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Improving Event Classification Using Gammatone Filter For Distributed Acoustic Sensing

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ABSTRACT

The phase optical time domain reflectometry (Φ-OTDR) system offers several advantages suitable for distributed acoustic sensing application. It has long sensing range, great anti-electromagnetic interference, and high sensitivity towards environmental vibrations. However, as a sensor system, the Φ-OTDR is limited to only collecting environmental vibrations without providing more useful information such as the location and types of events happening around the sensing region. Therefore, it requires an extensive data processing system to distinguish between different events happening within the sensing regions. In this paper, Simple Differential and Normalized Differential method were used to extract perturbation event prior to classification process comprising data organization, features extraction, and classification outcome were implemented. Gammatone Frequency Cepstral Cepstrum were used to handcraft features for classification and were obtained using Gammatone Filter processing. Classification scheme based on Support Vector Machine (SVM) is use as classifier where accuracy score 100%.

Keywords: Gammatone Frequency Cepstral Cepstrum (GFCC), Phase Optical Time Domain Reflectometry (Φ-OTDR), Support Vector Machine (SVM), Simple Differential (SD), Normalized Differential (ND)

1. INTRODUCTION

The Phase Optical Time Domain Reflectometry (Φ-OTDR) system has seen many applications in the field of pipeline monitoring [1], electric cables monitoring [2], perimeter fencing [3] and health building monitoring [4]. The strengths of the Φ-OTDR system include long sensing range [5], high sensitivity towards environmental vibrations [6] and great anti-electromagnetic interference [7] has made it a primary choice for distributed sensing application. However, the Φ-OTDR require specific processing methods to distinguish events detected by the sensor such as the differential method and K-Nearest Neighbour.

Y Shi et al. [8] proposed a small scale Convolutional Neural Network (CNN) model to process the Φ-OTDR signal. The CNN model was used to extract features from the temporal-spatial domain while multiple Machine Learning (ML) models were used to classify the features belonging to separate events. From their work, events such as walking and digging were distinguished with an accuracy of 91.77% within 6.01s. H Whu et al. [9] applied multi-scale wavelet decomposition to separate the temporal signal into different scales containing unique components. By merging specific components, intrusion signals can be obtained without the presence of external interferences. Results show they successfully classified events such as human intrusion and clapping interferences with 89.19% and 86.15% for precision and recall respectively.

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Another method proposed by F Jiang et al. [10] implement Mel Frequency Cepstral Coefficient (MFCC) and CNN. MFCC is a typical processing method for human auditory signal. The combination of these method used to classify events such as human digging and environmental noises with quite high precision of 98.02%.

Often, Gammatone Filter (GF) is used to approximate sound signal being synthesized by the human auditory system. The output from GF is known as Gammatone Frequency Cepstral Cepstrum (GFCC). The human auditory filter's purpose is to filter out frequencies that lies outside of its own frequency bandwidth. This is done by only allowing a certain range of frequencies to pass through the filter, resulting in reduced unwanted interference such as noise and improve system performance. In contrast to MFCC, the GFCC exhibits superior performance when processing data containing noise [11]. Besides that, GFCC is operable in both time [12] and frequency [13] domains and has seen many applications in the area of automatic speaker recognition [14], robust speech recognition [13] and underwater target feature extraction [15]. The time domain response of GFCC centered at frequency f is expressed by Equation (1).

$$g(f,t) = at^{n-1}e^{-2\pi bt}\cos(2\pi ft + \varphi) \tag{1}$$

Where a is output gain; t is time; n is the order of filter; φ is phase and b is bandwidth.

In this work, we propose to use GFCC as handcraft features, and Support Vector Machine (SVM) scheme for classification process of Φ-OTDR data. A comparative work between a Simple Differential (SD) method and a Normalized Differential (ND) method for event detection is used. Experimental results show that using the SM method for event detection exhibit better classification performance than the ND method; where i) handcraft feature points which are consistently scattered closer, and ii) significantly higher hyper-plane margin distance.

1.1 Experimental Setup and Signal Processing Methodology

The Φ-OTDR system deployed in this study is shown in Figure 1. As a primary light source, a distributed feedback laser consisting of an ultra-narrow line width 1550 nm is emitted by a laser diode as continuous light. The continuous light is modulated by an acoustic optical modulator (AOM) to produce sequences of pulses. The erbium-doped fiber amplifier (EDFA) is used to amplify those pulses and is split into two by a 99/1 optical coupler. The 1% portion of the pulse is used as a reference signal while the remaining portion is injected into the sensing fiber realized using a 1300m standard single mode fiber as fiber under test (FUT). The back-reflected Rayleigh signal is directed to detection and data collection by an oscilloscope by an optical circulator.

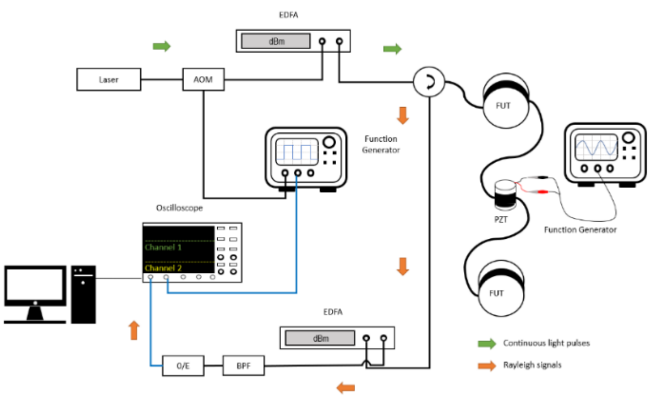


Figure 1. Φ-OTDR experimental setup

Two lead zirconate titanites (PZT) were wrapped around by a 20m long portion of the FUT at 1100m is used to simulate different event to be detected by the sensor. The PZT were vibrated at 300Hz, 700Hz and 900Hz. The Rayleigh backscattered light is amplified by a second EDFA and goes through a bandpass filter (BPF). It is then acquired, displayed and recorded by a digitized oscilloscope at a sample rate of 250MS/s. Data organizing and extraction is performed using Matlab software for the classification campaign.

In order to locate the presence of event induced by the PZT, observing the raw traces will not provide any valuable information, thus differential method needs to be applied. In this study, we analyzed two differential method, which include a simple differential method and normalized differential method proposed by Ashry et al. [16] to analyze the vibration events. Once the event was successfully detected by the system, the event was extracted and arranged into two separate datasets; i) simple differential and ii) normalized differential.

The simple differential method involves subtracting consecutive future traces with the initial trace and is described by Equation (2).

$$\Delta R = R_{i+1} - R_1, i \in (1, N-1) \tag{2}$$

Where, ΔR is the difference between two traces, R_{i+1} is the consecutive trace, R_1 is the initial trace, *i* is the ith number of the specific trace and *N* is the total number of traces acquired.

While the normalized differential method proposed by Ashry et al. aims to improve the SNR values of weak Rayleigh signal by equalizing the noise around the fiber cable. The method is illustrated by Equation (3).

$$\Delta R = R_{i+1} - R_i/R_i, i \in (1, N-1) \tag{3}$$

Where, ΔR is the difference between two traces, R_{i+1} is the consecutive trace, R_i is the ith number of the specific trace and *N* is the total number of traces acquired.

The method for classification by SVM is described by Equation (4).

$$\begin{bmatrix} min\frac{1}{2}(w)^2 \\ s.t.\, y^i(w^T x^i + b) \geq 1 \end{bmatrix} \tag{4}$$

Where (x^i, y^i) is the sample points and $w^T x + b = 0$ is the hyperplane.

2. CLASSIFICATION PROCESS

The event classification process involves three different phases; i) data organization phase, ii) features extraction phase and iii) feature classification phase. The data organization phase is required to arrange and manage the time domain data (300Hz, 700Hz and 900Hz pulse wave). Typically, the normal minimum amount of stress required to be induced on telecommunication fiber cables for the detection of an event is roughly 100nε [17]. For the Φ-OTDR system, every 1Hz of PZT vibration induces a range of a few hundred units of nε of stress [18]. Also, the PZT is normally set to not more than 20kHz for simulating vibration events [19]. Therefore, our testing of different PZT vibrations (300Hz, 700Hz and 900Hz) is enough to induce the minimum amount of required stress on the fiber cable, making it detectable by the Φ-OTDR system. Each pulse wave data is then extracted using the Simple Differential (SD) and Normalized Differential (ND) method. Lastly, the resulting extracted data is arranged to create two sets of dataset; i) extracted SD and ii) extracted ND.

For the feature extraction phase, each set of extracted datasets are wrapped into time-frequency domains using the Gammatone filter, also known as Gammatonegram. To produce GFCC, each row of Gammatonegram is then summed up together. Then, the GFCC data is truncated by selecting the peak range of interest to avoid high dimensionality problems. Every step thus far in the feature extraction phase is repeated for all 320 samples of data. The resultant data will be grouped into a 60:40 ratio for training and testing purposes of machine learning in the classification phase.

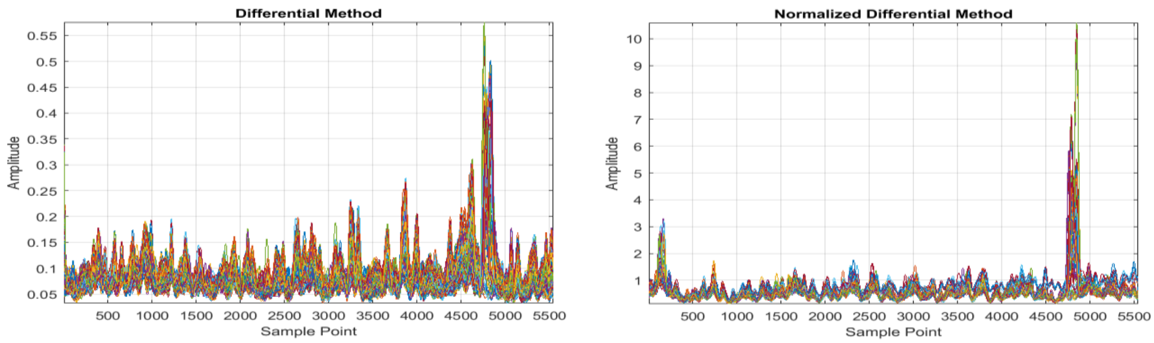
In the classification phase, SVM is used as the primary classification model. Firstly, K-fold cross-validation method was used to find train and test yield. Then, SVM is used to train the reference and trial dataset. Lastly, the detection results from the SD and ND method were evaluated using cross-correlation described by Equation 5. For reference, in Radio Detection and Ranging (Radar), often matched filter is used for detection task which employ the similar approach [20]. To measure the classification performance, 4-nearest neighbors were trained using the built-in *'fitcknn'* function in Matlab. Then, the confusion matrix result is obtained by correlating the results between the 4-nearest neighbour and to predict the response classifier using the built-in *'confusionmat'* in Matlab.

$$CCS(l) = \int_{-L}^{L} Gf_i\,(\tau - t) \cdot Gf_{i+1}(t) d\tau, -L < l < L \tag{5}$$

Where Gf_i is the detection output (SD and ND), i is the number of detection outputs, τ is the time delay and L is the length of the detection output.

3. RESULTS AND OBSERVATIONS

It can be observed from Figure 2(b) that a ND produces an overall higher amplitude reading, especially the detected event represented as a spike roughly between sample points 4750 and 4900 compared to SD shown in Figure 2(a). This is because the normalized differential method enhances the amount of noise equalization within and along the fiber enabling better detection of events, even in weak Rayleigh signals.



(a) (b)

Figure 2. Event Detection result using (a) Simple Differential (b) Normalized Differential

Figure 3(a) shows the position of the handcraft spike of GFCC, and Figure 3(b) show the truncated GFCC data of 300Hz, 700Hz and 900Hz pulse wave that the length has been shorten in order to avoid high dimensional problems for classification process.

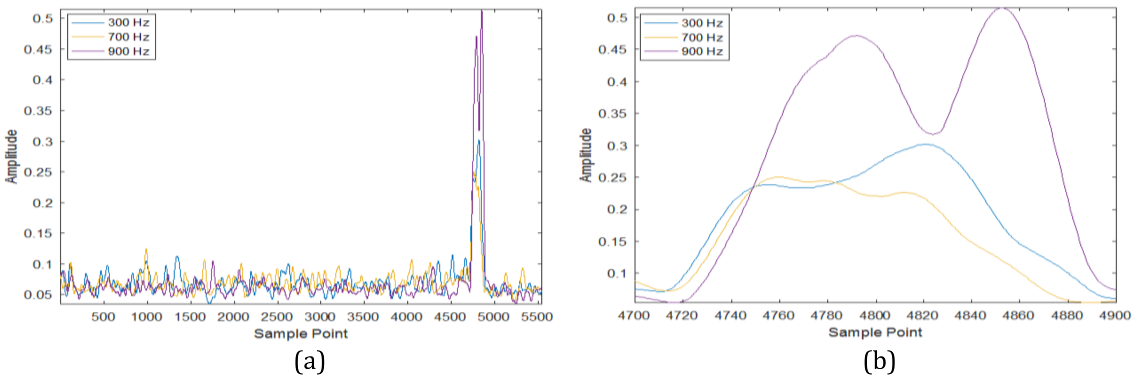


Figure 3. Feature Extraction, single point for each pulse wave for clarity purpose; (a) GFCC and (b) Truncation Data of GFCC

The classification results arranged into column; i) SD, and ii) ND is shown in Figure 4. It shows that the classification performance of SD method surpasses the classification performance of normalized differential method. This can be seen by the handcrafted point scatter for simple differential method that maintains their distance from the hyperplane as compared to normalized differential which is less consistent. Secondly, the features separation of the simple differential from the hyperplane has relatively larger margin compared to normalized differential method. From the points stated, it can be concluded that the extracted data using simple differential method provide significantly better performance than normalized differential method.

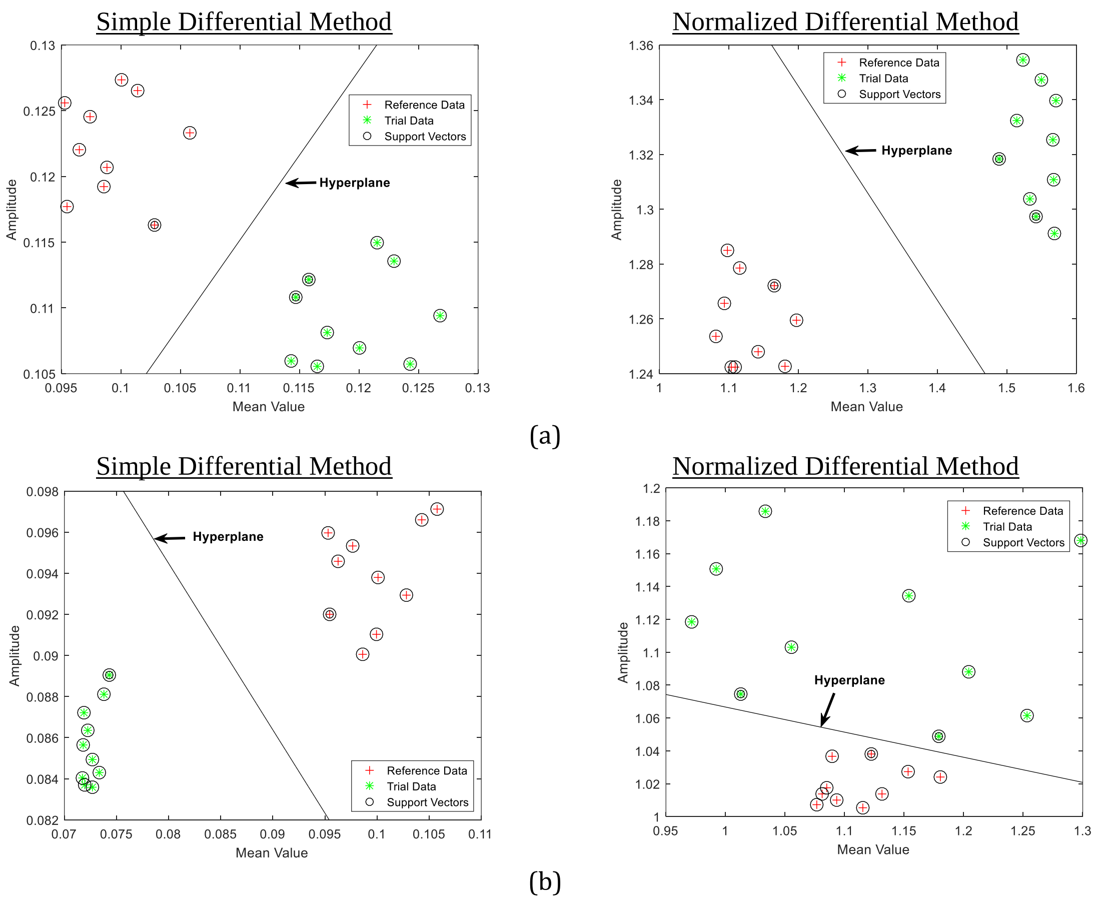


Figure 4. Classification results between reference data (300Hz) vs trial data
(a) 700Hz and (b) 900Hz

The cross-correlation score for each dataset is shown in Table 1. Based on the results, the score revealed by each dataset is acceptable with positive correlation. At this point, expected distinct cluster between pulse signal can be achieved. Moreover, a slight decrease in classification performance between output from method of detected might be expected.

The classification performance evaluated by the confusion matrix is shown by Table 2, Table 3, Table 4, and Table 5. From the results, it can be observed that the first two diagonal shows the correct classification by SVM, with all 10 feature points successfully being classified according to its class and none being wrongly classified. Hence, producing a 100% classification score. This is true since Figure 4 shows that every feature point lies within their own respective regions. Besides that, paramount cross correlation score of simple differentiation has contributed to better margin separation from hyperplane. Therefore, it can be concluded that the extracted data using the SD method provide significantly better performance than the ND method.

Table 1 Cross-Correlation Score

Pulse Signal (Hz)	Method of Detection	
	Simple Differential	Normalized Differential
300	0.8917	0.8969
700	0.7852	0.8130
900	0.8383	0.8337

Table 2 Confusion Matrices for Simple Differential of 300Hz and 700Hz

Output Class	10	0	100%
	0	10	100%
	100%	100%	100%
		Target Class	

Table 3 Confusion Matrices for Simple Differential of 300Hz and 900Hz

Output Class	10	0	100%
	0	10	100%
	100%	100%	100%
		Target Class	

Table 4 Confusion Matrices for Normalized Differential of 300Hz and 700Hz

Output Class	10	0	100%
	0	10	100%
	100%	100%	100%
		Target Class	

Table 5 Confusion Matrices for Normalized Differential of 300Hz and 900Hz

Output Class	10	0	100%
	0	10	100%
	100%	100%	100%
		Target Class	

This paper presents the fundamental classification results from collected data described in experimental setup shown in Figure 1. Classification results reveal data from simple differential method surpass the normalized differential method; i) handcrafted point scatter closer and ii) higher hyper-plane margin. Furthermore, it can be said that this strategy would be able to classify more data consisting of various events occurring at the same time. Also, GFCC has successfully been applied and used to improve the performance of event classification in distributed acoustic sensing. The GFCC works well with SD method where the classification result using SVM produced significantly larger hyper-plane margin and the handcrafted points scattered much closer. It is expected that this strategy would work fine with in detecting various event for different activities.

4. CONCLUSION

This paper has proposed a processing system to distinguish between different events happening within the sensing regions of the phase optical time domain reflectometry (Φ-OTDR) system. A comparison work between SD and ND have shown that the ND prove to be a better event detection method as it produces a higher amplitude/value reading. However, the classification result from the SD-GF combination have proved to be better than the ND-GF, achieving a confusion matrix score of 100% for classification performance.

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