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Variational Mode Decomposition-Based Threat Classification for Fiber Optic Distributed Acoustic Sensing

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ABSTRACT In this study, a novel method is proposed to detect and classify the threats for fiber optic distributed acoustic sensing (DAS) systems. In the study, phase-sensitive optical time-domain reflectometry (phase-OTDR) is realized for the sensing system. The proposed method is consisted of three main stages. In the first stage, Wavelet denoising method is applied for noise reduction in the measured signal, and difference in time domain approach is used to perform high-pass filtering. Autocorrelation is then used for comparing the signal with itself over time in each bin to remove uncorrelated signals. Next, the power of the correlated signals at each bin is calculated and sorted where maximum valued bins are considered as the event signal. In the second stage, Variational Mode Decomposition (VMD) technique is used to decompose the detected event signals into a series of band-limited modes from which the event signals are reconstructed. From the reconstructed event signals, higher order statistical (HOS) features including variance, skewness, and kurtosis are extracted. In the last stage, the threats are discriminated by implementing Linear Support Vector Machine (LSVM)-based classification approach to the extracted features. In order to evaluate the effects of proposed method on the classification performance, different types of activities such as digging with hammer, pickaxe, and shovel collected from various points of a buried fiber optic cable have been used under different Signal-to-Noise Ratio (SNR) levels (−4 to −18 dB). It has observed that the classification accuracy at high/moderate (−4 to −8 dB) and low (−8 to −18 dB) SNR levels are 79.5% and 75.2%, respectively. To the best of authors' knowledge, this research study is the first report to use VMD technique for threat classification in phase-OTDR-based DAS systems.

INDEX TERMS Distributed acoustic sensing, optical time-domain reflectometry, Rayleigh backscattering light, support vector machine, threat classification, variational mode decomposition.

I. INTRODUCTION

In recent years, use of fiber optic distributed acoustic sensing (DAS) has been attracting intensive attention in the field of vibration detection. Basically, it is based on the measurement of Rayleigh scattering that occurs when the light travelling in fiber optic cable is backscattered due to imperfections (known as ''scattering centers'') along the cable [1]. Theoretically, the mechanical vibrations due to the physical activities or events taken place around the cable cause fluctuations in the backscattered light. Interrogating these fluctuations then enable to detect and classify such activities. In this context, phase-sensitive optical time-domain reflectometry (phase-OTDR) technique has been developed for DAS during the last two decades [2], [3]. Unlike conventional OTDR, in phase-OTDR, pulses of highly coherent lights are used to transmit into a fiber optic cable, and for this reason, it is sensitive to relative phases of reflected fields from the scattering centers. Hence, it provides an efficient way for the monitoring of multi-point acoustic vibrations along the cable. Its effectiveness has been demonstrated in various applications such as crack detection of structures [4], [5], railroad monitoring [6],

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[7], traffic flow detection [8], vehicle detection [9], and intrusion detection [10]–[18].

It has already known that the backscattered signal sensed in a phase-OTDR based DAS system has generally quite low signal-to-noise ratio (SNR) which highly affects the vibration detection capability of the systems. Thus, several methods such as heterodyning [4], Fourier transforming [5], multi-dimension comprehensive analysis [7], polarization diversity detection [10], two-dimensional edge detection [11], Raman amplification [12], signal-noise separation [13], adaptive temporal/match filtering [14], [15], Wavelet denoising [6], [8], [9], [16], multi-scale permutation entropy and the zero-crossing rate [17], and difference in time-frequency domain [18] have been used to improve the threat/event detection performance. Although these methods provide promising results, it is still necessary to open new corridors in order to improve the quality of weak Rayleigh backscattered signal in event detection.

On the other hand, classifying physical events/threats constitutes an important stage of a phase-OTDR based DAS system which directly affects the system performance. Obviously, efficient techniques or approaches are required to achieve better classification accuracy. In this context, using advanced signal processing techniques can pave the way for improving the classification accuracy. One of the potential processing approaches could be an improved decomposition technique which is called as Variational Mode Decomposition (VMD) [19]. It is based on the concepts of Wiener filtering, analytic signal and frequency mixing or heterodyning. Due to its efficiency, it has been offered to apply in various applications including emitter identification [20], fluctuation analysis [21], and RF fingerprinting [22], [23]. So far, there is no evidence to use VMD technique in phase-OTDR-based DAS systems. Particularly, it can be employed to improve the accuracy of the features extracted from the detected event signals. Thus, with the help of the extracted features, it can be possible to achieve high classification accuracy.

In this study, it is aimed to propose an alternative method to detect and classify the threats for fiber optic DAS systems based on phase-OTDR. Unlike the other methods, this method uses Wavelet denoising, difference in time domain approach, and autocorrelation process together in event detection stage for the first time. Besides, to our best knowledge, this is the first method that uses VMD technique for threat classification. Basically, the proposed method is mainly consisted of three main stages. In the first stage of the proposed method, Wavelet denoising method is applied to remove the noise from the measured backscattered signal, and difference in time domain approach is used to perform high-pass filtering. In this stage, autocorrelation is also used for improving interferometric visibility of the events in all ranges (bins) along the fiber cable. Further, the power of the correlated signals at each bin is calculated and sorted. Hence, the maximum valued bins are considered to be the event signal. In the second stage, the detected event signals are decomposed into a series of band-limited modes by using VMD technique,

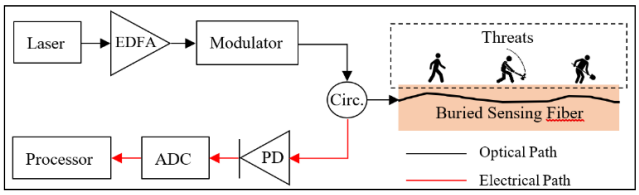

FIGURE 1. Phase-OTDR-based DAS system for threat detection.

and from these modes, the event signals are reconstructed. Moreover, from the reconstructed event signals, higher order statistical (HOS) features including variance, skewness, and kurtosis are extracted. In the last stage, Linear Support Vector Machine (LSVM)-based classification approach is implemented to the extracted features for discriminating the threats. In order to measure the effects of the proposed method on the classification performance, different types of activities collected from various points of a fiber optic cable have been used under different SNR levels. The results show the effectiveness of the proposed method in threat detection and classification.

The paper is organized as follows: In Section 2, the architecture of DAS system is overviewed. In Section 3, the proposed method is presented, and then experimental results are discussed to evaluate its overall performance. Lastly, in Section 4, conclusions are provided.

II. A BRIEF OVERVIEW OF DISTRIBUTED ACOUSTIC SENSING (DAS) SYSTEM

A typical phase-OTDR-based DAS system for threat detection is shown in Fig. 1. Components of the illustrated system have been already well defined in several sources [10], [13], [18]. Fundamentally, light pulses emitted from a narrow line width (< 1 kHz) continuous-wave (CW) laser source are amplified by an Erbium doped fiber amplifier (EDFA). The amplifier output is then sent to the acousto-optic modulator (AOM) which creates optical pulses before sending to buried sensing fiber by means of a circulator (Cir.). While travelling in the fiber, the optical pulse is exposed to Rayleigh scattering that causes a random intensity optical signal. When there is an external disturbance (typically vibrations on the ground nearby the fibre), the power of the Rayleigh backscattered signal generated from this external event is much larger than the background noise. The external disturbances (events) might be any vibration, such as walking, hitting, digging, etc. Time-frequency-energy variation of these disturbances induces phase changes on the backscattered light. Therefore, time-frequency energy characteristics of some expected events should be characterized well in order to develop a pattern recognition system. All these are discussed in detail in [24]. Next, the intensity of the optic lights modulated by these changes is easily detected by a photodetector (PD). The output of the PD is digitized using an analog-to-digital converter (ADC) to process the signal so that the threat can be detected, a direct detection approach using the backscattered light intensity directly is used without

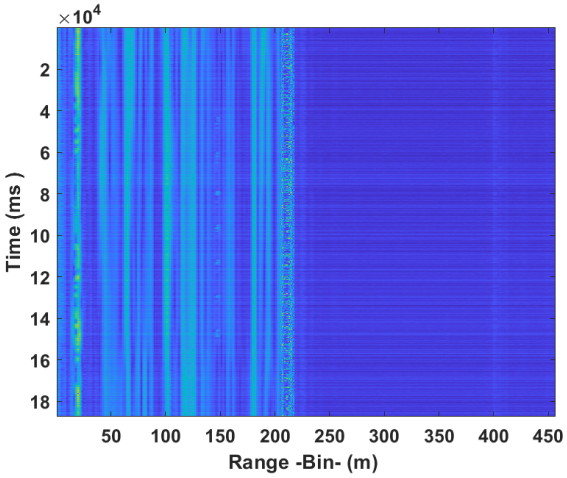

FIGURE 2. A raw DAS data.

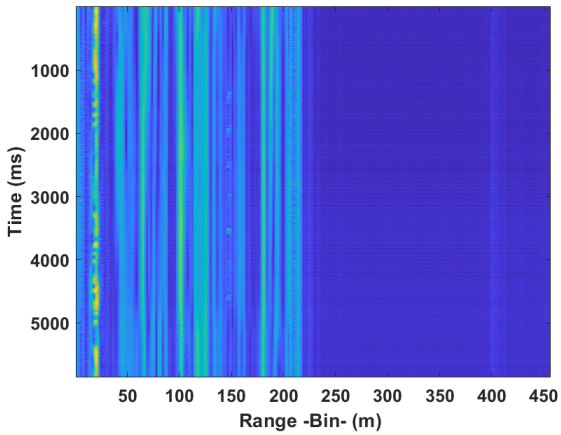

FIGURE 3. Denoised data.

any demodulation in this paper since it is easy to implement. However, in practice, it is not easy to extract a real event signal from the nonlinearly mixed signals. The proposed method that could be an alternative to alleviate this problem is presented in the following section.

III. THE PROPOSED METHOD

As mentioned previously, the proposed method is mainly consisted of three main stages: a) Event detection, b) Event reconstruction and feature extraction, and c) Event classification. Details of these stages are provided in the following subsections.

A. STAGE I–EVENT DETECTION

In the first step of the event detection, backscattered signal due to external events ($y(t)$) is needed to be extracted from the measured backscattered signal ($x(t)$). Simply, the relationship between $x(t)$ and $y(t)$ can be expressed as

$$x(t) = y(t) + n(t) \tag{1}$$

where $n(t)$ is considered as background noise that is typically presence in the cable due to thermal noise and cable characteristics. The aim is then to extract $y(t)$ from $x(t)$ by suppressing $n(t)$. To that end, the proposed method begins with removing noise from $x(t)$ by applying Wavelet denoising method [16] to clean up the signal. Wavelets are able to localize signal features to different scales. Hence, while removing noise from the signal, it is possible to preserve significant signal features. It is already known that a large number of wavelets can be used for both continuous and discrete analysis. In this study, DAS data for each channel is decomposed at level 5 using sym5 symlet wavelets [18]. As an illustration, a raw data of manual digging activity with pickaxe and denoised data obtained by applying Wavelet denoising are shown in Fig. 2 and 3, respectively.

After applying Wavelet denoising, difference in time domain approach is used to implement high-pass filter and also extract abrupt changes in the signal [18]. Before using this approach, the signal $x(t)$ needs to be digitized:

$$x[c,m] = y[c,m] + n[c,m], \tag{2}$$

where c is the measurement point on the cable ($c \in Z^+$), and m is the digital time index. The differencing in time domain between consecutive pulses can be then expressed as

$$\begin{aligned} &x_d[c,m] \\ &\quad = x[c,m+1] - x[c,m], \\ &\quad = (y[c,m+1] + n[c,m+1]) - (y[c,m] + n[c,m]), \\ &\quad = (y[c,m+1] - y[c,m] + (n[c,m+1] - n[c,m]), \\ &\quad = y_d[c,m] - n_d[c,m]. \end{aligned} \tag{3}$$

It should be noted that the differencing between consecutive pulses is relied on an assumption. According to this assumption, the background noise, due to external disturbance on the cable, does not change in a short time interval as opposed to Rayleigh backscattered signal. This case can be attributed to Parseval's relation which can be stated as

$$\sum_{m=0}^{N-1} |y_d[c,m]|^2 \gg \sum_{m=0}^{N-1} |n_d[c,m]|^2, \tag{4}$$

where N denotes the number of samples utilized in signal power estimation. Hence, in this method, a specific function to suppress the noise is not used. Obviously, only time domain differencing is used to perform high-pass filtering and extract abrupt changes. Fig. 4 shows a graphics illustrating difference in time domain approach for the denoised data obtained in Fig. 3.

As can be seen from the figure, although the events occurred in some bins can be recognized, further processes are required for improving interferometric visibility of the activities in all bins. In fact, as discussed in [18], it is necessary to apply time-domain low-pass filtering in order to remove high frequency components due to the noise which is amplified by high-pass filtering. Instead, in this study, autocorrelation is used for comparing the signal with a time-delayed version of itself in each bin. Indeed, this yields

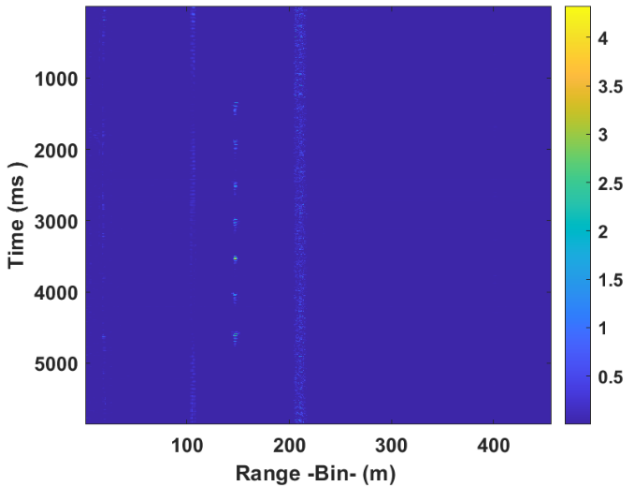

FIGURE 4. Difference in time domain approach applied on denoised data.

to comprehend the significant changes of the signals to reveal whether there is a significant relation between the signals or not. Theoretically, if N points are considered in time, the autocorrelation function $R(c, \tau)$ for a discrete signal $x_d[c, m]$ is calculated by [25], [26]

$$R(c, \tau) = \frac{1}{N} \sum_{m=1}^{N} x_d[c, m]\, x_d[c, m + \tau], \tag{5}$$

where τ is lag number. Then, highly correlated signals ($x_{dc}[m]$) exceeding a predefined threshold (Γ) for each bin are decided:

$$x_{cor}[c, m] = \begin{cases} x_d[c, m], & R(c, \tau) > \Gamma \\ 0, & \text{otherwise} \end{cases} \tag{6}$$

Thus, unwanted (uncorrelated) signals are removed so that the bins where the events are occurred can be detected as shown in Fig. 5. When compared to Fig. 4, it is clear that the unwanted signals presence in bins between 200 – 250 is completely removed, and thus interferometric visibility of the activities occurred in bins between 10 – 150 is considerably improved.

In the last phase of the event detection, power of the correlated signals at each bin, $P_x(c)$, is calculated as

$$P_x(c) = \sum_{m=0}^{N-1} |x_{cor}[c, m]|^2. \tag{7}$$

Then, the corresponding values are sorted in a vector $\mathbf{E}$ as

$$\mathbf{E} = sort\{P_x(c)\} \tag{8}$$

where $sort\{\cdot\}$ denotes the *sorting* operator that sorts the values of $P_x(c)$ in descending order as a sequence.

Finally, the maximum-valued bins are obtained by taking the maximum of the elements in $\mathbf{E}$ ($\max\{\mathbf{E}\}$). Therefore, the maximum-valued bins selected in $\mathbf{E}$ correspond to the candidates of event detection. The signals observed at these bins are then considered as the event signals.

B. STAGE II-EVENT RECONSTRUCTION AND FEATURE EXTRACTION

In this stage, the detected event signals are processed before classification. In fact, this stage has a vital importance in enhancing the detection performance of the system. Thus, the goal is to achieve robust features to be used in the event classification. To this end, the event signals detected from previous stage are decomposed and reconstructed, and then, HOS features are extracted from these reconstructed signals.

1) RECONSTRUCTION OF THE DETECTED EVENT SIGNALS

In order to reconstruct the event signals, VMD technique provided in [19] is utilized. Basically, it decomposes any real-valued signal s into a number of discrete modes s_z where $z = 1, \ldots, Z$. These modes have specific properties for reproducing the input signal, and has also limited bandwidth in frequency domain where each of them compacts around a center frequency ω_z. The bandwidth of a mode is evaluated as a specific norm of its Hilbert complemented. Then, by means of complex harmonic, the analytic signal is shifted. Alternate direction method of multipliers (ADMM) approach is used in order to solve the variational problem. Besides, to update the modes, Wiener filtering along with a filter are applied. Hence, each ω_z is updated as the center of gravity of the s_z power spectrum. Therefore, the Lagrangian multiplier that enforces the reconstruction of the input signal is updated. Briefly, to create a mode, the following scheme is applied:

- The corresponding analytic signal for each mode is computed by Hilbert transform,
- Frequency spectrum of the mode is shifted to baseband by heterodyning,
- The bandwidth of the mode is estimated by smoothing the demodulated signal which is also known as Wiener filtering.

Thus, the constrained variational problem is written as

$$\min_{\{s_z\},\{w_z\}} \left\{ \sum_z \left\| \partial_t \left[\left(\delta(t) + \frac{j}{\pi t} \right) * s_z(t) \right] e^{-j\omega_z t} \right\|_2^2 \right\}, \quad s.t. \sum_z s_z = f. \tag{9}$$

The optimization problem is then transformed into an unconstrained form by introducing the augmented Lagrangian $\mathcal{L}$:

$$\begin{aligned} &\mathcal{L}(\{s_z\}, \{\omega_z\}, \lambda) \\ &= \alpha \sum_k \left\| \partial_t \left[\left(\delta(t) + \frac{j}{\pi t} \right) * s_z(t) \right] e^{-j\omega_z t} \right\|_2^2 \\ &\quad + \left\| f(t) - \sum_k s_z(t) \right\|_2^2 + \langle \lambda(t), f(t) - \sum_k s_z(t) \rangle \\ &\quad + \langle \lambda(t), f(t) - \sum_k s_z(t) \rangle \end{aligned} \tag{10}$$

where α is the balancing parameter, and λ is the Lagrangian multiplier. The solution for the problem in (10) is found by employing a sequence of iterative sub-optimizations which is

called as ADMM) To employ this method, subproblems with respect to s_z and ω_z are required to solve. In this context, s_z is rewritten as a minimization problem such that:

$$\hat{s}_z^{n+1} = \arg\min \left\{ \alpha \left\| \partial_t \left[\left(\delta(t) + \frac{j}{\pi t} \right) * s_z(t) \right] e^{-j\omega_z t} \right\|_2^2 + \left\| f(t) - \sum\nolimits_i s_i(t) + \frac{\lambda(t)}{2} \right\|_2^2 \right\}. \quad (11)$$

After following the approaches given in [19], which are not stated here for the sake of simplicity, the resulting quadratic optimization problem can be written as in the following:

$$\hat{s}_z^{n+1} = \arg\min \left\{ \int_0^\infty 4\alpha (\omega - \omega_z)^2 \left| \hat{s}_z(\omega) \right|^2 + 2 \left| \hat{f}(\omega) - \sum\nolimits_i \hat{s}_i(\omega) + \frac{\hat{\lambda}(\omega)}{2} \right|^2 d\omega \right\}. \quad (12)$$

The quadratic problem can be then solved by

$$\hat{s}_z^{n+1}(\omega) = \frac{\hat{f}(\omega) - \sum_{i \neq z} \hat{s}_i(\omega) + \frac{\hat{\lambda}(\omega)}{2}}{1 + 2\alpha (\omega - \omega_z)^2}. \quad (13)$$

As for the subproblem with respect to ω_z, minimization problem is rewritten as:

$$\omega_z^{n+1} = \arg\min \left\{ \alpha \left\| \partial_t \left[\left(\delta(t) + \frac{j}{\pi t} \right) * s_z(t) \right] e^{-j\omega_z t} \right\|_2^2 \right\} \quad (14)$$

which can be solved, after the problem is transformed into a quadratic problem given that the optimization takes place in Fourier domain, as

$$\omega_z^{n+1} = \frac{\int_0^\infty \omega \left| \hat{s}_z(\omega) \right|^2 d\omega}{\int_0^\infty \left| \hat{s}_z(\omega) \right|^2 d\omega}. \quad (15)$$

Therefore, by substituting the solutions given in (13) and (15) into the ADMM method, an algorithm for VMD can be achieved. It can be summarized as provided in the following procedure [22]:

- Set n to 0 for initializing the modes ($\hat{s}_z^1$, ω_z^1, and $\hat{\lambda}_z^1$)
- Update $\hat{s}_z^{n+1}(\omega)$ provided in (13)
- Update ω_z^{n+1} provided in (15)
- Update Lagrange multiplier: $\hat{\lambda}^{n+1}(\omega) \leftarrow \hat{\lambda}^n(\omega) + \tau \left(\hat{f}(\omega) - \sum_z \hat{s}_z^{n+1}(\omega) \right)$ until the convergence $\sum_z \left\| \hat{s}_z^{n+1} - \hat{s}_z^n \right\|_2^2$.

2) FEATURE EXTRACTION

Once the event signals are reconstructed, the next step is to extract distinctive signal features from the reconstructed signals by exploiting instantaneous signal characteristics such as instantaneous amplitude $a(n)$, instantaneous frequency $f(n)$, and instantaneous phase $\emptyset(n)$. For a real-valued discrete signal in time domain $s(n)$, the analytic signal $s^a(n)$ can be expressed as

$$s^a(n) = s_I^a(n) + j s_Q^a(n) \quad (16)$$

where I and Q are the in-phase and quadrature components, respectively. These components are given by $s_I^a(n) = s(n)$, $s_Q^a(n) = H\{s(n)\}$ where $H\{\cdot\}$ denotes Hilbert Transform. Therefore, the instantaneous signal characteristics ($a(n)$, $\phi(n), f(n)$) can be calculated as

$$a(n) = \sqrt{\left(s_I^a(n)\right)^2 + \left(s_Q^a(n)\right)^2}, \quad (17)$$

$$\emptyset(n) = \tan^{-1}\left[\frac{s_Q^a(n)}{s_I^a(n)} \right], \quad (18)$$

$$f(n) = \frac{1}{2\pi} \frac{\emptyset(n) - \emptyset(n-1)}{\Delta n}. \quad (19)$$

Further, the biases superimposed by the data collection system are removed. To do that, receiver-induced linear component of the instantaneous phase is eliminated, and all characteristics are normalized [22]. Then, three HOS features (skewness, kurtosis, and variance) are calculated from $a(n)$, $\emptyset(n)$, and $f(n)$. Hence, a total of nine feature vectors are created to be used in event classification.

C. STAGE III–EVENT CLASSIFICATION

In the event classification stage of the proposed method, it is aimed to measure the effects of the proposed method on the classification performance. Although several approaches or techniques have been proposed for classification purposes, it is still necessary to achieve accurate results in classification of the detected events especially under realistic noise conditions. To that end, in the following subsections, the procedure for creating data under different noise conditions is described, and the details of the classification method employed to identify the events are presented.

1) DATA CREATION

Three types of activity were recorded from different points of a buried fiber cable. These events are: (1) Digging with hammer, (2) Digging with pickaxe, (3) Digging with shovel. Different levels of the channel noise were then added randomly to the records. While doing this, three datasets for each event were created by varying SNR levels. The ranges for the SNR levels were defined as: (a) low SNR (−8 to −18 dB), (b) high/moderate SNR (−4 to −8 dB). At each SNR range, there were 120 samples for each event. It should be also noted that SNR values of each dataset are distributed in approximately Gaussian distribution.

2) CLASSIFICATION AND RESULTS

Before making classification, the feature sets created in *Stage II* are divided into training and test sets for each event. Here, the feature sets are trained in order to make a relationship between the feature sets and the events, whereas, the test sets are used for estimating the performance of the classifier.

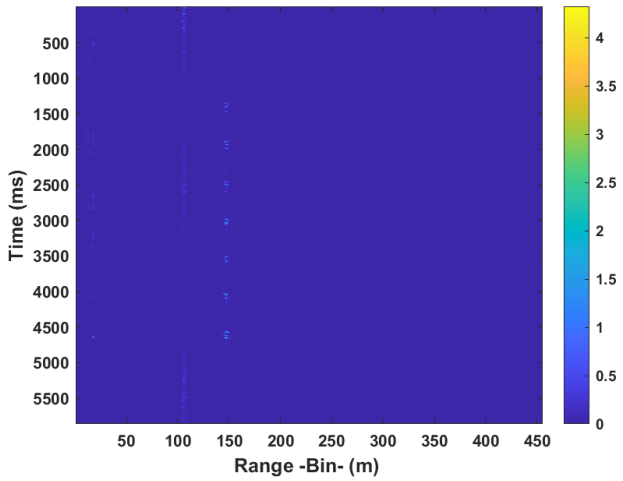

FIGURE 5. The detected bins where the events are occurred.

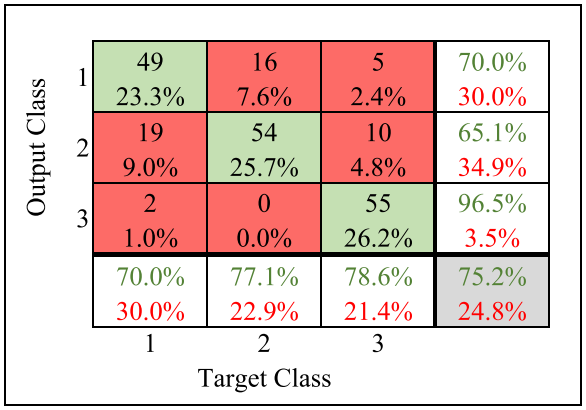

FIGURE 6. Confusion matrix for low SNR (−8 to −18 dB).

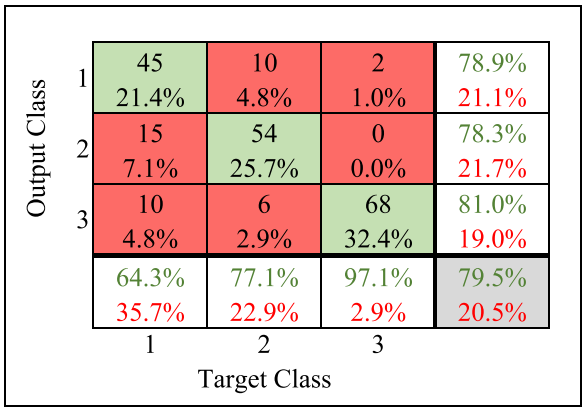

FIGURE 7. Confusion matrix for high/moderate SNR (−4 to −8 dB).

For classification, LSVM classifier has been employed due to its efficiency [22], [23]. Each training set consists of 70 (58%) out of 120 samples per event. The corresponding test set consists of the remaining 50 (42%) samples.

LSVM was trained with the training set, and its decision function was determined. The test set was then used to measure the classification accuracy. The confusion matrices of the LSVM classifier for the datasets under low SNR and high/moderate SNR are shown in Fig. 6 and Fig. 7, respectively. In confusion matrices, the number and the percentage of misclassified samples are represented by red coloured cells while the number and the percentage of correctly classified samples are represented by green coloured cells.

When the confusion matrices are analysed, it is observed that the classification accuracy at high/moderate and low SNR levels are 79.5% and 75.2%, respectively. It is clear that the accuracy is decreased by ∼4% under low SNR level. On the other hand, almost the same rates, 65.1% and 64.3%, are observed as the lowest classification accuracy at low and high/moderate SNR level, respectively.

IV. CONCLUSION

This paper presents a novel method to detect and classify the threats for phase-OTDR based fiber optic DAS systems. In the proposed method, threat detection is provided by a different approach which combines Wavelet denoising and difference in time domain methods with the autocorrelation process. For threat classification, on the other hand, VMD technique is used to extract HOS features (skewness, kurtosis, and variance) from the detected threats. In order to identify the threats, LSVM classifier is employed under different SNR levels. According to the classification performance results, it has obtained that the system becomes effective at identifying of physical activities such as digging with hammer, pickaxe, and shovel which are taken place around the buried fiber cable. More specifically, it has observed that better performance (∼4% higher accuracy) could be achieved at higher SNR levels (−4 to −8 dB). But still, it has shown that acceptable classification performance (75.2%) could also be achieved at lower SNR levels (−8 to −18 dB).

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