k=1}^{K} u_k^{(n+1)}(\omega) \right) \tag{5}$$

where $x(\omega)$ is the Fourier transform of $x(t)$, $u_k^{(n)}(\omega)$ and $\lambda^{(n)}(\omega)$ are the n-th iterations of $u_k(t)$ and $\lambda(t)$ in the Fourier domain, respectively, $\omega_k^{(n)}$ is the n-th iteration of ω_k, ω is the frequency parameter, and τ is the Lagrange multiplier step.

When $\frac{\sum\limits_{k=1}^{K} \left\| u_k^{(n+1)}(\omega) - u_k^{(n)}(\omega) \right\|^2}{\left\| u_k^{(n)}(\omega) \right\|^2} < \varepsilon$ is satisfied, the iteration terminates. Where ε is the convergence parameter.

2.2. Principle of the Volterra Model

The Volterra model is a time-domain analysis method that can accurately express the objective laws of dynamic systems. The prediction parameters of the Volterra model are more sensitive to state changes, and, by taking them as feature quantities, they can be used to analyze the state changes of the system.

Let $V(n) = [v(1), v(2), \cdots, v(n)]$ be the IMF component of the submarine cable vibration signal obtained by VMD decomposition, which is reconstructed in phase space using the delayed coordinate method [14], then:

$$V'(n) = [v(n), v(n-\tau), \cdots, v(n-(m-1)\tau)] \tag{6}$$

where m is the embedding dimension and τ is the time delay; let $V'(n)$ be the input and the output be $y(n) = x(n+1)$, then, the Volterra level expansion is [15]:

$$v(n+1) = h_0 + \sum_{i_1=0}^{m-1} h_1(i_1)v(n - i_1\tau) + \sum_{i_1,i_2=0}^{m-1} h_k(i_1, i_2)v(n - i_1\tau)v(n - i_2\tau) \tag{7}$$

where $h_k(i_i, \cdots, i_k)$ is the k order Volterra nucleus.

Let the coefficient vector $W(n)$ be:

$$W(n) = [h_0, h_1(0), h_1(1), \cdots h_1(m-1), h_2(0,0), h_2(0,1), \cdots, h_1(m-1, m-1)]^T \tag{8}$$

The input signal vector $Z(n)$ is:

$$\begin{aligned} Z(n) = \; & [1, v(n), v(n-\tau), \cdots v(n-(m-1)\tau), \\ & v^2(n), v(n), v(n-\tau), \cdots, v^2(n-(m-1)\tau)]^T \end{aligned} \tag{9}$$

Then, Equation (7) can be expressed as:

$$v(n+1) = Z^T(n)W(n) \tag{10}$$

The normalized least-mean-square adaptive algorithm is used to solve the above equation and obtain an accurate value of the coefficient vector $W(n)$, which is used to obtain the model parameters representing the signal characteristics. The VMD decomposition is performed on the submarine cable vibration signal, and each IMF component obtained from the decomposition is solved to obtain the vector coefficients $W(n)$, which are formed into the initial feature matrix A:

$$A = [W_1, W_2, \cdots, W_k]^T \tag{11}$$

Then, the problem of solving the eigenvalues of the vibration signal of the submarine cable can be transformed into the problem of solving the singular values of the matrix A. Let the singular values be $p = \{p_1, p_2, \cdots, p_k\}$ and normalize them [16], the singular value entropy is:

$$H = -\sum_{i=1}^{k} P_i \ln P_i \tag{12}$$

where P_i is the ratio of the i-th IMF component's singular value to the whole singular value.

2.3. SVM Principle

SVM can be used to identify sample data, and the classification interval between samples can be maximized by constructing a classification hyperplane [17]. The optimal plane problem for SVM can be represented as:

$$w \cdot \phi(x_i) + b = 0 \tag{13}$$

where w is the weight vector, ϕ is the objective function, and b is the hyperplane constant term. The optimal hyperplane problem can be equated to solve the following problem:

$$\begin{cases} \min \phi(w, \xi_i) = \frac{1}{2}\|w\|^2 + C \cdot \xi_i \\ s.t.\ [w \cdot \phi(x_i) + b] - 1 + \xi_i \geq 0, \xi_i \geq 0 \end{cases} \tag{14}$$

where C is the penalty parameter and ξ_i is the relaxation variable. The sample optimal vector classification function is:

$$f(x) = \operatorname{sgn}\left(\sum_{i=1}^{n} \alpha_i^* y_i K(x_i, x_j) + b^*\right) \tag{15}$$

where $\operatorname{sgn}(\cdot)$ is the function that represents the return integer variable, α_i^* is the optimal Lagrange multiplier, b^* is the classification threshold, and $K(x_i, x_j)$ is the kernel function.

2.4. VMD-Volterra-SVM Algorithm Flow

Figure 1 shows the algorithm flowchart for the VMD-Volterra-SVM algorithm. The algorithm decomposes the vibration signal using VMD, establishes Volterra prediction models for each decomposed mode, and uses the Volterra model parameters to form an initial feature-vector matrix. The algorithm then calculates the singular value and singular value entropy of the feature-vector matrix. The singular value entropy is used as a feature quantity and fed into SVM for training. After meeting the termination condition, the algorithm is used to classify and identify the test set.

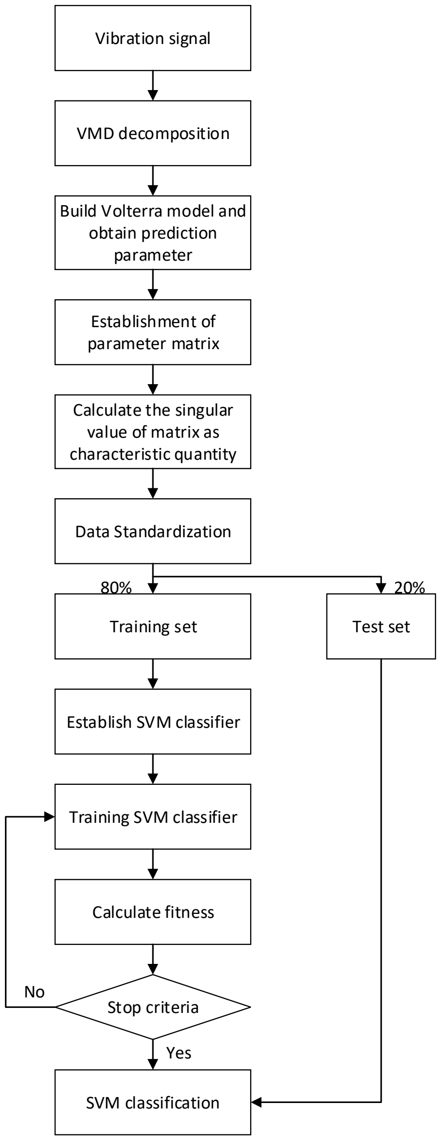

Figure 1. The VMD-Volterra-SVM flow chart.

3. Simulation Analysis

3.1. Finite Element Model Building

A submarine cable is a type of cable laid on the sea floor; it is mainly used to transfer data and energy across the ocean. Its structure is usually composed of conductors, insulating materials, sheathing, and optical fibers. Among them, optical fiber, as an important part of a submarine cable, mainly plays the role of optical signal transmission, to achieve the goal of undersea communication and data transmission. By injecting optical signals into optical fibers, the vibration data of marine cables can be obtained by detecting the reflection and scattering of optical signals, thus realizing the status monitoring and fault diagnosis of marine cables. Vibration data can be analyzed and processed at land-based centralized control stations to realize real-time monitoring and provide early warning of submarine cable status. In the application to marine cables, the finite element analysis method can effectively simulate the vibration of a marine cable in the process of anchor breaking. By obtaining the vibration acceleration data from the optical unit, it is possible to accurately detect the change of vibration acceleration of the optical unit when anchor damage occurs.

To sum up, a 500 kV single-core optical fiber composite submarine power cable with a diameter of 180 mm is selected as the research object in this paper, and finite element simulation is carried out to obtain the vibration acceleration of the optical unit at the time of anchor collapse. The submarine cable contains 12 layers, including a copper conductor, conductor shield, XLPE insulation, insulation shield, and buffer water barrier. To reduce the computational effort, the model is simplified to ensure computational accuracy. Among them, because the thicknesses of the conductor shield and insulation shield are too small and the mechanical properties are similar to those of XLPE insulation, the conductor shield, XLPE insulation, and insulation shield can be combined into one layer [18], and the simplified model is shown in Figure 2, in which the conductor shield and insulation shield are omitted and combined in the XLPE insulation layer.

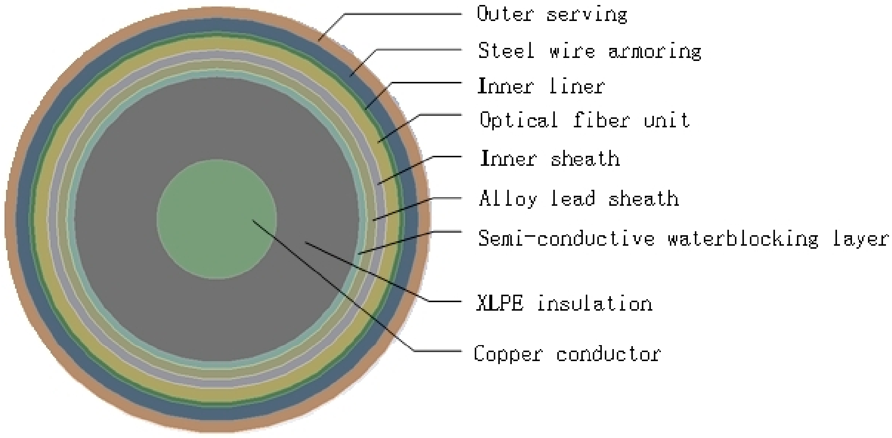

Figure 2. Simplified model structure of the submarine cable.

Since sea cables are mostly laid in offshore waters, where there are a large number of small ships, their anchors pose the greatest threat to sea cables. The anchors on small ships are selected as references in this paper; when anchor damage occurs, the contact area between the ship anchors and sea cables is small, and the anchor damage is basically irrelevant to the shape of the ship anchors; therefore, the ship anchors can be considered as equivalent to a trapezoid body for calculation. Set the mass of the anchor to m = 140 kg, volume to V = 0.038 m^3, projection of the anchor bottom against the water surface to A = 0.048 m^2, seawater density to ρ_w = 1030 kg/m^3, seawater resistance coefficient to C_D = 1.1, medium gravity acceleration to g = 9.8 m/s^2, velocity of the anchor striking the cable to v, ignore the influence of sea tide on the anchor, and use the motion equation of a ship anchor in the process of falling, which is as follows:

$$mg - \rho_w V - \frac{1}{2} C_D \rho_w A v^2 = 0 \tag{16}$$

According to Formula (16), the velocity, of v = 7 m/s, when the anchor strikes the sea cable can be obtained. The overall model of anchor damage is shown in Figure 3, and this model is 1 m long.

Anchor damage is a part of the large deformation dynamics process. Therefore, we use the LS-DYNA module in Workbench to solve it. In the finite element analysis, mesh partitioning has an important impact on the reliability of the calculations. Therefore, Workbench provides a variety of mesh division methods. In order to ensure the accuracy of the calculation and reduce the number of meshes as much as possible, this paper chooses the combination of swept mesh division and mapped phase mesh division.

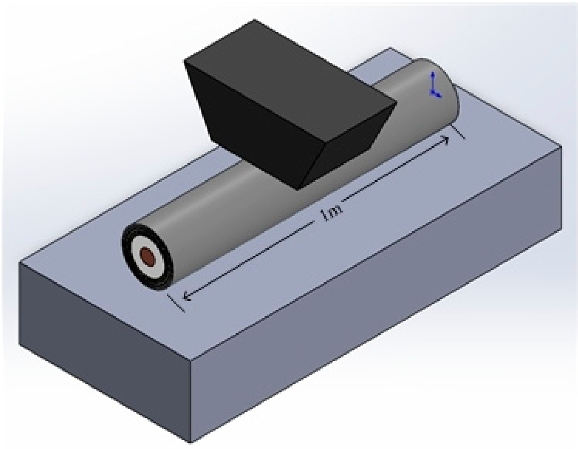

Figure 3. Anchor damage overall model diagram.

After mesh partitioning, a gravitational acceleration of 9.8 m/s^2 is applied to the entire model, and a downward velocity v is applied to the anchor separately. In this paper, v is taken as 7 m/s. To prevent the anchor from sliding during the anchor smashing process, the movement of the anchor in the x and z directions is constrained so that the anchor can only move in the y direction. Since the anchor damage failure only occurs locally in the submarine cable, the length is much smaller than the total length of the submarine cable, so the two sections of the submarine cable can be completely fixed with the bottom end on the soil.

3.2. Finite Element Simulation Results

The vibration acceleration of the light unit was extracted and the vibration acceleration curve of the ship anchor acting on the cable within 0−0.3 s was drawn, as shown in Figure 4a. Under the influence of the sea velocity, the cable will also vibrate under the action of the wave force when the anchor is not broken. In [19], under the condition of a uniform wave scour with a period of 1 s and a velocity of 2 m/s, a finite element model of the sea cable scour by the sea wave was established. The flow direction of the model was the x direction. By referring to the simulation results of the model, the vibration acceleration curve of the sea cable under the action of a wave force, as shown in Figure 4b, was obtained.

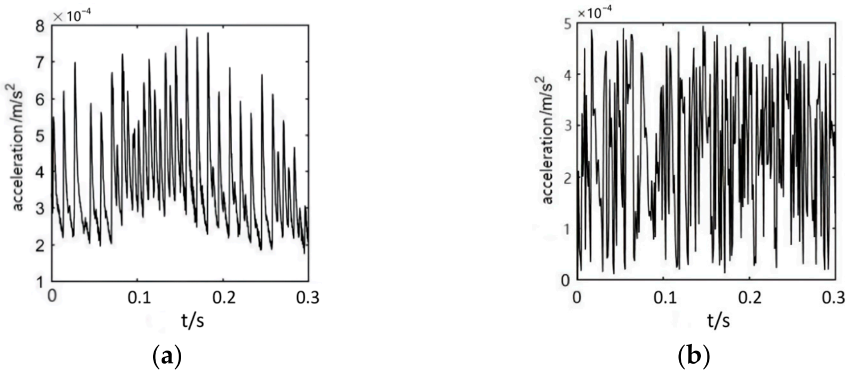

Figure 4. Vibration acceleration curve of the submarine cable. (**a**) Vibration acceleration curve at the moment of anchor smashing; (**b**) vibration acceleration curve at the moment of scouring.

4. VMD-Volterra-SVM Algorithm Validation

4.1. VMD Decomposition and Feature Extraction

The VMD decomposition is performed on the vibration signal of the submarine cable obtained in Section 3.2. α is taken as 2000, the Lagrange multiplier step τ is taken as 0, the number of IMF decomposition K is taken as 5, the convergence parameter is taken as 10^{-7}, the decomposed modal components are obtained, and the waveforms of each modal component are shown in Figure 5. The horizontal axis represents time, measured in seconds, while the vertical axis represents the magnitude of the acceleration. From Figure 5, it can be seen that the VMD decomposition results are more reasonable and can effectively suppress the modal mixing phenomenon.

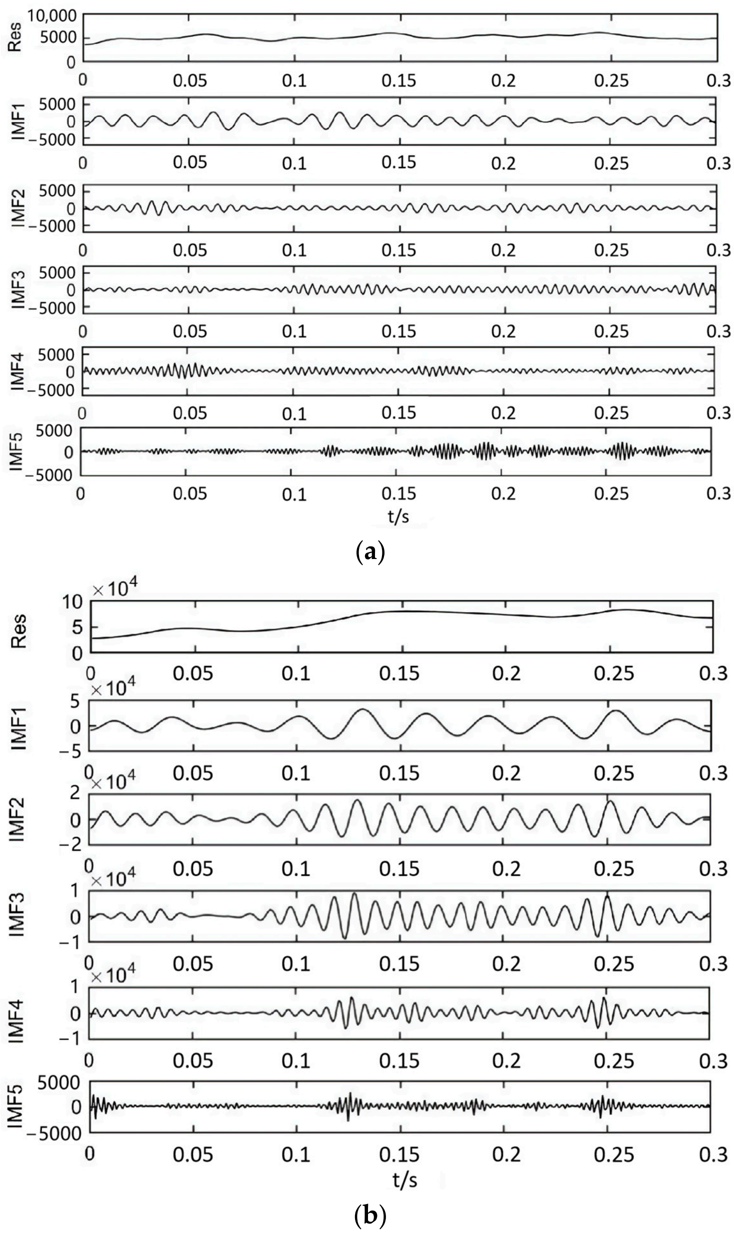

Figure 5. The VMD decomposition waveform of a submarine cable vibration signal. (**a**) Scouring vibration signal decomposition; (**b**) anchor smash vibration signal decomposition.

One hundred groups of each type of vibration signal were taken, and the VMD decomposition was performed on each set. A Volterra prediction model was established for each modal component of the decomposition. The Volterra model parameters were formed into an initial eigenvector matrix, and their singular values and singular value entropy were calculated to extract a total of 200 groups of feature values. Table 1 shows the extracted singular values and singular value entropy based on the first three sets of samples of the two types of vibration signals.

Table 1. Singular values and the entropy of singular values for different submarine cable states.

Submarine Cable Status	Sample	IMF1	IMF2	IMF3	IMF4	IMF5	H
Scrubbing	Sample 1	2.5037	1.1586	0.6795	0.3894	0.1958	1.5193
	Sample 2	2.5023	1.1659	0.6775	0.3954	0.1965	1.5237
	Sample 3	2.5113	1.1548	0.6804	0.3904	0.2005	1.5272
Anchor smash	Sample 1	2.3902	1.0962	0.5535	0.2973	0.1159	1.2056
	Sample 2	2.4037	1.0804	0.5221	0.2932	0.1522	1.2061
	Sample 3	2.3954	1.0965	0.5361	0.2896	0.1561	1.2105

According to Table 1, the singular value entropy solved for the scouring vibration signal of the sea cable is maintained at about 1.52, while the singular value entropy solved for the anchor smash vibration signal is about 1.20. The fluctuation of the singular value entropy between samples of the same type is small, while there is a significant difference in the singular value entropy between samples of different types. This indicates that the Volterra model established after VMD decomposition can effectively extract the characteristics of the submarine cable vibration signals in different states, and improve the reliability of the submarine cable anchor damage identification.

4.2. Fault Identification Results and Analysis

The singular value entropy extracted in 4.1 was sent to SVM for training as a data set composed of eigenvalues. Specify the output label of the scouring vibration signal as 1 and the output label of the anchor smashing vibration signal as 2. The 200 sets of feature values obtained in 4.1 are fed into the SVM as the data set for training, and the first 80% of the feature values corresponding to each type of signal in the data set are used as the training set and the last 20% as the test set, which results in 160 training samples and 40 test samples.

The SVM was used to identify and classify, and the parameters of the SVM algorithm were determined. The penalty parameter C of the SVM and non-negative relaxation factor ζ_i were combined to search for optimization, and the particle swarm optimization algorithm was used to select the parameters. The value range of c was [0.1, 100], and the value range of ζ_i was [0.01, 1000]. Finally, the optimal parameters are c = 3.586 and ζ_i = 2.248.

The hyperparameters involved in the VMD-Volterra-SVM algorithm are shown in Table 2. The recognition and classification results are shown in Figure 6.

Table 2. The VMD-Volterra-SVM algorithm parameters.

Hyperparameter	Size	Hyperparameter	Size
Quadratic penalty factor α	2000	Convergence parameter ε	10^{-7}
Lagrange multiplier step τ	0	Penalty parameter	3.568
Number of IMF decomposition K	5	Non-negative relaxation factor ζ_i	2.248

As shown in the figure, the VMD-Volterra-SVM model made correct judgments for all 40 samples tested, and the classification running time was 10.36 s; thus, the effectiveness of this method can be verified.

As a comparison, the EMD and EEMD methods were used to decompose the above signals in turn, to establish the Volterra model for each IMF component and obtain the singular value entropy, and to set the same parameter part in the three algorithms consistently. The SVM classification algorithm was also used to identify the test samples, and the results are shown in Figures 7 and 8.

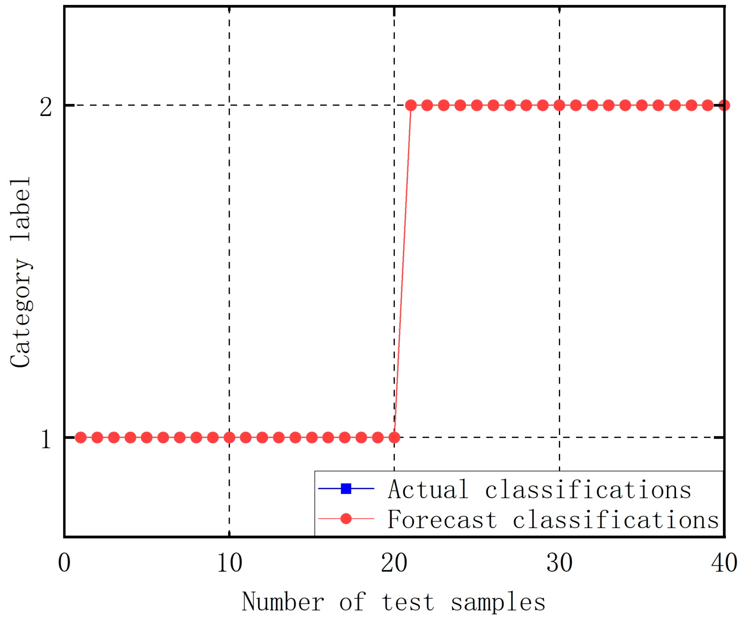

Figure 6. Anchor smash fault identification results based on the VMD-Volterra-SVM method.

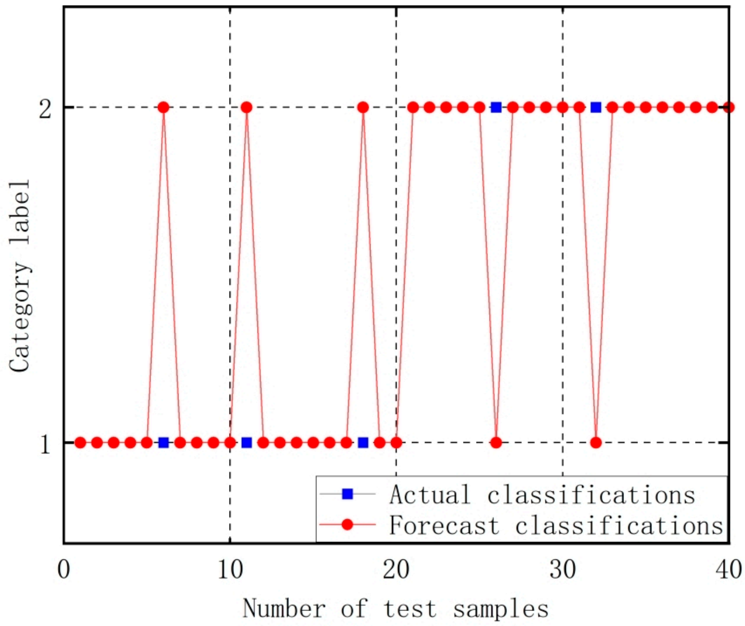

Figure 7. Anchor smash fault identification results based on the EMD–Volterra–SVM method.

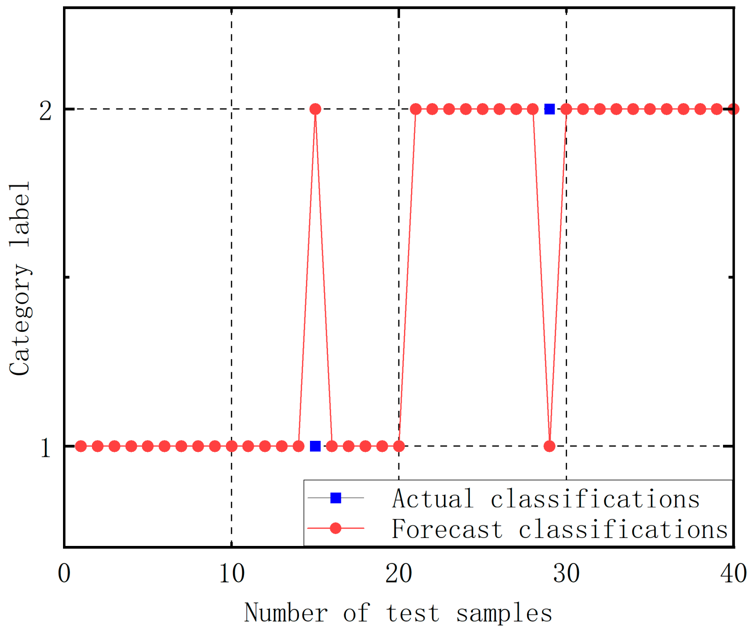

Figure 8. Anchor smash fault identification results based on the EEMD–Volterra–SVM method.

As can be seen from the figure, among the 40 test sets, the recognition results of the EMD method have a total of five test samples with recognition errors, the recognition accuracy is lower than 90%, and the classification running time is 13.26 s. The recognition results of the EEMD method have a total of two test samples with recognition errors, and the classification time was 11.49 s. Table 3 shows the confusion matrix analysis table of VMD, EMD, and EEMD.

Table 3. The VMD, EMD, and EEMD confusion matrix analysis table.

Confusion Matrix			**True Value**	
			Scrubbing	**Anchor Smash**
Predicted Value	VMD	Scrubbing	20	0
		Anchor smash	0	20
	EMD	Scrubbing	17	2
		Anchor smash	3	18
	EEMD	Scrubbing	19	1
		Anchor smash	1	19

This shows that, although the classification accuracy of EEMD is higher than that of EMD, it is lower than that of VMD. This is because, although EEMD can suppress the endpoint effect and modal confusion of EMD to a certain extent, it still cannot completely avoid them. Compared with the above three methods, the VMD-Volterra-SVM model has the highest recognition accuracy, the fastest classification running time, the lowest algorithm complexity, and a better classification effect, which indicates that the VMD method can extract the information from individual frequency bands in the signal more effectively than the EMD and EEMD methods, and provides a strong guarantee for the subsequent extraction of anchor damage fault characteristics.

5. Conclusions

This paper proposes a new identification algorithm based on the VMD-Volterra-SVM algorithm to address the problem of low accuracy in identifying submarine cable anchor damage. Firstly, a vibration model of the submarine cable under anchor impact is established, and finite element analysis is used to simulate and analyze the vibration signals of the cable during scouring and anchor impact. Then, the VMD algorithm is used to decompose the vibration signals of the cable, and a Volterra prediction model is established for each modal component. The singular value entropy is calculated as the feature value of the cable vibration signal. Finally, the SVM algorithm is used to identify the submarine cable anchor damage. The proposed algorithm significantly improves the accuracy of identifying submarine cable anchor damage.

The analysis of submarine cable vibration signals using this method resulted in correct judgments for all 40 test samples, demonstrating its effectiveness. Compared with the EMD and EEMD methods, in the forty test samples, EMD had five misjudgments, and EEMD had two misjudgments. It can be seen that the classification accuracy using the VMD method is higher than that using the EEMD method, and both methods have a higher classification accuracy than the EMD algorithm. In terms of running time, the VMD method has the shortest running time, followed by the EEMD method, and the EMD method has the slowest classification time. The results indicate that the VMD-Volterra-SVM model is more accurate and faster in extracting the fault features of submarine cable anchor damage compared to the other two methods. The algorithm also has lower complexity but higher accuracy in identifying faults.

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