Chapter 14
Sound Vibration Signal Enhancement for Bearing Fault Detection by Using Adaptive Filter: Adaptive Noise Canceling and Adaptive Line Enhancer

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Abstract This paper investigates the effectiveness of the adaptive filter, ANC, and ALE to improve vibration and sound signals. These signals have been used to detect the natural development of bearing defects for machine diagnosis applications. However, during measurement, these signals have been corrupted by the noise that was coming from other machine parts. In this work, the noise has been successfully removed by using an adaptive filter. Two types of adaptive filters will be compared which are the adaptive noise canceling (ANC) and the adaptive line enhancer (ALE). This investigation is carried out by collecting the vibration and sound signal from a bearing that has been loaded with 20 kg mass and rotated with fixed 1500 rpm. This bearing is continuously rotated for 40 h. It was shown that the ANC filter is more efficient compared to ALE with the least mean square error.

Keywords Machine diagnosis · Bearing fault detection · Adaptive filter

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14.1 Introduction

The defect machine components can be detected based on the changing of their signal characteristics [1, 2]. However, the change of signal characteristics from the defect machine component is difficult to be detected and evaluated since the defect machine signal usually will be corrupted by other signals which are called as noise that came from another machine components [3, 4]. Therefore, this noise signal needs to be removed so that the true signal from the defect machine component easily can be detected.

Several available methods can be used to remove the unwanted signal. One of the well-known methods was the fixed filter such as low pass, high pass, bandpass, and band stop filter [5]. These fixed filters are applied to remove the unwanted signal based on frequency range [6]. By setting the cut off, the unwanted frequency range, these unwanted signals can be filtered. As a result, only the signal of interest has remained. However, the fixed filter has several drawbacks where ranges of frequency components that need to be removed must be determined first. Otherwise, the signal of interest will be removed unintentionally. The challenge is to determine accurately the range of the cut-off frequency.

To overcome the drawbacks of these filters, the blind source separation (BSS) algorithm has been introduced. BSS is a technique that can be used to separate the mixed signals into individual signals without the need to know the frequency range of the unwanted signal. Instead of that, the BSS separates the mixed signal based on the reference signal. These reference signals can be obtained by attaching sensors to each source of signal in the machine system that contributes to the mixed-signal [7, 8]. During the separation process, the BSS algorithm assumed that each source signal is statistically independent or de-correlated. However, in the actual manufacturing system, all the component or machine part are connected hence the signals will influence each other. As a result, the reference signal will be no more independent. Therefore, such a situation will contribute to fault detection accuracy.

Adaptive filters use as the same as the BSS principle to remove unwanted signals but with improved algorithms. Due to that, this technique has known to be applied in diverse applications such as telecommunication [9, 10], sound recognition [11, 12], image processing [13], medical fields [14, 15], and machine diagnostics [16, 17]. However, the current practice in machine diagnosis applications typically used a single source signal as a reference signal. The single source signal may provide only partial information that can be obtained due to inherent limitations of sensor that have varying degrees of uncertainty. Hence multiple sensors may improve the signal enhancement.

In this paper, vibration and sound signals are used to detect the fault generate from bearing while the relationship and their effectiveness are investigated. The tested bearing is run to failure for 40 h continuously. Along with this work, a growth index is proposed to indicate the growth level of bearing deterioration. The noise signal that compounded the vibration and sound will be cleaned by using an adaptive filter algorithm.

14.2 Methodology

14.2.1 Theory

The adaptive filter is a well-known and reliable technique that is able to remove unwanted signals without the need to know the characteristics of unwanted signals. This is because the adaptive filter automatically adjusts the filter coefficients based on the reference signal that highly correlates with the unwanted signal in a mixed signal. The coefficient correlation is based on the minimum square error (MSE) of the adaptive filter output. The lower MSE value, the unwanted signal will be closer to the reference signal. Therefore, the adaptive filter will reiterate to adjust the coefficients until the MSE is minimal. Once the MSE is minimal, the adaptive filter structure is in optimal design. Least mean square (LMS) and recursive least square (RLS) algorithms are the common algorithms employed by the adaptive filter to dictate the filter of how to adjust the coefficients. Due to its simplicity, the LMS algorithm is used in this paper. Figure 14.1 shows the operation of the adaptive filter.

From Fig. 14.1, the adaptive filter is started once the mixed-signal and reference signal is driven into an adaptive filter. The mixed-signal that is denoted as $u(n)$ contains two-component signals which are $s(n)$ and $v(n)$ where each of them represents as machine defect signal and unwanted signal, respectively. While the reference signal is denoted as $v_o(n)$ is highly correlated with the unwanted signal $v(n)$ in the mixed signal.

$$u(n) = s(n) + v(n) \tag{14.1}$$

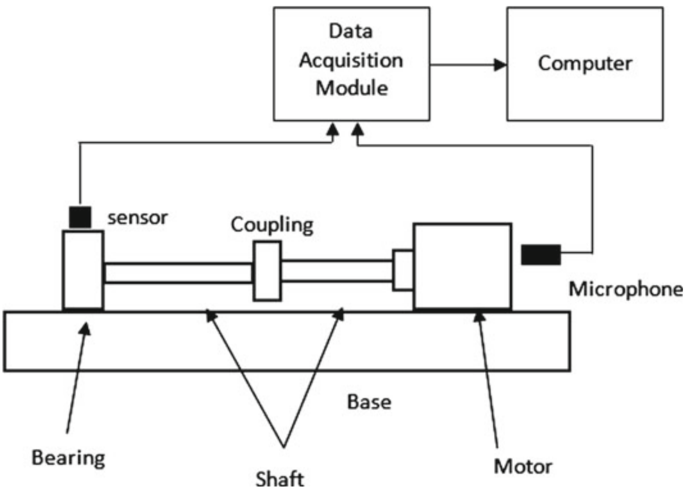


Fig. 14.1 Fault simulator device

$$v_o(n) \sim v(n) \tag{14.2}$$

With an initial set of filter coefficients, the filter will adjust the reference signal characteristics and force as possible to match with the unwanted signal in mixed signals. This filtered reference signal is denoted as $y(n)$ and can be described as following:

$$y(n) = \sum_{i=0}^{M-1} \vec{w}_i(n)u(n-i) \tag{14.3}$$

where M is the filter length, $\vec{w}_i(n)$ is the filter coefficients, and $u(n-i)$ is the primary input with a previous adjustment step.

After the $y(n)$ is obtained where its beliefs have been adaptively filtered to match with an unwanted signal component in the mixed-signal component, the subtraction process will be performed between the mixed-signal with $y(n)$ and can be described as the following equation:

$$e(n) = u(n) - y(n) \tag{14.4}$$

$$e(n) = [s(n) + v(n)] - y(n) \tag{14.5}$$

where $y(n) \approx v(n)$.

The error signal $e(n)$ then can be used to indicate how well the noise is eliminated from the mixed signal by using a statistical performance function known as a mean square error which can be calculated as follows:

$$J\left[|e(n)|^2\right]_{\min} \tag{14.6}$$

$$\varepsilon = \frac{J_{\min}}{\sigma^2_{\mathrm{ref}}} \tag{14.7}$$

where $J_{\min}$ is a mean square, $\sigma^2_{\mathrm{ref}}i$ is the variance of the reference signal, and ε is the scale of the optimal filter. As mentioned before, the mean square needs to be minimal since it will affect the scale of the optimal filter design and indicates how close $y(n)$ the signal is with $v(n)$. The scale of the optimal filter is known in between the range $0 \le \varepsilon \le 1$. If ε is zero, the adaptive filter with the optimum filter coefficient has perfectly eliminated the unwanted signal from the mixed signal whereas on the other hand if ε is 1, the adaptive filter does not eliminate the unwanted signal at all. Therefore, if ε is not minimal, that means that the y (n) signal is not close enough with v (n), thus a new set of adaptive filter coefficient needs to be adjusted. The filter coefficient can be readjusted by updating the filter weight based on the following Eqs.

(14.8) and (14.9). In this work, two types of an algorithm will be used which are the adaptive noise canceling (ANC) and adaptive line enhancer (ALE). The filter weight coefficient for both algorithms can be found at the following equation, respectively.

$$\vec{w}(n+1) = \vec{w}(n) + \mu.e(n).\vec{\mu}(n) \tag{14.8}$$

$$\vec{w}(n+1) = \vec{w}(n) + \mu.e(n).u(n-i) \tag{14.9}$$

where μ is the step size of the adaptive filter, $\vec{w}(n)$ is the filter coefficient vector, $e(n)$ is an error signal, and $\vec{\mu}(n)$ is the filter input vector. Based on this weight filter coefficient, the adaptive filter will remove the unwanted signal to reduce the residual of random variables by using the following equation.

$$x(n) = \frac{u(n) - \overline{u}}{\sigma} \tag{14.10}$$

where $x(n)$ is the pre-processed signal, $\overline{u}$ is the mean value of $u(n)$, and σ is the standard deviation of cleaned $u(n)$.

14.2.2 Simulation Work

The simulation of the mixed signal is carried out to test the effectiveness of the adaptive filter to remove the unwanted signal that has been mixed with an actual signal. Since there are two types of signals used in this work, which are vibration and sound, two synthetic mixed signals will be generated by using the command function in MATLAB.

The synthetic mixed signal that represents the vibration signal contained two-components signal where each of them has frequency component of 5 Hz and 20 Hz respectively and can be modeled as the following equation:

$$u(n)_1 = s(n) + v(n) \tag{14.11}$$

$$u(n)_1 = 2\sin(2\pi 5t) + \sin(2\pi 20t) \tag{14.12}$$

While for the second synthetic mixed signal that represents the sound signal, two component signals are mixed where each of them has frequency component of 50 Hz and 200 Hz respectively and they can be modeled by using the following equations:

$$u(n)_1 = s(n) + v(n) \tag{14.13}$$

$$u(n)_1 = 2\sin(2\pi 50t) + \sin(2\pi 200t) \tag{14.14}$$

Both have been compounded with the random signal that represents a noise signal and has a standard deviation of 0.5006 to make it more realistic.

The simulation of the mixed signal has been carried out to test the effectiveness of the adaptive filter for the classification process before the adaptive filter is applied to classify the real mixed signal.

The first mixed signal is simulated using Eq. (14.16) where $s(n)$ represents a signal coming from the defect machine component signal and $v(n)$ represents the signal coming from other components in the same machine. These two signals are mixed to become $u(n)_1$ signals. Both sinusoidal signals are sampled 1000 times in 1 s

$$u(n)_1 = s(n) + v(n) \tag{14.15}$$

$$u(n)_1 = 2\sin(2\pi 120t) + \sin(2\pi 50t) \tag{14.16}$$

The second mixed signal is simulated from Eq. (14.18) where $s(n)$ represents a signal coming from the defect machine component and $\text{rand}(n)$ represents a signal coming from a random noise signal.

$$u(n)_2 = s(n) + \text{rand}(n) \tag{14.17}$$

$$u(n)_2 = 2\sin(2\pi 120t) + \text{rand}(n) \tag{14.18}$$

These $s(n)$ and $\text{rand}(n)$ signals are mixed to produce a distorted $u(n)_2$ signal. The sinusoidal signal is sampled 1000 times in 1 s while the random noise is characterized by a standard deviation of 0.5006 and the number of data points is 10001. Both mixed signals $u(n)_1$ and $u(n)_2$ are taken as primary input and driven into adaptive filters for classification process.

14.2.3 Experimental Works

The real mixed signal has been generated from the simulator device as illustrated in Fig. 14.1. This test simulator device consists of a DC geared motor driving at a speed of 200 rpm. This motor is connected to a bearing through a shaft and a coupling.

In the first test, the vibration signal from the defect bearing component is taken where it is mixed with the vibration signals coming from the other parts of the test simulator device. The Vibration signal coming from a defect-free similar bearing from the test simulator device is taken as the reference signal while the delay version of the mixed signal is used as the reference signal.

For the second test, the sound signal from the defect motor component is taken where it is mixed with the sound signals coming from the other parts of the test simulator device. Similarly, the sound signal coming from the defect-free motor in the test simulator device during rotation is used for the reference signal for the ANC filter while the delay version of mixed-signal is used as the reference signal for the ALE filter.

In this experiment, the vibration signal is captured by a MEMS accelerometer type ADXL202 while the sound signal is captured by the microphone. Both signals were then transferred into the data acquisition module using the National Instrument USB6210 model for the digitizing process before the filtering process can be carried out by the computer.

In the first test, the vibration signal from the defect bearing component is taken where it is mixed with the vibration signals coming from the other parts of the test simulator device. The Vibration signal coming from defect-free similar bearing from the test simulator device is taken as the reference signal for the ANC filter while the delay version of the mixed signal is used as the reference signal for the ALE filter. For the second test, the sound signal from the defect motor component is taken where it will be mixed with the sound signals coming from the other parts of the test simulator device. Similarly, the sound signal coming from the defect-free motor in the test simulator device during rotation is used for the reference signal for the ANC filter while the delay version of mixed-signal is used as the reference signal for the ALE filter.

14.3 Results and Discussion

14.3.1 Simulation Results

This section discusses the classification result for the simulation of the mixed vibration signals. Figures 14.2 and 14.3 show the result of signal classification for mixed signal $u(n)_1$ that has changed the signal pattern by using the ANC and ALE filter respectively. The result shown in Fig. 14.3c is the classified signal from the mixed signal by using the ANC filter while Fig. 14.4c shows the result of the classified signal $s(n)$ by using the ALE filter. Generally, both filters succeed to classify the unknown signal of interest from the mixed signal, however, the classified signal by using the ANC filter is more accurate than the ALE filter since the optimal design for the ANC filter is $\varepsilon = 0.0014$ while $\varepsilon = 0.0666$ for ALE. Therefore, in this simulation result, the ANC filter is more accurate than the ALE filter for classification of the mixed signal.

Figures 14.4 and 14.5 show the results of signal classification from the simulation of the mixed sound signal $u(n)_2$ by using ANC and ALE, respectively. The result shown in Fig. 14.4c shows the classified signal $s(n)$ from mixed signal by using the ANC filter while Fig. 14.5c shows the classified signal $s(n)$ from mixed signals by

Fig. 14.2 Classification of mixed simulated vibration signal from noise by using ANC filter, **a** original defect signal, **b** mixed signal, **c** classified defect signal by using ANC

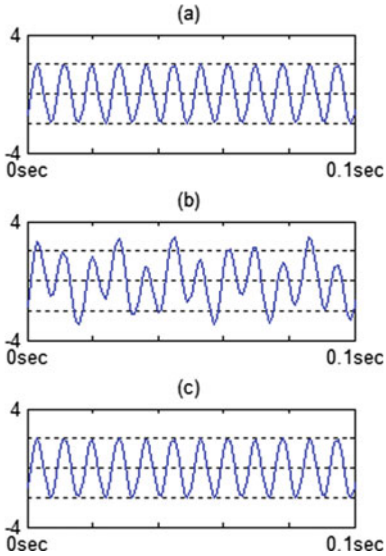
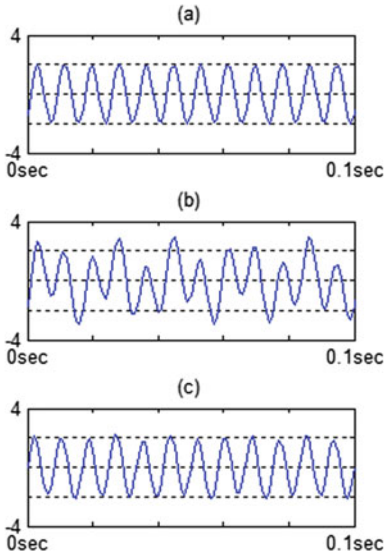


Fig. 14.3 Classification of the mixed simulated sound signal from noise by using ALE filter, **a** original defect signal, **b** mixed signal, **c** classified defect signal by using ALE



using the ALE filter. Generally, both ANC and ALE filter succeeded to classify the signal $s(n)$ from being distorted. However, the classified results by using ANC show more accuracy than ALE since the normalized least square error is $\varepsilon = 0.0151$ for the ANC adaptive filter while $\varepsilon = 0.1382$ for the ALE adaptive filter. Therefore, in this simulation result, the ANC filter is more accurate than the ALE filter to classify mixed signals.

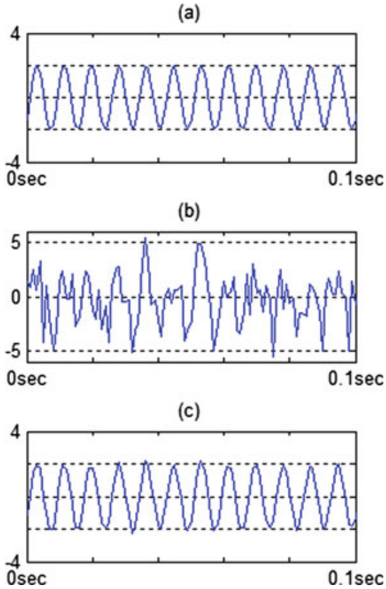


Fig. 14.4 Classification of defect signal from mixed simulation sound signal by using ANC filter **a** original defect signal, **b** mixed signal, **c** classified defect signal by using ANC

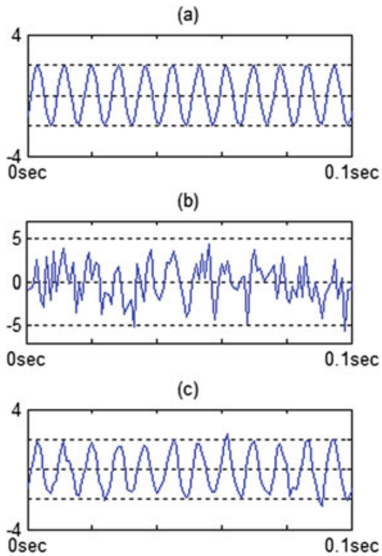


Fig. 14.5 Classification of defect signal from mixed simulation sound signal by using ALE filter, **a** original defect signal, **b** mixed signal, **c** classified defect signal by using ALE

14.3.2 Experimental Results

This section discusses the classification result by using a real mixed signal which is obtained from the fault simulator device. For the first test, the mixed vibration signal from the defected bearing is taken as the primary input for ANC and ALE filter as

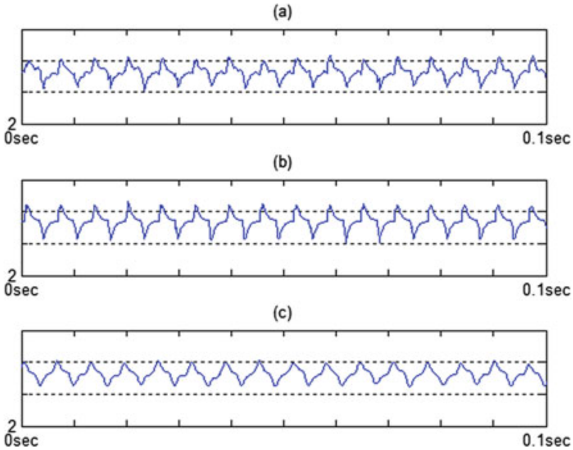


Fig. 14.6 Bearing signal classification process **a** distorted vibration signal from a fault simulator device, **b** classified vibration signal from the defected bearing by using ANC adaptive filter, **c** classified vibration signal from the defected bearing by using ALE adaptive filter

shown in Fig. 14.6a. As can be seen the defected vibration signal Fig. 14.6a is having little fluctuation affected by other vibration signals that are coming from another component. Figure 14.6b, c show the clean result of the classified bearing signal obtained from the ANC and the ALE adaptive filter, respectively. Generally, both filters succeeded to classify the defect signal from the defected bearing component from the mixed signal. However, the classified signal from the ANC filter is more accurate than the ALE filter since the least square error shown is 0.0109 and 0.109, respectively.

For the second test, the sound signal from defect motor as shown in Fig. 14.7a is taken as the primary input signal into the ANC and the ALE filter. The pattern sound signal from the defect motor is changed when it is mixed with other sound signals. Figure 14.7b, c show the result of the classifying defected motor signal from the mixed signal by using the ANC and the ALE adaptive filter, respectively. Generally, both filters succeed to classify the defect signal from the defected motor. However,

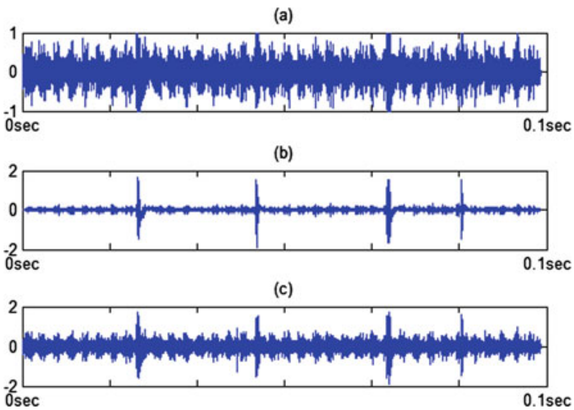


Fig. 14.7 The motor signal classification process **a** the mixed sound signal from fault motor in simulator device, **b** classified sound signal from the faulty motor by using ANC adaptive filter, **c** classified sound signal from the faulty motor by using ALE adaptive filter

ANC adaptive filter shows more accurate than ALE adaptive filter to classify the defect motor signal from mixed signal since the least square error of classifying signal by ANC filter is $\varepsilon = 0.0427$ while ALE filter is $\varepsilon = 0.0441$.

14.4 Conclusion

Two types of adaptive filters known as the adaptive noise canceller (ANC) and adaptive line enhancer (ALE) have been used to classify the signal of interest from the mixed signal. Generally, the simulation and experimental work showed that both adaptive filters succeed to classify the defect signal from the mixed signal. However, based on the least mean square error, the ANC filter is more accurate than ALE. This is probably due to the fact that reference input used in ANC has many signal components correlated in mixed signals due to noise source at the machine body part. However, even though the ALE filter is less accurate than ANC, the ALE filter is more practical to apply in a real environment for fault detection application since the ALE filter does not need the reference signal which is hard to obtain in an actual complex machine.

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