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Oil Debris Signals Enhancement Based On Wavelet Analysis for Wind Turbine Condition Monitoring

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Abstract

Oil debris signals are applied to monitor lubricant oil conditions and fault diagnosis of a wind turbine. However, the signals will be influenced by the vibration of transmission mechanism and background noise, hence false alarms and undetected particles will limit sensors ability in examining fine particles in oil debris. This paper presents an approach to enhance the performance of oil debris signals. The de-noising of signals used a wavelet filtering to remove the vibration of a wind turbine, and then set a threshold to remove the background noise which caused by the system of measurement. The effectiveness of this enhanced measurement system is tested by using simulated and experimental signals.

Keywords*: oil debris signals, condition monitoring, wind turbine, fault diagnosis, wavelet filtering*

1. Introduction

On line monitoring of wind turbine condition is benefit to maintain a safe, reliable and productive in power generation. The advances in signal processing and fault detection have focused extensive research development of the wind turbine fault detection and condition monitoring domain. Oil debris detection is commonly used in most failure wind turbine because of harsh operating conditions and heavy load. Most of the oil particle detections in this field are classified as indirect or direct methods. Fault diagnosis based on vibration, fiber-optic and acoustic emission [1] are the most widely applied indirect technique because of the appropriate sensors and suitable established analysis methods. Most research on vibration, fiber-optic and acoustic emission based monitoring are reported in literature. Oil debris analysis on the other hand is a classical direct method which detects the wind turbine (or components) status in view of the size and count of the metal particles in the lubricant oil. Through analysis fine metal particles in the oil lubricant, it is able to diagnose latent faults in the early phase which might not be tested by acoustic emission or vibration based techniques. However, oil analysis technique has received more less attention contrast to the indirect techniques. Hence, in this study we pay close attention to oil debris condition monitoring.

There are several oil debris analysis techniques including magnetic chip collection, off line oil analysis, and on-line particle examination. The chip collection by using a magnetic collector which captures the metallic particles. When the quantity of particles in the lubricant oil arrives a predefined threshold, an alarm system then warn the operators[2]. The off line oil analysis technique, which collected and analyzed samples from the lubricant oil in a laboratory. Oil debris signal analysis is an on line oil condition monitoring equipment which installed in the oil recover lines, and offering a full flow passage way for the lubricant oil. The sensor will examine the metallic particles which pass through it. Oil debris monitor is based on perception the electromagnetic

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disturbances that produced by the passing metallic particles [3]. When every metal particle passing, the sensor will generates a signal that similar to a sine function. After processing the signal, then the device is able to detect an estimate lever of fatigue-induced material deterioration in the wind turbine components. The adaptive noise cancellation method removes the vibration interference to enhance the sensor system output signal by applying a reference vibration sensors mounted with the oil debris sensor. However, this would increase cost, complicate hardware and need more operation. The adaptive line enhancement technique, a series of the above background noise cancellation method, is applied to enhance the oil sensor system output signal [4]. The approach applied a delayed scheme in the measured signal which acted as the reference signal obtained through the vibration sensor, and without any additional hardware equipment. Though the full-band adaptive filtering performs well while meets slowly varying or stationary vibrations, the long convergence time of this algorithm becomes a block to obtain appropriate results. The more fast convergence, the more significant to real time condition monitoring of the wind turbine. Hence a wavelet based sub-band adaptive filtering technique is applied to obtain fast convergence and to process non-stationary signals [5]. The adaptive filtering executed the sub-band decomposition result which acquired by wavelet analysis. And the outputs will feed to a noise variance estimation algorithm to calculate the noise variance in every sub-band. The calculation results will apply to reduce the background noise through a threshold de-noising method [6]. However, the wavelet threshold de-noising which is used to reduce the wideband noise that cannot be removed by an oil debris monitor. The proposed de-noising method is evaluated through the experimental data from an oil debris sensor contain vibrations signals by a vibrator.

This paper hereafter is organized as follows: section 2 introduces the adaptive filtering method in vibration interference reduction. Section 3 discusses the decrease of the background noise applied a threshold technique. And a noise variance calculation algorithm is proposed in this section. The proposed oil debris signal experimental results are presented in section 4. Section 5 concludes this paper.

2. Adaptive Filtering and Application of Vibration Signal Removal

The ferromagnetic metallic particles natures generate signals are shown in Figures 1. From the Figure, the signal amplitude mainly depends on the mass of the ferromagnetic metal particles [7]. The output signals are monitored while the oil lubrication system operation. The software computes the number of measured particle signals and detects every particle size by corresponding phase information and amplitude. Therefore, an estimate of the wind turbine component damage level will be detection, and then an alarm of system health state would schedule time for maintenance. The sensor system has shown better function compared with the normal magnetic chip collector because of its' sensitive to non-ferromagnetic debris.

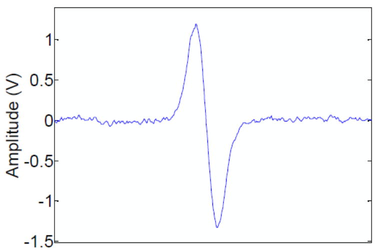

Figure 1. Sensor Output Signal of a Metallic Particle

However, the vibration interferences and noise level decided the minimum detectable particle size. As most measuring sensor systems the output of the system will be apt to affect by the noise and vibration interferences that include the signatures interest. The vibration interferences of the structure as addition of a combination signals in the sensor output. Because of the similarity between the metallic particle signal and the vibration interference signal often result in false alarm and leak detection. While the background noise which because of the electrical system flaws does not distribute as the vibration interferences, also influences the system performance. And this is especially in detecting very thin particles while the feebly signal will be easily covered by the background noise.

In Figure 2(a), the output signal of a small particle mixture background noise signal which sampled at 4000 Hz. As it shown in the Figure, the signal is detected in this case, however the background noise band can not be ignored. Figure 2(b) shows the output signal of the same particle mixture vibration interferences which generated by a vibrator. As it shown in the Figure, the signal of metallic particle from the measured signal almost can not be examined, not to mention estimate the associated particle size. Therefore, the main of this research is to decrease background noise and reduce vibration interference so as to enhance the sensor system performance in detecting very thin particles.

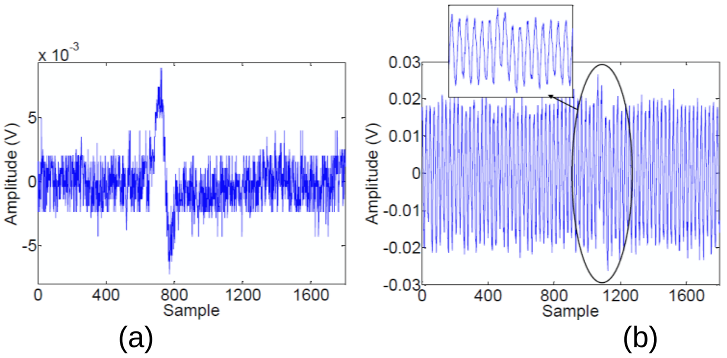

Figure 2. Sensor Output Signal of a Metallic Particle a) Without Vibration Interferences and, b) with Vibrations Interference

An adaptive filter is used to remove the vibration interference while the prior knowledge about both oil particle signal and vibration interferences is available. The filter through adjusting the parameters to estimate the absent information.

The signals frequency dependent on the metallic particles moving speed which associated with the lubricating oil flow speed. And the vibration frequency lies on the vibration nature of the structure where the oil particle sensor mounted. Therefore, both signal and vibration interference properties are based on the working conditions which are not known beforehand in the filter design. Hence, an adaptive algorithm to adjust filter parameters according to the working conditions is necessary. Such an algorithm is based on the variant of the adaptive noise cancellation and was applied to the classical detection problem of examining a sine wave in background noise [8]. The adaptive line enhancement block diagram is illustrated in Figure 3. This approach uses a delayed signal of the primary input as the reference signal; hence need not to separate the reference signal sources.

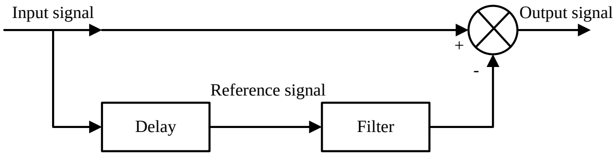

Figure 3. Block Diagram of the Enhancement Technique

This method can be applied to process the vibration interferences in the oil particle signal to avoid the employ extra vibration sensors and associated equipment. Since the metallic particles move randomly, then there may no correlation between the corresponding signals. Then, it's reasonable to assume that the nature of the mechanical systems vibration normally does not transform drastically over a very short time. Consequently, through this algorithm it would be possible to examine and remove the vibration interferences.

2.1. Normalized Line Mean Square

The least mean square adaptive algorithms provide a more robust tracking behavior and used in time varying communication channels [9]. The coefficients of the stochastic gradient vector are proportional to the magnitude of the coefficients of the delayed tap input vector. Therefore, when a coefficient is large, the filter will suffer from the gradient noise amplification problem. In order to overcome this difficulty, the weight update algorithm as follows

$$W_{k+1} = W_K - \mu\hat{\nabla}_k = W_K + \frac{2\mu}{\left\|X_{k-D}\right\|^2} X_{k-D}\varepsilon(k) \tag{1}$$

2.2. Frequency Vibration Disturbance

As the feature of the oil particle signal is applied to estimate the quantity of metallic debris content in the lubricating oil that is very significant to the adaptive filter effectively eliminate the vibration interferences with minimal distortion of the particle signal. In this section we study the level of disturbances introduced to the extracted particle signal by the adaptive line enhancement. The main purpose is to decrease the intensity of disturbances by appropriately selecting the design parameters such as filter length and delay duration. Consider the mixture of particle signal and vibration interference signal, as the signal input to the algorithm. We can have

$$s(k) = \sin\left(\frac{2\pi f_s(k-C)}{SR}\right) \quad \text{For} \quad C \le k \le C + \frac{SR}{f_s} \tag{2}$$

In the above equation, C is a positive constant reflecting the location of the particle signature, f_s is the frequency of the particle signal (Hz), SR is the sampling rate (Hz), and S_R/f_s is the largest integer less than or equal to S_R/f_s. In this equation, for simplicity we assume that the vibration interference v (k) is as simple as a single harmonic. As vibration interference can be decomposed to similar harmonic components, the assumption is reasonable for theoretical analysis of the proposed algorithm. Therefore, the mixture model we can write as

$$x(k) = s(k) + A\sin\left(\frac{2\pi(f_s+\Delta_f)k}{SR}\right) \quad (0 \le k < N) \tag{3}$$

Where N is the signal length and Δ_f represents the disparity between the frequencies of the simulated vibration interference and particle signal.

When the input x (k) and the reference input X not correspond to a particle signal ,then the adaptive filter has reached the optimum solution. When the input signal x(k) reaches a particle signal, we can have

$$X_{k-D} = \sin\left(\frac{2\pi(f_s+\Delta_f)(K-D-L+i)}{SR}\right) \quad \text{for} \quad 1 \le i \le L \tag{4}$$

Where D is the delay between the primary input x(k) and delayed reference signal and L is the filter length. We can write

$$\delta_C^{C+\frac{SR}{\omega}+1} = \sum_{k=C}^{C+\frac{SR}{\omega}} \frac{2\mu}{\left\| X_{k-D} \right\|^2} X_{k-D} \varepsilon_k' \quad (5)$$

Equation (5) shows that δ_C is a vector formed by the mid L points of the cross correlation between samples of the input and vibration interference signal with frequency and a full period of a sine function with frequency f_s. The squared Euclidean distance, of the weight vector from the optimum solution reaches the maximum. When the frequency of the particle signal and the vibration interference and are almost identical. Then the disturbance of the weight vector of a particle signal increases as the vibration signal.

The deviation of the optimum solution lead to a period of disturbance in the output which return back to zero after a period time because of the feature of the filter. This period status starts at the beginning of the particle signal in the primary input. And the duration is decided by the convergence rate of the filter. This result is useful for selection of the box size of the sensor. Therefore, this will add the difference between the particle signature frequency and the vibration interference frequency , then decrease the chance for f_s to reach zero. As a consequence, by using the adaptive filter vibration interferences can be reduced effectively.

2.3. Selection of Adaptive Filter Parameters

The adaptive filter can accept both negative and positive delay lengths similar to backward and forward predictions respectively. And the error energy reaches minimum at a negative delay something of the kind to backward prediction, with an absolute value equal to the filter length. The delay of the input signal is used as a reference input to the filter; the particle signal will appear in the reference signal with a delay of D samples. The observations are demonstrated by simulations. The oil debris signal shown in Figure 4 is simulated. Where f s 100Hz, sampling rate SR=4000 Hz, the filter length L=100 and the delay D=1500 samples. And the signal is mixed with a harmonic interference. As show in Figure 4, by selecting proper delay can reduce the intensity of the total disturbances. Therefore, selection of appropriate delay length value is a challenging task. Under stationary condition, the larger filter length leads to the better results. And it should pay attention to that the larger the filter length the higher the effect of the output of the filter under non stationary condition. In addition, because of the presence of background noise, larger filter length will bring about the higher miss adjustment. As a result, the filter length should be selected in accordance with the intensity of background noise and the level of vibration interferences. Therefore, a beforehand knowledge relating the signal under analysis is necessary for appropriate setting the filter length.

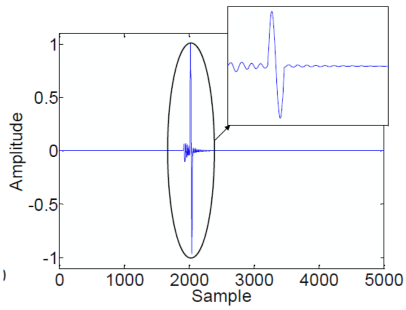

Figure 4. The Output of the ALE Algorithm for the Signal Mixture of Figure

3. Improve Performance of Adaptive Filtering

In real condition where the vibration feature of the wind turbine system changes all the time, the convergence rate acts as an important role. Failure to track such variations may result in little improvement in the quality of the oil particle signal. And convergence rate feature of the adaptive filter is studied in this section and a sub-band wavelet filter is suggested to insure an acceptable convergence rate.

3.1. Adaptive Wavelet Filter

The wavelet transform in adaptive filtering has been proposed in [10]. This approach is similar to the discrete Fourier transformation and has the advantages of wavelet transform where the time varying feature of the signal cannot be proper represented by weighted sum. In order to acquire a more uniform spectral density for the signal input we decompose the measured signal into different frequency sub-bands using the wavelet packet technique. Hence, offer the result of wavelet decomposition to adaptive sub-band filters. Wavelet method is a summarization of the orthogonal wavelet decomposition. In wavelet packet analysis both the wavelet coefficients and the approximation coefficients will be decomposed into another series of coefficients and approximation coefficients. Hence, using the wavelet packet analysis filter-bank, the adaption of the adaptive filter is performed at a decreased sampling rate, basing on the level of decomposition. On this occasion, the decomposition of the analysis generates needless confusing components into the filters which are bad to the performance of the adaptive filter algorithm.

To relieve the above difficulties, stationary wavelet transform is applied in this study. The wavelet transform is a variation of the orthogonal wavelet decomposition which follows each decomposition level. In other words, each detail and approximation wavelet coefficient data includes the same number of points as in the original input signal. Such over-sampling of the analysis outputs will alleviate the aliasing problem, and result in fast convergence rate of the adaptive filter. Therefore, the low and high pass filters are adjusted at each level by setting them to zeroes.

3.2. Relief of the Background Noise

The adaptive filter method utilizes the correlation between the vibration signal components in the input and a delayed signal to reduce vibration interferences. As a result, this technique leaves the background noise intact and a separate de-noising is required to handle it. In order to improve performance in convergence rate, the proposed sub-band filtering also provides a flexible algorithm making it capable of processing the background noise. This was succeeded by setting a threshold ahead of the synthesis. Therefore, either hard or soft threshold can be used as the general threshold value.

$$T = \sigma\sqrt{2\ln N} \tag{6}$$

Whereσis the standard deviation of the background noise and N is the number of data points of the measured data. However, this equation wants knowledge of the background noise. A method is used to estimate the background noise variance while no particle moves through the sensor and without vibration interferences. This estimation is performed before the sensor starts. However, the initially estimatedσcan not adapt to the varies in the feature of the background noise, it may make the performance of the proposed method useless. The changes in the nature of the background noise are very usual in practice condition for the changes in environment such as electrical interferences generated by the nearby instruments or temperature variation. Therefore, an on line noise estimation algorithm would be applied. The impulsive and intermittent features of the oil debris signal can be applied to this situation.

Because of the impulsive nature of the oil debris signals, the value of estimation dull to the abnormal value. The Median Absolute Deviation (MAD) method is generally used for such condition. In this approach, the noise variance in each sub-band is estimated based on the median of the wavelet coefficients. However, the performance of the method worsen considerably while the number of particles that contained in the measured signal increase rapidly. This is because in such situation the median of the dataset deflected from the designed median of Gaussian noise hence results in a large deviation. Therefore, an on-line noise variance estimation algorithm is proposed. In addition to the impulsiveness, the intermittent feature of the oil particle signal of interest is incorporated into this method.

Due to the intermittent characteristic of oil debris signals, the adaptive filter processed signal contains not only background noise but also consecutive metallic particle signals. Hence, Iterative on-line noise variance estimation (IVE) is proposed. These interval features are illustrated in Figure 5. Hence, by eliminating the portions of the signal related to the particle signals, a series of background noise samples is achieved. Based on the noise samples, a direct estimate of noise variance is computed. However this method is represented based on time domain signals, also can be used for wavelet domain. In order to wipe off the wavelet coefficients related with oil particle signals from the relevant frequency band. Firstly, this approach calculates a value of threshold and keeps every wavelet coefficients. In addition, the threshold should be counted in view of the "real" noise variance as showed in the universal threshold. Yet, the "real" noise variance is the value that we are searching for.

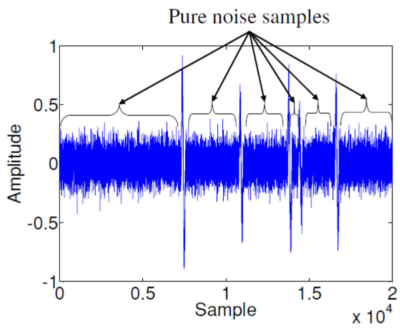

Figure 5. A Simulated Mixture of Particle Signatures and Background Noise

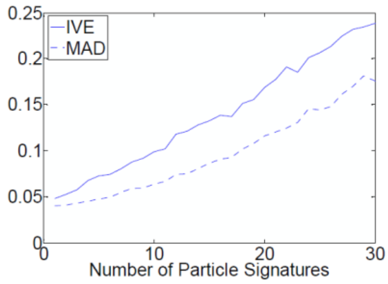

Figure 6. The Effect of IVE and MAD

To estimate the property of this approach, a set of simulated particle signals were produced at a sampling rate of 4 KHz, each covering from 1 to 30 randomly located particle signals. The noise variance relating to each frequency band of a wavelet packet decomposition was evaluated using MAD, and IVE approaches, respectively. For simulated data covering a specific number of oil debris signals, 1000 realizations were produced to count the mean and variance of the evaluation results. According to the results, the MAD and IVE approaches both show favorable performance when the particle signals contained a small portion of the dataset. While a vast number of slow moving particles and a vast portion of the dataset is contained of particle signals, the evaluation results acquired by using both approaches worsen. Therefore, a better comparison between MAD and IVE method should be made at a lower particle moving speed. Figure 6 distinctly shows that the deviation introduced by the MAD method rises quickly with the enhanced particle signal content, reaching a deviation of 127% of the real noise variance. Hence, the proposed IVE method is used in this study to eliminate the broadband background noise.

4. Experimental Evaluation

In this experiment an iron particle from 100~125□□in diameter is used. The signal amplitude of the metallic particle without vibration interference is 0.6 V. The output of the oil debris sensor is supplied to a card and collected at 4000 Hz sampling rate. The signal processing was done by using MATLAB.

Figure 7(a) shows the output subjected to vibrations while the metallic particle moves through it. The relating frequency domain is shown in Figure 7(b). The enhancement of the amplifier and the function generator were fixed throughout the experiment, the vibrations produced by a vibrator showed moderate signs of non-stationary. This non-stationary is also response to the disturbance signal and can be percept through detecting the measured signal of Figure 7(a).

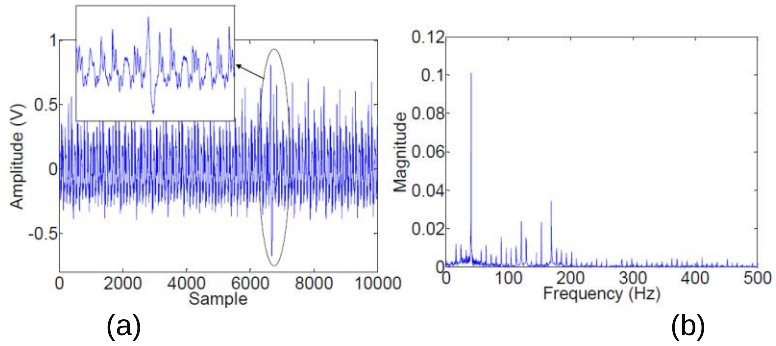

Figure 7. (a) Measured Signal Subjected to Vibrations, (b) The Power Spectrum of the Signal

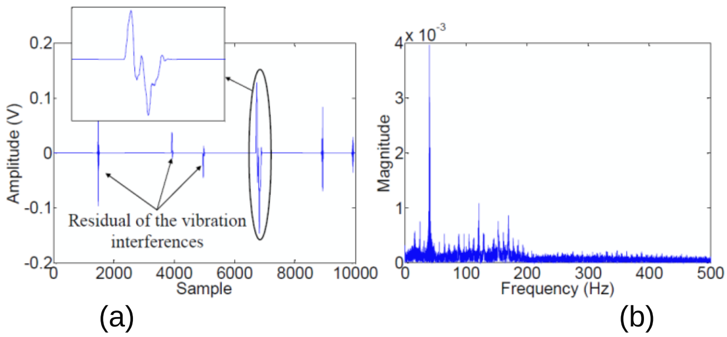

Figure 8. (a) Enhanced Signal , (b) the Associated Power Spectrum

The wavelet coefficients relating to every frequency band were supplied to separate adaptive line enhancers to eliminate the vibration interferences. The length of the filter weight vector L=3200 and delay interval D = - 3200. The step size value □□is gradually increased, all the vibration interferences were successfully eliminated from the final de-noised signal. The processed wavelet coefficients are supplied to the IVE background noise variance estimator and the threshold wipes off the remaining noise components. And the threshold wavelet coefficients will be applied to reconstruct the enhanced signal as we can see in Figure 7(c). The frequency of the enhanced signal is shown in Figure 7(d). Apparently, the signal of metallic particle is clearly examined. The phase of the metallic particle signal is maintained and the amplitude decreased slightly to 0.56 V contrast to the designed 0.6 V.

5. Conclusion

In this paper, an oil particle signals enhancement approach is proposed to improve fault detection and condition monitoring of a wind turbine. This study focuses on the mixtures oil particle signals, which background noise and vibration interferences generated by machine elements. As for the mixture signals, we propose a wavelet filtering based method to enhance the oil debris signals. It has shown that the mixture oil particle signals follow distribution. According to this result, a wavelet filtering is formulated to estimate the amplitude of vibration generated impulses. It is shown that the interference of vibration has diminished the demodulation effect. Hence, a wavelet technique is proposed to remove the vibration interference in order to effectively enhance the measured signal. And partly purified wavelet coefficients are applied to estimate noise variance. Then, the variance of estimated noise is used to decide the threshold value of the wavelet coefficients to reconstruct the enhanced signals. The results have shown that the proposed method effectively removed the intense vibration interferences and intrinsic background noise.

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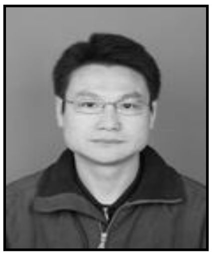

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