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Variational Mode Decomposition-Based Event Recognition in Perimeter Security Monitoring With Fiber Optic Vibration Sensor

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ABSTRACT Recognition of different kinds of human intrusions from the environmental disturbance with high efficiency is still a challenging task in perimeter security monitoring with fiber optic vibration sensor, since the vibration signals induced by these events are highly similar to each other, and it can not be directly discriminated by the signals. In this paper, an intelligent event recognition scheme is proposed to improve its performance in complicated environmental applications. In this event recognition scheme, a variational mode decomposition based kurtosis feature combined with a zero crossing rate feature is used as the input feature vectors. A support vector machine is used to classify the input feature vectors into the corresponding categories. A series of field tests show that the proposed scheme can accurately and rapidly classify wind disturbance and three typical patterns of human intrusions such as waggling the fence, climbing the fence and knocking the fence. The average identification rate of 100.0% and 96.9% are achieved for the wind disturbance and human intrusion events, respectively. The recognition processing time can be controlled less than 0.4 s. Thus, the intelligent event recognition scheme can fully satisfy the online monitoring requirements for practical applications.

INDEX TERMS Optical fiber, vibration sensing, intelligent recognition, signal analysis, feature extraction, support vector machine.

I. INTRODUCTION

Distributed fiber optic perimeter security system is a pre-alarm system based on safety monitoring technology, which can detect and locate the vibrational signals along with the sensing fiber link [1]–[4]. Due to the advantages of simple structure, wide monitoring range and fast response, this kind of sensing technology has been successfully applied in various perimeter security fields such as airport guarding, oil or gas pipeline and many other security monitoring applications [5]–[8]. However, in these applications, the environmental disturbance factors such as wind and other circumstance factors are inevitable and can seriously deteriorate the sensing performance of the distributed fiber optic perimeter security based system, leading to a high false alarm rate (FAR). Thus, it is an urgent task to accurately recognize the human intrusion events from the environmental disturbance with high efficiency.

Up to the present, many methods based on intelligent recognition have been made to improve the performance of the fiber optic perimeter security based system. Liu *et al.* [9] proposed a wind disturbance event discrimination scheme, which can recognize three kinds of human intrusions by taking multiscale wavelet decomposition based features and incremental support vector machine. However, this kind of scheme is not efficient, due to too much time of splitting the detected signal into multiple frequency bands by using wavelet decomposition algorithm. Marie *et al.* [10] proposed an empirical mode decomposition (EMD) based feature extraction method, which by combining a probabilistic neural network to realize the recognition of the intrusions. However, the EMD algorithm has problems of mode mixing and endpoint effect during the decomposition process [11]–[13]. Thus, the feature vectors based on the EMD algorithm lack

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robustness which can seriously influence the target event recognition accuracy. Mahmoud and Katsifolis [14] reported a robust recognition scheme, which by using a kind of level crossing based feature vector and a supervised neural network to realize the event recognition. However, the scheme strongly relies on a threshold which is without an accurate basis, leading to this scheme can hardly be applied in practical applications. Huang *et al.* [15] reported a feature extraction method based on filter bank in the frequency domain, and utilized an artificial neural network to realize intrusion events recognition. However, this kind of scheme is quite complex in the process of feature extraction. Meanwhile, the feature vectors only involve the feature information in the frequency domain, and it can only distinguish two types of intrusion events.

To solve the problems described above such as low recognition accuracy and efficiency which exist in current recognition and classification schemes. In this paper, we propose and demonstrate a variational mode decomposition (VMD) based intelligent event recognition scheme, which can accurately distinguish the human intrusions from the wind disturbance. In the scheme, the feature vectors are constructed with the VMD based kurtosis value and the zero crossing rate (ZCR). The VMD algorithm is a kind of novel self-adaptive signal decomposing algorithm firstly proposed by Dragomiretskly and Zosso [16]. The algorithm is simple in the process of computation and it has a superior capability in processing multi-component temporal signals. To the best of our knowledge, this is the first time that the VMD algorithm is used for the fiber optic perimeter security system. Kurtosis is a dimensionless parameter and very sensitive to pulse signal [17], which can be directly calculated by using the given non-stationary series. ZCR is a classical feature extraction algorithm in the time domain for non-linear series. By using all the aforementioned features in the frequency domain, statistics and time domain, a more comprehensive feature vector can be built for the distributed fiber optic perimeter security based sensing system. Moreover, based on the proposed feature vectors are extracted by the means of simultaneously decomposed mode, the recognition efficiency of the proposed scheme can be further improved. A series of field experiments show that the proposed intelligent event recognition scheme can accurately identify human intrusions from the wind disturbance with high efficiency. Therefore, a much lower FAR value can be achieved in the fiber optic perimeter security sensing system.

In this paper, the proposed intelligent recognition scheme will be expounded in the dual Mach-Zehnder interferometry (DMZI) based fiber optic perimeter security system. DMZI is a classical structure of the distributed fiber optic vibration sensing system, thus, it can be used as an example for the proposed event recognition scheme validation. This paper is organized as follows. We first illustrate the principle of the intelligent event recognition, analyze the VMD algorithm, the feature extraction process and the support vector machine (SVM) classifier. Then, the DMZI based fiber optic security monitoring system and the experimental design will be briefly described. Finally, the event recognition experiments will be carried out.

II. PRINCIPLE OF INTELLIGENT EVENT RECOGNITION

The proposed event recognition and classification scheme consists of three stages, as shown in Fig. 1. The first stage is the original sensing signal preprocessing based on VMD algorithm. The second stage is feature extraction. The feature vectors include the calculation of kurtosis feature values based on VMD algorithm and the time domain features based on ZCR algorithm. The last stage is SVM based intelligent event recognition and classification, which discriminate the feature vectors of the given sensing events into different relevant categories to realize the event recognition.

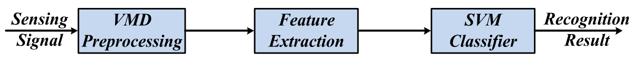

FIGURE 1. Flowchart of intelligent event recognition algorithm.

A. VMD PREPROCESSING

VMD is a non-recursive signal processing method, which can decompose a multiple components signal into different intrinsic mode functions (IMFs) [11]. Each mode is a narrow bandwidth with different center frequencies. Thus, the VMD algorithm can avoid the end effect and the mode mixing problem in the decomposition process of the time series signal. Fig. 2 illustrates the comparative analysis between the VMD and EMD algorithm for a simulated signal, where s denotes the original signal that can be defined as:

$$s = 0.5 \times s1 + 0.4 \times s2 + 0.4 \times s3 + 0.1 \times randn(size(s1)) \quad (1)$$

where $s1$, $s2$, and $s3$ can be expressed as $s1 = \cos(2 \times \pi \times 4 \times t)$, $s2 = \cos(2 \times \pi \times 24 \times t)$, $s3 = \sin(2 \times \pi \times 288 \times t)$, and *randn* is the Gaussian function. All the modes of the simulated signal are arranged in the ascending and descending frequency order for the VMD and EMD algorithm, respectively. During the decomposition process of the VMD algorithm, each mode can restore the corresponding original signal without signal distortion. Compared with VMD, it is evident that the EMD algorithm had a serious end effect and signal distortion during the process, as indicated in Fig. 2(b). The bold squares in Fig. 2(b) show the signal distortion in the process, thus, the mode mixing problem will occur in the EMD algorithm.

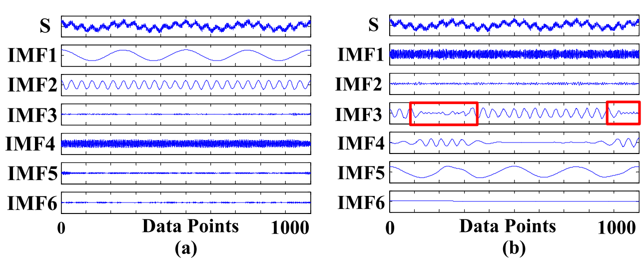

FIGURE 2. The comparison between VMD and EMD algorithm. (a) VMD algorithm. (b) EMD algorithm.

The specific decomposition process of the VMD algorithm is as follows: Firstly, by using Hilbert transformation to obtain the unilateral frequency spectrum. Secondly, shifting the frequency spectrum of each mode to the base band. Thirdly, by using the demodulated signal to obtain the bandwidth of each mode. Finally, the results of the VMD algorithm can be converted into a constrained variational problem as [18]:

$$\min_{\{u_k\},\{w_k\}} \left\{ \sum_k ||\partial_t[(\delta(t) + \frac{j}{\pi t}) * u_k(t)]e^{-jw_k t}||_2^2 \right\}$$
$$s.t. \sum_{i=1}^{k} u_i = x(t) \tag{2}$$

where $x(t)$ is the given time series signal to be decomposed, $\{u_k\}=\{u_1, u_2, \ldots, u_k\}$ are the modal function set, $\{w_k\}=\{w_1, w_2, \ldots, w_k\}$ are the center frequency set, ∂_t represents the partial derivative of the function with respect to t, $\delta(t)$ represents a unit pulse function, k represents the mode index, j is the imaginary unit, $*$ denotes the convolution.

To solve the constrained problem in the above equation of (2), a quadratic penalty term α and a Lagrangian multiplier λ were introduced to convert the aforementioned constrained problem into an unconstrained optimization problem as:

$$\begin{aligned} &L(\{u_k\}, \{w_k\}, \lambda) \\ &= \alpha \sum_k ||\partial_t[(\delta(t) + \frac{j}{\pi t}) * u_k(t)]e^{-jw_k t}||_2^2 \\ &\quad + ||x(t) - \sum_k u_k(t)||_2^2 + \left\langle \lambda(t), x(t) - \sum_k u_k(t) \right\rangle \end{aligned} \tag{3}$$

where α denotes the quadratic penalty parameter, λ denotes the Lagrangian multiplier. The unconstrained optimization problem given in equation (3) can be solved by using a classical alternate direction method of multipliers (ADMM) based algorithm that generates different decomposition modes and the corresponding center frequencies. Based on the ADMM algorithm, the u_k and w_k can be updated in the following two equations:

$$\hat{u}_k^{n+1}(w) = \frac{\hat{x}(w) - \sum_{i\neq k} \hat{u}(w) + \frac{\hat{\lambda}}{2}}{1 + 2\alpha(w - w_k)^2} \tag{4}$$

$$w_k^{n+1}(w) = \frac{\int_0^\infty w|\hat{u}_k^{n+1}(w)|^2 dw}{\int_0^\infty |\hat{u}_k^{n+1}(w)|^2 dw} \tag{5}$$

where n denotes the number of iterations, $\hat{}$ represents the Fourier transform. Specifically, the results of the equation (4) and (5) are the specific decomposition mode components and its corresponding central frequencies. For more details about VMD algorithm can be found in [19].

Based on the characteristics of the sensing event signal acquired by DMZI based intrusion sensor, the mode function stands for the sensing signal component as well as the meshing frequency of the sensing system. The changes in the distribution of the vibration intrusions with different kinds of vibration sensing events can be decomposed into individual components based on the VMD algorithm. Therefore, the IMF components decomposed by the VMD algorithm can be used as an effective feature description for the sensing event.

B. FEATURE EXTRACTION

Extraction of effective features is the key issue for the event recognition and classification, which can greatly affect the recognition results of a classifier. Feature extraction can be regarded as the process of low loss dimensionality reduction for the given original signal. From the mathematical point of view, that is to transform an N dimension vector to an M dimension vector, where $M < N$. More importantly, the given original signal can be represented by the feature vector in some aspects. In this study, we firstly decomposed the original sensing signal into different IMF components by using the VMD algorithm, which can stand for the different frequency characteristics in different scales. Based on each IMF components possess the characteristics of small changes and unsteady, we chose to calculate the kurtosis coefficient values of each IMF components as the feature description of the given sensing event, which will concurrently include the feature information both in frequency domain and statistics.

Kurtosis is a dimensionless statistical parameter that can indicate the peakedness and impulsiveness of a time series [20], and it can be used for testing the shape characteristic of a time series when compared to a Gaussian distribution. The kurtosis parameter is only estimated by a finite length time window, and the parametric value depends on the length of the time series. Because kurtosis is highly sensitive to small changes of the non-stationary signal, thus, the corresponding kurtosis coefficients can effectively describe the distribution of the sensing signal and the peakedness of the signal waveform. Based on the characteristics of the kurtosis and VMD, a more accurate feature description of the sensing signal which collected by the DMZI based sensing system can be built. The specific process of the feature extraction is as the following two steps:

Step 1: By using the VMD algorithm, decomposition of the N length sensing signal into Q layers of IMF modes and calculation of the kurtosis coefficient value for each IMF mode that can be defined as in [21]:

$$\tilde{K}_i = \frac{E\{(IMF_i(n) - \mu)^4\}}{\sigma^4} \quad (i=1, 2, \ldots, Q, n=1, 2, \ldots, N) \tag{6}$$

where μ and σ represent the mean and standard deviation value of the corresponding IMF component, $E\{\cdot\}$ represents the expectation operation.

Step 2: Normalization of the kurtosis coefficient value in the above equation (6) which can be expressed as:

$$V_i = \frac{\tilde{K}_i}{\sum_{i=1}^{Q} \tilde{K}_i} \quad (i = 1, 2, \ldots, Q) \tag{7}$$

Therefore, the feature vector consists of kurtosis and VMD algorithm can be constructed as $F = [V_1, V_2, \ldots, V_Q]$.

To enrich the feature description of the sensing event, we merged the ZCR feature into the above mentioned feature vector F. Thus, the final feature vector of the given signal can be constructed as $F = [V_1, V_2, \ldots, V_Q, ZCR]$. ZCR is a measured parameter of number of times in a given time interval that the frequency of the value sign passes through the zero value in the time interval. To some extent, the ZCR can indicate the amplitude value frequency for the given time interval. The definition of the ZCR is shown as follows [22]:

$$ZCR = \frac{\sum_{n=1}^{N} |sign[x(n) - sign[x(n-1)]]|}{2N} \tag{8}$$

where $x(n)$ is the given time series, N is the sample length for the given time interval, $sign[]$ is a symbolic function which can be expressed as:

$$sign[x(n)] = \begin{cases} -1, & x(n) \leq 0 \\ 1, & x(n) > 0 \end{cases} \tag{9}$$

C. SVM CLASSIFIER

SVM is a novel type of learning algorithm derived from the statistical learning theory [23]. With superior advantages compared with the artificial neural network, SVM has been successfully applied for events recognition and classification [24]. The key idea of SVM is to map the non-linear data into a high dimensional feature space by some kinds of non-linear mapping functions. So that the non-linear classification problem can be converted into a linear classification problem in the high dimensional space [25]. The SVM consists of three layers: input layer, nonlinear mapping layer and output layer. The architecture of SVM can be portrayed in Fig. 3, the *sign* in the output layer node represents a symbolic function which means that the SVM is a binary output.

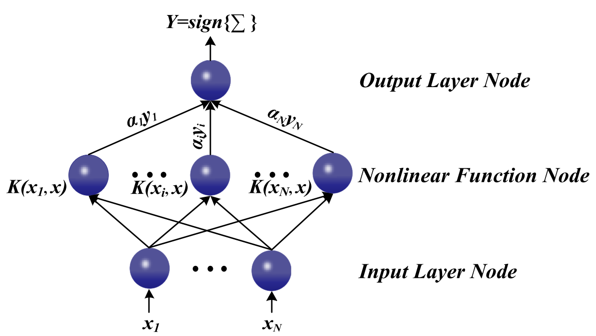

FIGURE 3. The architecture of support vector machine.

Take a binary classification problem as an example, we will briefly illustrate the classification principle of SVM. $\{(x_i, y_i)|i = 1 \cdots N\}$ were assumed as the linear separable sample data, where $x_i \in R^N$ is the input parameter of the ith sample, N is the number of the total training samples, $y_i \in \{-1, 1\}$. The purpose of the training sample data for SVM is to build a function which can classify the testing data into the relevant category. The function of the binary classification problem can be defined as [26]:

$$y_i[(w \cdot x_i) + b] \geq 1(i = 1, \ldots, N) \tag{10}$$

where w is a normal vector, b is a constant. When the sample data is not linearly separable in low dimension, the nonlinear discriminate function can be used for mapping the original non-linear sample data into a high dimensional space. The discriminate function is given in [27]:

$$f(x) = sign[\sum_{i=1}^{N} \alpha_i y_i K(x, x_i) + b] \tag{11}$$

where α_i represents the weight coefficients between the adjacent layer nodes, $K(\cdot)$ represents the kernel function.

Recognizing and classifying the vibration events along the sensing fiber is a typical multi-classification problem. There are several kinds of multi-class strategies have been successfully used for multi-class recognition and classification [28]. Based on the sample numbers, a kind of one-versus-one (OVO) multi-class strategy is used to realize the event recognition in this paper [29]. For M categories of classification problem ,a combination of $M(M\text{-}1)/2$ binary sub-classifiers are constructed by using the training data. In the testing process, we chose the commonly voting algorithm of ''Max-Wins'' to recognize and classify the unknown category event.

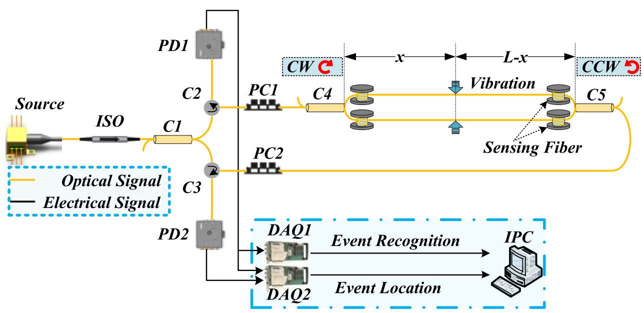

FIGURE 4. Schematic diagram of DMZI based vibration sensing system. ISO: isolator; C1, C4, C5: 3 dB optical fiber coupler; C2, C3: optical circulator; PC1, PC2: polarization controller; PD1, PD2: photodetector; DAQ1: data acquisition card for events discrimination; DAQ2: data acquisition card for events location; IPC: industrial personal computer.

III. DUAL MACH-ZEHNDER INTERFEROMETRY VIBRATION SENSOR

A. EXPERIMENTAL SETUP

DMZI is a typical fiber optic perimeter security system, which by utilizing a phase-modulation sensing method to detect and locate the vibration intrusions along the sensing fiber. Fig. 4 gives the set up of the DMZI based fiber optic perimeter security sensing system [30]. A commercial distributed feedback (DFB) laser with narrow linewidth was used as the sensing light source. The output of the light source first passed through an isolator and launched into coupler C1, and then the coupler C1 splits it into two equal parts of light beams. The two parts of light then pass through a couple of polarization controllers and propagate oppositely in the

DMZI structure which consists of coupler C4 and C5. The two polarization controllers in the sensing system are used to maintain the polarization state of the sensing light beams. In the DMZI part, the light beams which carried with the abnormal vibration sensing information will interfere at their corresponding coupler C4 and C5, respectively. The interference outputs are detected by the photodetectors PD1 and PD2 after optical circulator C2 and C3, respectively. Then, the sensing signals are acquired simultaneously by the two data acquisition cards DAQ1 and DAQ2, respectively. Specifically, DAQ1 is used for sensing events discrimination and DAQ2 is used for vibration event location which is acquired by calculating the time delay between the time domain interference signals received by the PD1 and PD2 [31]–[33]. Finally, the two path signals are analyzed and processed by an industrial personal computer(IPC).

B. EXPERIMENT DESIGN

The experimental configuration of the DMZI based fiber optic perimeter security system as illustrated in Fig. 4. The commercial DFB laser was used as the light source with a wavelength of 1550 nm, a line-width less than 50 kHz and an output power of 3.5 mW, respectively. Based on the practical application conditions, the data sampling rate of DAQ1 was set as 1 kHz and the sampling duration of each trail was set to 3 s. And the data sampling rate of DAQ2 was set as 10 MHz and its corresponding sampling duration time was set to 0.3 s. The sensing data acquired by DAQ1 and DAQ2 were processed and analyzed at the IPC (CPU: i7-4770, RAM: 16 GB, Clock: 3.4 GHz). A 2.25 km long chain link perimeter fence was built up. To enhance the sensing sensitivity of the vibrations, the sensing cable was affixed to the fence by hose clamps in a sinusoidal manner. And for the purpose of enhancing the SNR of the vibration sensing system, the armored cable with 4 cores was used as the sensing cable, which was portrayed in Fig. 5.

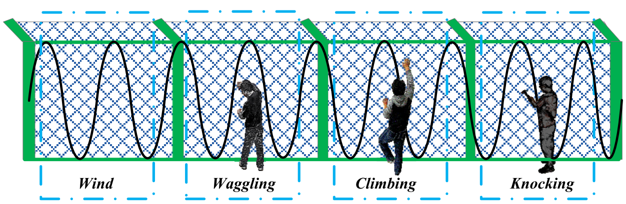

FIGURE 5. Four typical vibration sensing events.

IV. EXPERIMENTAL RESULTS AND ANALYSIS

A. SIGNAL PREPROCESSING BASED ON VMD

The wind disturbance signal and other three kinds of human vibration signals are decomposed into six layers of IMF components by the VMD based algorithm in this study and the quadratic penalty term α was set as 200 based on the theoretical and classical applications in previous studies. The decomposition results are illustrated as Fig. 6, where s indicates the detected vibration signal, IMFith represents the specific decomposition component. The reasons for six layers decomposition in this study are as follows: Firstly, in the process of event recognition, both factors of accuracy and efficiency should be considered concurrently. Based on this idea, we experimentally employed four-layer, five-layer, and six-layer decomposition modes, and found that the recognition rate increased with the layers increase when the decomposition layers were below six. Secondly, based on the principle of VMD algorithm, if the decomposition layer is too large, it will lead to the problem of modal center frequency overlap in the process of decomposition [34]. Moreover, a bigger decomposition layer can degrade discrimination efficiency because of time consumption. Therefore, the number of decomposition modes finally was set to be six in this paper.

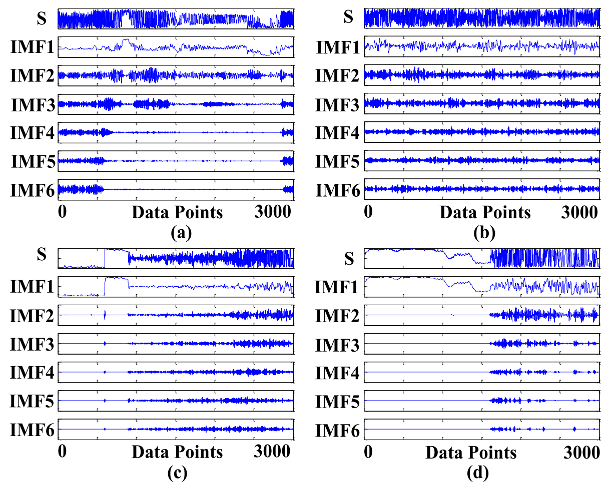

FIGURE 6. Four kinds of vibrations and their corresponding IMF components through VMD algorithm. (a) VMD of wind disturbance signal. (b) VMD of waggling signal. (c) VMD of climbing signal. (d) VMD of knocking signal.

As analyzed in the previous section, the IMF frequencies of each type signal were ascended from low to high which is contrary to the EMD algorithm. The decomposition IMF components of the given four types of sensing events in Fig. 6 are distributed over different frequency bands. The vibration information for the given sensing signals was mainly concentrated within the low frequency components. Thus, the low frequency components can be used for choosing the sensitive mode components. Compared with other three human made vibration intrusions, the signal fluctuations of the wind disturbance event signal presented the characteristic of randomness and more severe. The IMF decomposition components of wind signal are obviously different with human intrusion events in both low and high frequency components. Therefore, it is an effective way to extract the useful frequency feature information through the VMD based decomposition components.

B. FEATURE EXTRACTION

Fig. 7 gives the four kinds of original vibration signals and their counterpart normalized VMD based kurtosis feature vectors. From Fig. 7, it is evident that the normalized feature vectors of all the four patterns indicate different variation

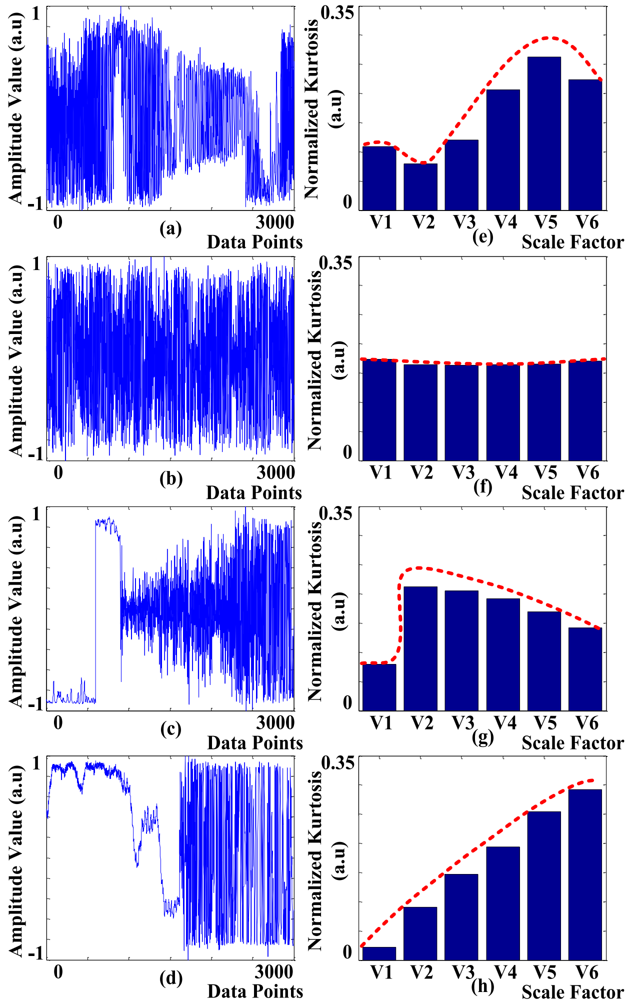

FIGURE 7. Four kinds of vibrations and their corresponding feature vectors. (a) Wind disturbance signal; (b) Waggling signal; (c) Climbing signal; (d) Knocking signal; (e) Feature vectors of wind; (f) Feature vectors of waggling; (g) Feature vectors of climbing; (h) Feature vectors of knocking.

trends. Specifically, the feature vectors of the wind are changing from V_1 to V_6 in an irregular sinusoidal manner. Due to the fluctuation of the waggling event signal changes evenly distributed all the sampling duration, thus, the normalized kurtosis values of each IMF components are highly similar to each other. The normalized feature values of the climbing events are evidently different from the waggling events. The first feature value is lower than the rest of values, and the feature value keeps falling after V_2. As for the knocking events, all of the normalized feature values are generally keep rising in total. From the analysis we can get the conclusion that the features of the wind events are different from the features of other three human vibration events. Since the wind disturbance event is a kind of random vibration signal for the vibration sensing system. Thus, the counterpart feature values present some kind of randomness. And it could be confused for other three kinds of human made intrusion events. Compared with the wind disturbance event, the human intrusion events indicate the characteristics of regularity for its corresponding kurtosis feature values. Therefore, human intrusions could be easily discriminated from each other by the VMD based kurtosis feature vectors.

As mentioned in the previous section, in order to enrich the feature vectors of the given sensing signal. The ZCR values of the given four sensing events were also calculated. Specifically, the ZCR value of the wind disturbance event is 0.231 and the ZCR values of other three human intrusion are 0.383, 0.317 and 0.088, respectively. With the ZCR values of the four vibrations are all different, thus, it can further enrich the above mentioned feature information. Especially, for the ZCR value of the wind disturbance is obviously different from the other three human intrusion events, thereby, the ZCR feature can efficiently overcome the problem of the VMD based kurtosis features. Therefore, building a feature vector as $F = [V_1, V_2, \ldots, V_6, ZCR]$ is an effective feature extraction algorithm for the fiber optic perimeter monitoring sensing system.

C. EVENT RECOGNITION

To further verify the vibration signal is induced by the wind disturbance event or the human intrusion event, the waggling event and the knocking event are applied on the sensing fiber by the same person with 70 kg, the climbing event is applied by a person with 83 kg, as illustrated in Fig. 5. And 626 field data samples are implemented through the given four kinds of typical vibrations. Specifically, the training samples of each kind of vibrations are constructed with 60 trials to train the SVM classifier and build the non-linear mapping function. It should be noted that more training data samples can build a more comprehensive mapping function, which will lead to a higher identification rate. But it will require the classifier to undergo much longer training time. In order to satisfy both factors of accuracy and efficiency in practical applications, the 240 data samples of the given four typical vibrations are used as the training trails. Then, the rest of the samples are used as the testing trials which contain 110 vibrations for wind interference events, 276 vibrations for other three kinds of human intrusion events, including 101 waggling events, 62 climbing events and 113 knocking events.

To study the validity of the proposed event recognition scheme, we conducted the entire feature vector $F = [V_1, V_2, \ldots, V_6, ZCR]$ and only VMD based kurtosis feature vector as $[V_1, V_2, \ldots, V_6]$ to distinguish the given vibration events. As a comparison, the multiple events discrimination scheme based on EMD algorithm proposed by Liu *et al.* [35] has also been implemented in this paper. From Table 1, the only VMD based kurtosis feature vectors show better events recognition performance with an average identification rate of 84.45% when compared to the EMD algorithm of 79.05%. And with the feature vector of ZCR is added, the performance of the given four types, especially for wind interference event has a considerable improvement. The average identification rate of given four types is 97.67%. Specifically 100.0% for the wind disturbance events and 96.9% for the human intrusion events. Thus, the recognition

TABLE 1. Recognition results of four typical patterns by using different kinds of recognition schemes.

Event	EMD method	[*K1, K2, ..., K6*]	[*K1, ..., K6, ZCR*]
Wind	65.5%	60.9%	100.0%
Waggling	59.4%	90.1%	94.1%
Climbing	98.4%	90.3%	98.4%
Knocking	92.9%	96.5%	98.2%

results can directly prove that the wind disturbance events can be accurately discriminated from the human intrusion events through the proposed intelligent event recognition scheme.

Table 2 shows the average recognition processing time for a single vibration event. From Table 2, it can be seen that the proposed method has an obvious superiority compared with the EMD based method in the feature extraction stage and recognition stage. And the total recognition processing time of the proposed scheme (0.335 s) is lower than the EMD based scheme (3.449 s). Thus, verifying the proposed method allows for continuous on-line perimeter security monitoring.

TABLE 2. Comparison of recognition processing time between the proposed scheme and EMD scheme.

Processing Time	The proposed method	The EMD method
Feature Extraction	0.314 s	3.244 s
Events Recognition	0.021 s	0.205 s
Total Time	0.335 s	3.449 s

V. CONCLUSION

In this paper, we theoretically proposed and experimentally demonstrated a vibration event recognition scheme, which has been realized by combining VMD, kurtosis, and ZCR with SVM in DMZI based perimeter security system. The given vibrational signals are decomposed into a series of IMF components based on the VMD algorithm as the signal preprocessing step. Following this process, the VMD based kurtosis features are extracted. And by combining the ZCR features in the time domain, the proposed event recognition scheme through SVM classifier can accurately discriminate human intrusion events from the wind disturbance. A series of experimental results show that the average identification rate is up to 100.0% for the wind testing samples, and 96.9% for the given three types of human made intrusions. The discrimination efficiency is also high which can achieve 0.335s in the whole recognition process. As a comparison, the EMD based recognition scheme is also implemented in this paper. The recognition results both in accuracy and efficiency of the proposed scheme are apparently superior to the EMD based scheme. Therefore, the proposed scheme has a quite promising application prospect in the fiber optic perimeter security system.

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