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Characterization of DWT as Denoising Method for φ-OTDR Signal

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ABSTRACT

DAS system based on φ-OTDR technique suffers from random noises that affect the signal-to-noise-ratio of the extracted signals. This results in high false alarm rate, reducing the capabilities of the systems to detect vibration signals. This paper presented a thorough analysis of a denoising method using discrete wavelet function (DWT). We implemented and compared different mother wavelets such as Symlet 4, Haar, Daubechies 4 (Db4), Biorthogonal 4.4 (Bior4.4), Coiflets 3 (Coif3), Discrete approximation of Meyer wavelet (dmey), Fejér-Korovkin filters 8 (fk8) and Reverse Biorthogonal 6.8 (rbio6.8), using multiple levels of decomposition. Four denoising thresholds, Empirical Bayes, Universal Threshold, Stein's Unbiased Risk Estimation (SURE), and Minimax Estimation (Minimax) were characterized using soft threshold rule. From the results obtained, the combination of the Daubechies 4 wavelet function, level 3 decomposition, SURE denoising threshold with soft threshold rule produces the best denoising performance on the φ-OTDR data.

Keywords: φ-OTDR, wavelet denoising, signal processing

1. INTRODUCTION

Distributed acoustic sensing (DAS) systems based on phase optical time domain reflectometry (φ-OTDR) has been a subject of detailed investigation in monitoring applications due to its capability and reliability of detecting minute strains of multiple vibrations and acoustic events induced by external vibrations along its entire fibre length. The DAS system exploited the Rayleigh scattering in an optical fibre which has high sensitivity toward disturbances and provides real-time monitoring. This system has been adopted in various monitoring applications such as pipeline monitoring, intrusion along perimeter detection, seismic monitoring, and railway monitoring [1]–[4].

However, the φ-OTDR signals can be heavily affected by the noises from vibration of surrounding events and noises from the configuration setup which include the laser phase noise, the stochastic nature of Rayleigh backscattering, the laser frequency drift, the thermal noise in electrical and optical component, and the finite extinction ratio of optical modulator [5]–[8] . These noises cause a large spike-like pattern in the raw data. The noises affect the SNR of the φ-OTDR traces, which causes low visibility of the interference signals, thus produces unreliable vibration measurement of actual real vibration activities. This in the end might cause false alarm to trigger.

To reduces the noise, researchers have proposed different denoising techniques with the aims of improving the signal-to-noise (SNR) and increase the detection capabilities. To date, current SNR improvement focuses on post-processing algorithms such as moving average and moving

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differential [9], wavelet transform (WT) [10],[11], empirical mode decomposition [12],[13] and image-based processing such as 2-Dimensional edge detection [14] and 2D bilateral filtering algorithm [15].
Although other researchers have explored wavelet transform in the φ-OTDR application, a detailed methodology on the selection process of the mother wavelet, level of decomposition, and threshold rules was not discussed at length. These steps are important steps in denoising the signals. This paper aims to compare and contrast a battery of denoising method by applying them to the acquired φ-OTDR signals. The best wavelet combination will be determined based on the calculated SNR.

2. METHODOLOGY

2.1 φ-OTDR set up

The architecture of the DAS system exploited the scattering losses in fibre, particularly Rayleigh scattering. DAS system based on φ-OTDR technique consists of optical fibre which acts as the sensors to the measures backscatter light from that gated optical pulses into the fibre along its entire length. A detector is used to measure the reflected light (Rayleigh signal) from the fibre as pulses of light travel along with the fibre. The acquired backscatter signal at the receiver end consists of coherence interference of the backscatter signal at different points along with the fibre within a single pulse [16].

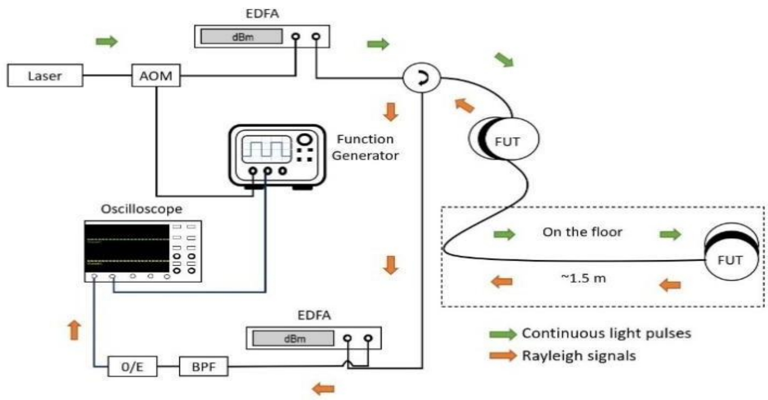

Figure 1. shows the a) Rayleigh backscattering traces coming from each pulse propagating in the fibre b) Configuration setup

φ-OTDR technique is first accomplished using the direct detection configuration displayed in Figure 1(b). The light source is an ultra-narrow linewidth distributed-feedback laser operating at 1550.12 nm. An acoustic-optic modulator converts the continuous light from the laser diode into a sequence of pulses (AOM) and the pulse repetition period and width were set using a function generator. The modulated pulses then were injected into fibre under test (FUT), and the Rayleigh backscatter signals pass through another amplification using a second EDFA where a bandpass filter is used to remove amplified spontaneous emission (ASE) from the EDFA. A photodetector (PD) was then used to detect the Rayleigh Teledyne LeCroy HDO6104 Digitizing Oscilloscope was used to collect and process the information.

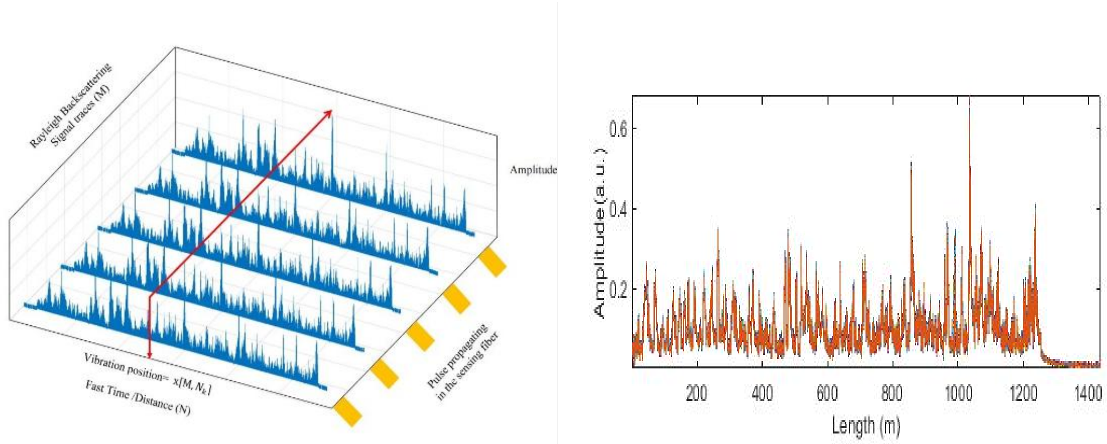

Figure 2. shows the a) Rayleigh backscattering traces coming from each pulse propagating in the fibre b) superimposed 5000 Rayleigh traces

The raw Rayleigh backscattering coming from each pulse propagating in the fibre can also be regarded as two-dimensional arrays x (M, N), as shown in the Figure 2(a). N is the number of sampling points for each trace, while M represents the number of traces that propagate in the fibre within the specified time interval. 5000 Rayleigh signal traces were reconstructed in the time domain from data gathered within 100 milliseconds, as illustrated in Figure 2. (b). When a disturbance occurs on the sensing fibre at position N_k along the row vector, the disturbance signal can be extracted through one-dimensional array v[M,N_k].

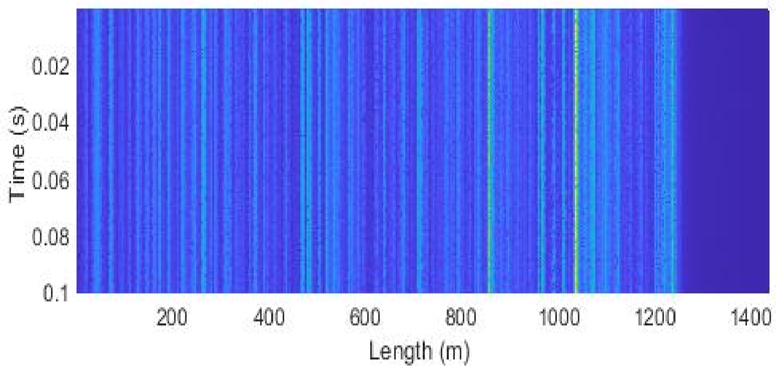

Figure 3. shows the image constitute to the reconstructed Rayleigh signal traces

Since observing the rebuilt data gives little information on the vibrations event shown in Figure 3, a normalized differential method proposed by Ashry et al. [17] was used to process the raw traces. From the differential signals obtained, the detected vibration signals in the FUT was extracted which is located at 980 m. However, the signals were corrupted due to the random noises existed in the system, thus signal denoising is required to recover and reconstruct (smoothen) the signals.

2.2 Discrete Wavelet Transform (DWT)

Wavelet methods are widely used for denoising non-stationary signals due to their ability to reduce noises without losing any important temporal information. The noises in the Rayleigh signals overlap with the desired signals information, thus wavelet denoising can be used to remove the background noises through Gaussian distributed approach. This approach assumed that the original signal, R, which is given by signal of interest, r is corrupted by additive white Gaussian noise (AWGN), n, which can be represented by $R = r + n$. Wavelet's method aims to suppress the noise, n, and recover the r. However, for the case of φ-OTDR systems, the noises are neither defined nor known, thus, the purpose of denoising these signals are to remove the noise from the real signal with minimum error.

Discrete wavelets transform (DWT) decomposes a signal using a pair of complementary filters and down samplers to eliminate unnecessary samples from the filters' output. The signals pass through a series of lowpass (LPF) and high pass (HPF) filters to decompose the signal. The signal passes through LPF to get the approximation coefficients and simultaneously processes through an HPF to generate the detail coefficients for each step, with down-sampling by two. The DWT equation is given as

$$DWT[n, a^j] = \sum_{m=0}^{N-1} x[m].\frac{1}{\sqrt{a^j}}\psi\left(\frac{n}{a^j}\right) * [m-n] \tag{1}$$

where N is the length of the signal, n is the delay parameter and ψ is the mother wavelet. Also, because wavelet function is orthogonal and symmetric, and different wavelet functions have distinct characteristics, the decomposition of the signal using different wavelets produces different outcomes, thus the denoising impact will vary.

2.3 Algorithms

The DWT is a powerful tool for analyzing non-stationary data such as φ-OTDR signals. Figure 4 gives the process of noise removal in φ-OTDR signals using wavelet denoising.

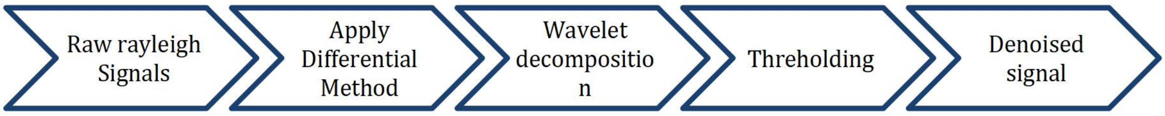

Figure 4. Filtering process for φ-OTDR signals

The DWT of φ-OTDR signals involved the following steps: (i) Signal decomposition: using wdenoise function in MATLAB, that denoised the signals by the selection of the Mother wavelet, and decomposition level. (ii) Selection of denoising threshold and threshold rules parameter to the wavelet coefficient. (iii) Reconstruction of clean signals through inverse discrete wavelet transform.

2.3.1 Selection on mother wavelet and decomposition level selection

The mother wavelet chosen will affect the precision of the wavelet transform based denoising output. If the form of the wavelet is similar to the shape of the differential signals, the wavelet provides excellent denoising performance. Since there are no universal wavelets that work on every signal, this research focuses on determining the most suitable wavelet specifically for φ-OTDR signals. Wavelet families consist of Symlets, Daubechies, Coiflet, BiorSplines, Reverse Bior, and others which contain different wavelets function with different orders. We implemented a Symlet 4, Haar, Daubechies 4, Biorthogonal 4.4, Coiflet 3, Discrete approximation of Meyer wavelet, Fejér-Korovkin filters 8, and Reverse Biorthogonal 6.8 wavelet functions in this research to find the most suitable wavelet combination that produces the best results based on φ-OTDR data. For denoising, the desired signal, choosing the best decomposition level for wavelet threshold denoising is equally crucial. Typically, the decomposition level is determined by the trial-and-error method, and in this study, composition levels 3, 5, 7, and 9 were used to determine the optimal decomposition level for different wavelet functions.

2.3.2 Thresholding Selection

Threshold selection is a direct and essential influencing element in the process of wavelet threshold denoising and choosing a different threshold will result in a different denoising effect. A few denoising thresholds used to determine the denoising threshold for the desired data are available in the MATLAB toolbox such as Empirical Bayes, Minimax, SURE, and Universal Threshold.

Empirical Bayes (Bayes): This technique employs a threshold rule based on the assumption of independent prior distributions for measurements provided by a mixture model. Due to the fact that measurements are utilized to estimate the weight in the mixture model, the approach performs better with a greater number of samples [18].

Minimax Estimation (Minimax): This technique employs a set threshold that is chosen to achieve the best possible performance in terms of mean square error when compared to an ideal procedure [19] . The equation to find the optimal threshold can be represented as followed

$$thr_{minimax} = \begin{cases} 0.3936 + 0.1829 * (log(n)/log(2)), & |n| > 32 \\ 0 & |n| \leq 0 \end{cases} \tag{2}$$

Stein's Unbiased Risk Estimate (SURE): It is a level-dependent threshold and based on Stein's unbiased risk estimate (SURE) [20]. The SURE threshold can be expressed as followed

$$SURE(\lambda; x) = d - 2.(i: |C_i| < \lambda) + \sum_{i=1}^{d} [min(|C_i|, \lambda)]^2 \tag{3}$$

Where C_i is the wavelet coefficient, and d is the number of elements in noisy signal denotes cardinality.

Universal Threshold (UniversalThreshold): This technique employs a fixed-form threshold that maximizes performance by a factor proportional to log(length(X)). The constant universal threshold can be defined as followed:

$$\lambda = \sqrt{2Ln(N)} \tag{4}$$

There are a few threshold rules that can be applied such as median, mean, soft, and hard. However, soft and hard thresholds were usually used. The term "hard threshold" refers to the process of setting elements to zero when their absolute values fall below the threshold. Meanwhile, soft threshold zeros any detail coefficients with absolute values less than the threshold, the remaining coefficients are narrowed towards zero.

The effectiveness of a signal denoising approach is determined by how precisely the technique can eliminate noise from signals while retaining as much information about the original signal as possible. To evaluate the suggested system's performance in this study, we employed one distinct metrics: signal-to-noise ratio (SNR). SNR is a frequently used performance metric for assessing the performance of signal filtration approaches between Rayleigh signals and denoised signals.

$$SNR = log \left| \frac{\sum_n \varkappa(n)}{\sum_n [x(n) - \varkappa(n)]^2} \right| \tag{5}$$

3. Results and discussion

Denoising φ-OTDR signals play an important role in pre-processing step before analyzing the acoustic signals detected by the system. Any noises that interrupt the data acquisition will result in a false alarm, thus reducing the efficiency of the detection systems. To reduce the noise, the effectiveness of wavelet method has been studied extensively .

The implemented wavelet functions were evaluated and compared based in its SNR performance. The SNR was calculated using Equation 5, and it has to be as high as possible. Additionally, the performance of several levels of wavelet decomposition utilizing various wavelet functions were also examines. Selected levels were 3, 5, 7, and 9. Table 1 shows the performance index of the proposed methodology.

Table 1 Performance index for different wavelet functions and level of decomposition

No	Wavelet Function	LEVEL = 3	LEVEL = 5	LEVEL = 7	LEVEL = 9
		SNR	SNR	SNR	SNR
1	Symlet 4	13.8369	13.5342	13.4319	13.4125
2	haar	13.6739	13.4045	13.3163	13.2992
3	Db4	13.8808	13.5178	13.3953	13.3814
4	Bior 4.4	13.8632	13.4603	13.3567	13.3401
5	Coif3	13.8116	13.4572	13.3287	13.3031
6	dmey	13.7016	13.3912	13.2719	13.2405
7	fk8	13.7580	13.4452	13.3549	13.3460
8	Rbio 6.8	13.6255	13.2582	13.1088	13.0789

From the table, level composition 3 shows the best results in performance parameter, where it has the highest SNR value compared to other levels of decomposition. In fact, the SNR slightly deteriorate at higher decomposition level of the function. While for the mother wavelet chosen, Symlet 4, Db 4 and Bior 4.4 wavelet functions show exceptionally better results compared to haar, Coif3, dmey, fk8, and Rbio 6.8 in terms and SNR, with an average of 13.8481, however, the SNR value for DB4 was slightly better than Bior 4.4, which is 13.8808. It should be noted that the denoising and threshold rule was in default mode, which means that Empirical Bayes with soft thresholding were being used.

Following that, the influence of various denoising thresholds were examined. The soft threshold rule was chosen here to preserve the signal's original structure, ensuring that the denoised signal retains all of its information. Four denoising threshold, indicated in Table 2, examined Empirical Bayes, Universal Threshold, Stein's Unbiased Risk Estimation (SURE), and Minimax Estimation (Minimax).

Table 2 Performance index for different wavelet functions and denoising threshold

No	Wavelet Function	Bayes	UNIVERSAL THRESHOLD	SURE	Minimax
		SNR	SNR	SNR	SNR
1	Symlet 4	13.8369	8.3528	14.9742	10.4951
2	haar	13.6739	8.4218	15.0037	10.4649
3	Db4	13.8808	8.5380	15.5031	10.6331
4	Bior 4.4	13.8632	8.4382	14.8780	10.5649
5	Coif3	13.8116	8.4495	14.9950	10.5786
6	dmey	13.7016	8.4727	14.9279	10.5431

7	fk8	13.7580	8.6555	15.0174	10.6940
8	Rbio 6.8	13.6255	8.3638	15.0450	10.4710

The SURE threshold technique employing the soft threshold rule performs the best, achieving the highest SNR (15.5031) in comparison to the other methods. The best wavelet transformation results were obtained by combining the Db4 wavelet function with level 3 decomposition and SURE threshold technique with soft threshold rule.

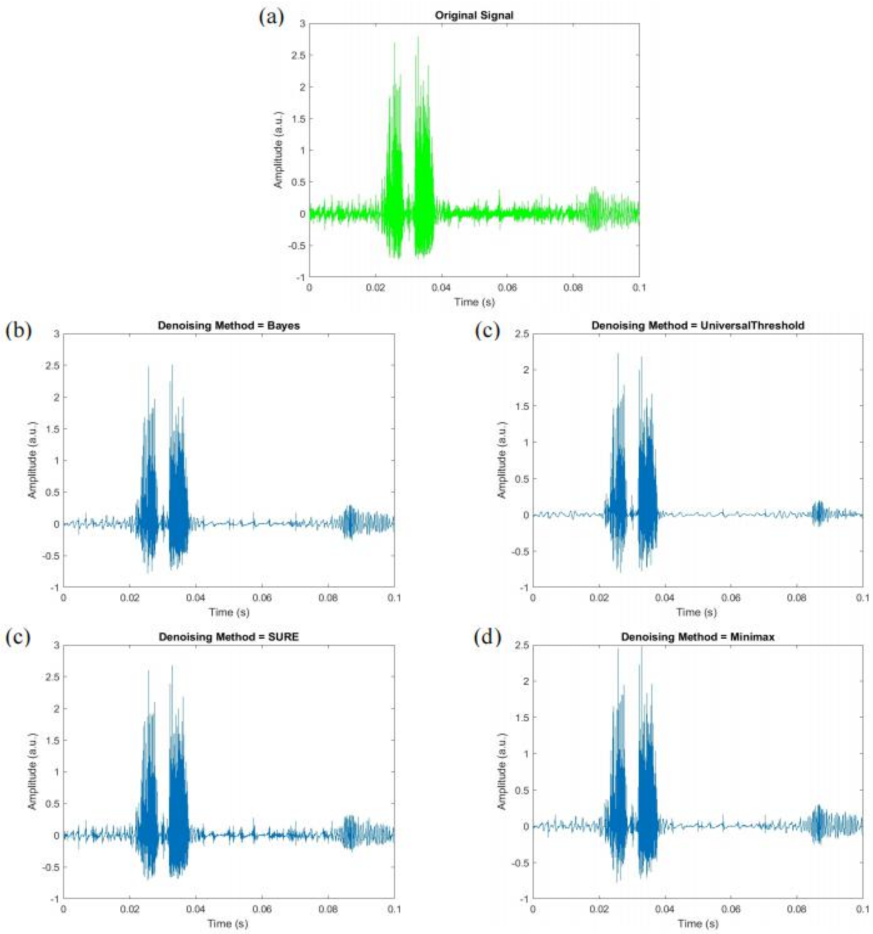

Figure 5. shows the Daubechies 4 wavelet with different denoising threshold a) original signal b) Empirical Bayes c) Universal Threshold d) SURE e) Minimax

Figure 5 shows the denoising signals, with different denoising thresholds using the soft threshold rule. From the denoised signals obtain, using SURE threshold with soft threshold rules remove noises from the original signal, while preserving the original signal's structure obtaining highest SNR compared to others. Thus, through this study, Daubechies 4 wavelet with 3 levels of decomposition, using SURE denoising threshold employing soft threshold produces the best results in terms of the SNR calculated.

3. CONCLUSION

This paper presented an approach for determining the optimal combination by underlying the mother wavelet, level of decomposition, and thresholding method for φ-OTDR data. SNR was calculated and used to compare the performance of each parameter. The initial findings demonstrate that when the level of decomposition is increasing, the SNR drop which is not ideal for denoising performance. Decomposition at level 3 yields the best results regardless of the mother wavelet, while Symlet 4, Daubechies 4, Coiflets 3, and Bior Orthogonal 4.4 all perform excellently, while Daubechies 4 obtains the highest SNR, making it the ideal mother wavelet for our signals. Then we compare the denoising threshold which concludes that the SURE threshold with soft threshold rule performs the best achieving the highest SNR. From this research, we can conclude that having a unique combination of thresholds and wavelets is critical in removing noises from our system. This result provides the best WT selection for our systems, which will be used in the next phase of our project.

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