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A study on transient enhancement for fault diagnosis based on an active noise control system

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Abstract

Active noise control (ANC) is a more effective technique used for acoustic noise cancelation in comparison with passive approaches which are difficult and expensive to implement, especially for cancelling the noise in the low frequency range. In the ANC system, an anti-noise signal is introduced to suppress the primary noise to produce a residual which is used for updating the adaptive filter coefficients. In this paper, a method of transient content enhancement for fault detection and diagnosis is investigated based on a laboratory ANC system. A number of simulation studies are conducted to evaluate the performance of the method using a typical filtered-x least mean square (FXLMS) algorithm under different types of noise signals. In the mean time, the algorithm is also adapted to achieve feature extraction under the condition of maintaining its noise cancelation performance. Moreover, experimental studies were carried out using noise signals from a heavy duty diesel engine to further demonstrate the performance obtained from simulation studies. The simulation and preliminary experimental results show that the investigated ANC algorithm can obtain an effective noise cancellation for sinusoidal signal in low frequency band and provide a residual signal with more non-stationary contents for developing diagnostic features.

Keywords: Active noise control, FXLMS algorithm, Condition Monitoring, Transient

1. Introduction

The primary purpose of an active noise control (ANC) system is to reduce the acoustic noise level and the corresponding noise audibility to improve the environment being quieter and friendlier. An ANC system works on the principle of destructive interference between the sound fields generated by an original primary sound source and a secondary source, whose acoustic outputs can be controlled. This is achieved in practice by minimizing the signal power of error microphone, which is a measure of the acoustic pressure at downstream of secondary loudspeaker.

In the past decades, ANC principles were applied in bearing fault detection under low signal-to-noise conditions [1-3]. Generally, the system for applying ANC can be described as follows: a reference transducer was attached to the machine in the vicinity of the bearing to be monitored. This principal microphone contains the signal carrying the information relating to the fault condition combined with uncorrelated background noise. The secondary reference transducer was used to detect the background noise, and therefore obtains information correlated in some way to the noise measured by the

principal transducer. This secondary position could, for example, be a compressor or gearbox, and should not contain information relating to the fault. The reference transducer was adaptively filtered to produce an output that is close to the principal uncorrelated noise, which is then subtracted from the principal input, resulting in attenuation of the background noise.

De-noising and extraction of the faulty signals are very important for fault diagnostics, especially for early fault detection, in which the faulty features are often very weak and embedded in noise. Therefore, it is necessary to enhance the data reliability and improve the accuracy of the signal analysis. The use of adaptive filters for extracting fault signal from background noise is based on the assumption that the frequency components of fault signal should be different with frequency of the noise. For example, the background noise is continuous while the fault is transient. The transient behavior implies that the frequency components shall be spread out over many frequency bins due to its impulsive temporal characteristics [4]. Additionally, for many sources of background noise, the spectral content is quite low. The engine noise signal is inherently periodic in nature based on the primary excitation modes of the rotating structures [5].

The ANC technique can be implemented in conjunction with widely used signature analysis techniques such as spectrum analysis, time domain statistics and cepstrum analysis to improve the overall detection and diagnostic ability of these conventional techniques in the presence of severe noise.

2. Active noise control algorithm

2.1 Feed-forward FXLMS ANC algorithm

The filtered-x least mean square (FXLMS) algorithm [6] is a typical control algorithm applied in active noise control. It was originally proposed by Morgan in 1980 [7]. A similar work was also carried out by Widrow [8] for feed-forward control in the context of adaptive control. Furthermore, active control of sound in ducts was implemented by Burgess in 1981 [9]. In the FXLMS algorithm, an identical filter is placed in the reference signal path for the weight update of the LMS algorithm, so-called filtered-x (FXLMS) algorithm. The FXLMS algorithm, which is an alternative form of the LMS algorithm, can be used when there is transfer function in the secondary path following the adaptive filter.

The block diagram of a typical feed-forward control system used for active noise control in ducts is shown in Figure 1. This system consists of two loudspeakers for primary and secondary noise sources generation, and two microphones used to measure reference noise and error signals, respectively. Primary noise signal $x(n)$ is sensed using a reference microphone located ahead of the secondary noise source. The error microphone is used to measure the residual error $e(n)$. Based on the reference signal $x(n)$ and error signal $e(n)$, the ANC controller generates the anti-noise $y(n)$ that drives the secondary loudspeaker to suppress the primary noise. This anti-noise is 180^0 out of phase with respect to the original noise which needs to be cancelled. The spacing

between the microphone and the secondary source loudspeaker enables causality and high coherence between the upstream noise sensor and the sound to be cancelled.
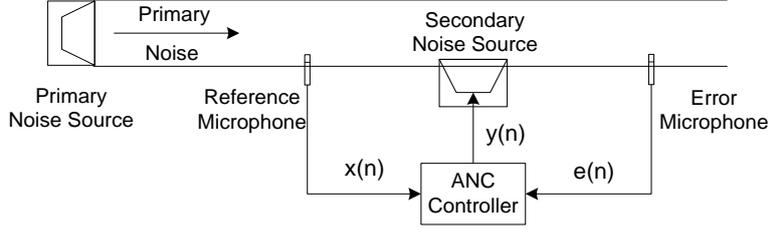

Figure 1 Feed-forward active noise control system

The schematic diagram of the FXLMS algorithm for ANC controller is shown in Figure 2, where $x(n)$ and $e(n)$ denote the input signal measured by reference microphone and error microphone, respectively. $d(n)$ is the desired signal, $W(z)$ and $S(z)$ denote transfer functions of the adaptive filter and the secondary path plant, $\hat{S}(z)$ is the estimate of $S(z)$. In the following expression, L denotes the length of adaptive filter and time index *n* is the current sample time, similarly, *n*-1 is the previous sample time.
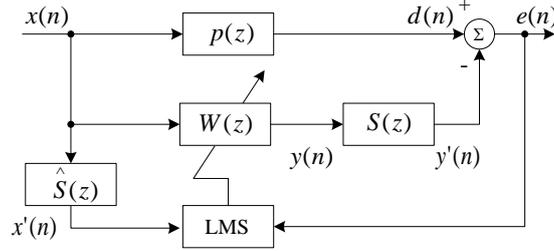
Figure 2 Schematic diagram of feed-forward FXLMS algorithm

The output of adaptive filter is

$$y(n) = \boldsymbol{x}^T(n)\boldsymbol{w}(n), \tag{1}$$

while $\boldsymbol{x}(n)$ and $\boldsymbol{w}(n)$ are given in equation (2) and (3)

$$\boldsymbol{x}(n) = [x(n) \cdots x(n-L-1)]^T \tag{2}$$

$$\boldsymbol{w}(n) = [w_0(n) \cdots w_{L-1}(n)]^T. \tag{3}$$

The adaptive coefficients update formula can be expressed as

$$\boldsymbol{w}(n) = \boldsymbol{w}(n-1) - \mu \boldsymbol{x}'(n)e(n), \tag{4}$$

where μ denotes the step factor and $\boldsymbol{x}'(n)$ is the filtered reference signal

$$\boldsymbol{x}'(n) = \hat{\boldsymbol{s}} * \boldsymbol{x}(n). \tag{5}$$

$\hat{s}$ stands for the estimation of secondary path impulse response which is time invariant, so that its dependence on the time index n is suppressed. It is defined as

$$\boldsymbol{s} = [s_0 \cdots s_{L-1}]^T. \tag{6}$$

The iterative adaptation of the weights in equation (4) utilizes gradient descent method to assign filter tap coefficients such that the power of observed error signal $e(n)$ is minimized.

2.2 Detection scheme

De-noising is a crucial step to enhance the data's reliability and improve the accuracy of the signal analysis via removing the noise and highlighting the interested signals.

Adaptive noise cancelling method can be applied for fault diagnosis because of its different behaviors for steady-state signal and transient signal. If the signals are stationary and have invariant statistical properties, the algorithm will converged and the residual error is minimized after a short time. When the state of signal changes, ANC algorithm automatically re-adjusts its coefficients and the error rapidly increases and fluctuates before minimizing. Therefore, the position of transient signal occur can be viewed obviously.

On the other hand, the ANC system has good noise attenuation performance for periodic background noise, whose frequency is low but amplitude is much higher than one of the transient signal. The adaptive filter could be capable of tracking the statistics of non-stationary signals if the changes in the statistics occurred slowly in comparison with the convergence time of the adaptive filter. However, the transient content in the signal is short duration and cannot provide enough time for algorithm convergence. Therefore, the transient signal which contains faulty characteristics is extracted form background noise.

In details, the primary noise is used to generate acoustic signal. This signal contains mainly periodic background noise and weak signal or transient signal. Then, reference and error microphones detect the reference noise and residual error signal. When the ANC processing starts, compute anti-noise and update adaptive filter coefficients using ANC algorithm using the new detected reference noise and residual error. The anti-noise would be sent out through secondary loudspeaker to suppress primary noise. The adaptive filter coefficients computed in this sample time is prepared for next sample. The residual error is the desired signal that reduced periodic background noise from primary noise.

2.3 Secondary path modelling

The FXLMS algorithm requires knowledge of the impulse response of the physical secondary path. Adaptive system identification is a common technique applied to get the transfer function of the secondary path. The diagram of system identification is illustrated in Figure 3, where $S(z)$ is an unknown system to be identified and $\hat{S}(z)$ is a digital filter used to model secondary path. The secondary path response can be

obtained from a predetermined error minimization algorithm by exciting both the unknown system $S(z)$ and the digital model $\hat{S}(z)$ with the same input white noise $u(n)$.

The basic concept is that the adaptive filter (model) adjusts itself and causes its output to match that of the unknown system. When the difference (error signal) between the physical system response $y(n)$ and adaptive model response $\hat{y}(n)$ has been minimized, the adaptive model reproduces $S(z)$ or provides an approximation to it.
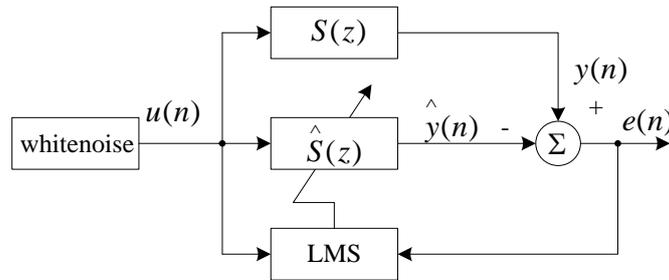

Figure 3 Block diagram of secondary path modelling

The model shown in Figure 3 is desired to learn the structure of the unknown system from knowledge of its input $u(n)$ and output $y(n)$. Compute adaptive filter output

$$y(n) = \sum_{l=0}^{L-1} \hat{s}_l(n)x(n-l) \qquad (7)$$

where $\hat{s}_l$ is the lth coefficient of the secondary path estimation filter $\hat{S}(z)$ at time n.

Assuming that the unknown time-invariant system $S(z)$ can be modeled by an FIR filter of order L, the estimation error is given as

$$e(n) = y(n) - \hat{y}(n) = \sum_{l=0}^{L-1} [\hat{s}_l(n) - w_l(n)]x(n-l), \qquad (8)$$

where s_l is the impulse response (or parameters) of the unknown plant.
And the update coefficients using LMS algorithm are given as

$$\hat{s}_l(n+1) = \hat{s}_l(n) + \mu x(n-l)e(n), \quad l = 0, 1, \ldots, L-1. \qquad (9)$$

After the algorithm convergence, the adaptation is terminated and coefficients $\hat{s}_l$, $l = 0, 1, \ldots, L-1$ which are the estimation of s_l, can be used in the ANC system.

3. Simulation analysis of fault diagnosis based on ANC

The objective of this paper is to separate weak signal or transient signal from the periodic signal. Simulation model is set up according to the algorithm shown in Figure 2. The primary and the secondary path models are actual transfer function obtained via experiment. The input and error signals are recorded for data analysis. First, single

frequency is used as input signal to study the attenuation of sinusoidal signal. Then, mixed signal of sinusoidal and small amplitude white noise (transient signal) are applied as input to evaluate the performance of proposed method in diagnostic feature extraction.

In the following figures, $x(n)$ presents the signal which is called primary noise in algorithm before ANC processing while $e(n)$ denotes signal named residual error signal after ANC processing.
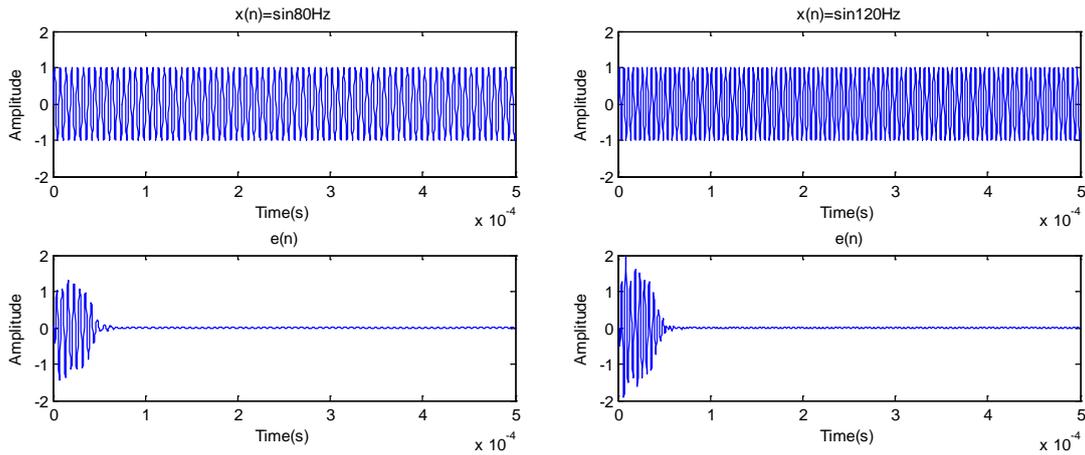
(a) 80Hz　　　　　　　　　　　**(b) 120Hz**
Figure 4 Simulation results for sinusoidal signal

Figure 4 shows simulation results for 80Hz and 100Hz sinusoidal signal. It can be seen that the residual signal after algorithm convergence is identical close to zero. From the simulation results, the ANC system has good noise cancelation capability for sinusoidal noise.
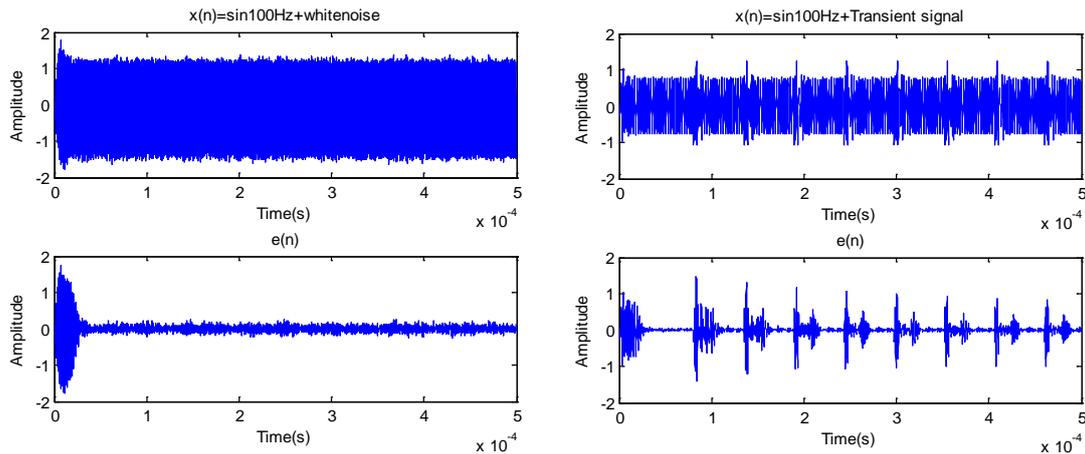
(a) Weak signal extraction　　　**(b) Transient signal extraction**
Figure 5 Simulation results for mixed signal

Figure 5(a) shows simulation results for 100Hz sinusoidal signal which adds small amplitude white noise to verify the ability of weak signal extraction. Figure 5(b) gives out the cancelling results for mixed signal in which the 100Hz sinusoidal signal is

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embedded transient signal. The non-stationary components which denote diagnostic feature are extracted under the condition of maintaining the noise cancelation capability of the ANC system.

4. Experimental setup

The experimental setup of ANC system is shown in Figure 6. It consists of a duct, an ANC controller, primary and secondary loudspeakers, reference and error microphones, and an amplifier with two channels for the two loudspeakers. The ANC controller use TMS320VC5509A digital signal processor (DSP) as the core processor. The adaptive signal processing algorithm is realized in the ANC controller, resulting in the creation of the anti-noise wave form. This signal is sent out via the power amplifier before being sent to the cancelling loudspeaker. In the experiment, the primary noise is generated by PC and sent to the power amplifier though a sound card.

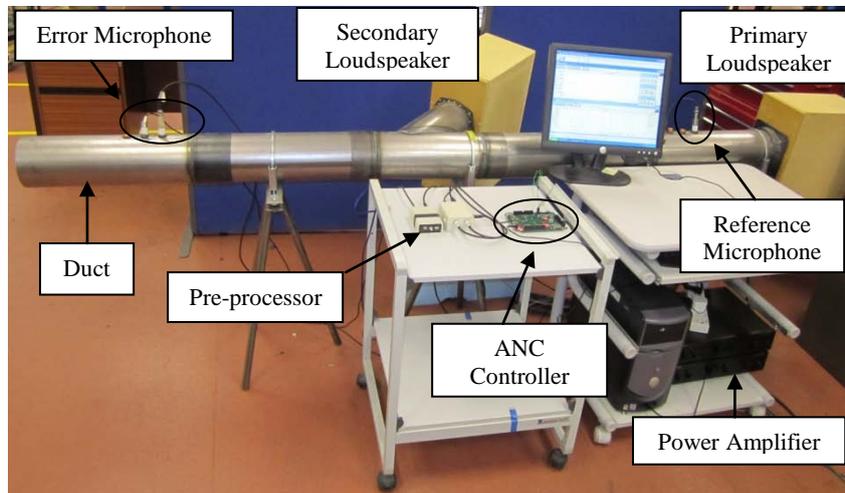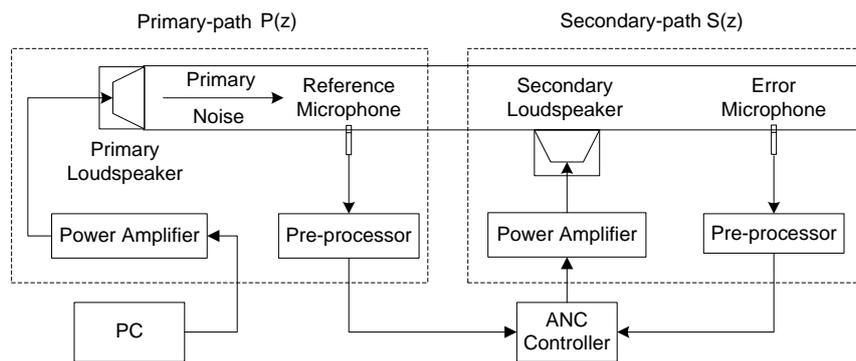**Figure 6 Experimental setup of ANC system**

Figure 7 Schematic diagram of laboratory ANC system

The schematic diagram of for the laboratory ANC system is shown in Figure 7. The primary path includes a power amplifier, a primary loudspeaker, a reference microphone, a pre-processor and the duct module between primary loudspeaker and reference microphone. The secondary path is composed of a power amplifier, a

secondary loudspeaker, a pre-processor, a microphone for measuring error signal and the duct module between secondary loudspeaker and the microphone.
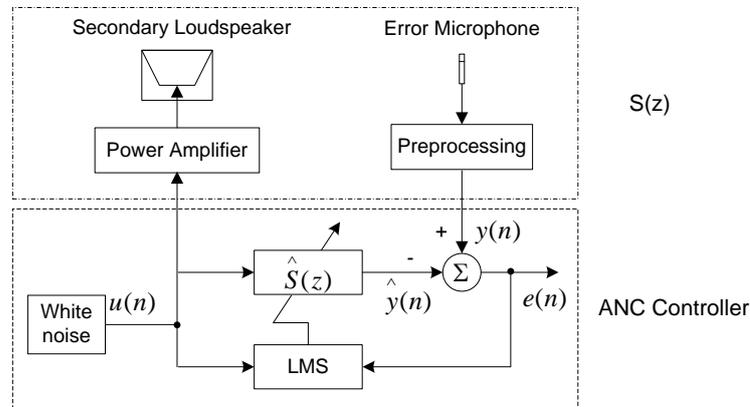
Figure 8 Schematic diagram of secondary path modelling

The setup of secondary path identification is shown in Figure 8. White noise is internally generated by the ANC controller as the input of cancelling loudspeaker after power amplifier. White noise generated internally and error signal detected by microphone are used to update the adaptive filter coefficients which are used to model the secondary path.
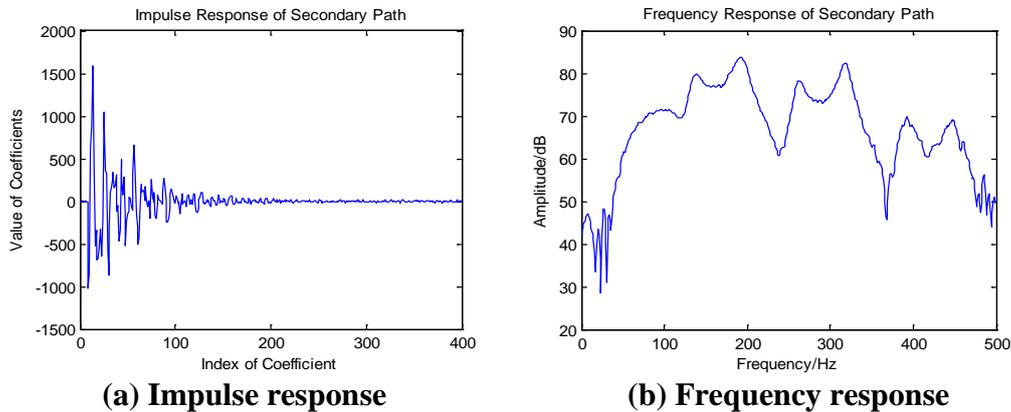
(a) Impulse response   **(b) Frequency response**
Figure 9 Secondary path model in experiment

The impulse response and frequency response of secondary path are illustrated in Figure 9. It can be seen from Figure 9(b) that the frequency response of $S(z)$ below 50Hz and above 350Hz is about 20dB lower than that of mid frequency range This means that the performance of the ANC system in the low response range will degrades in cancellation noise, because the anti-noise signal magnitude cannot be sufficiently high due to system configuration. Therefore the simulation study is mainly focused on the frequency range from 50Hz to 350Hz.

5. Experiment results and discussion

In the experiment, the same primary noise with simulation was applied to test and verify simulation study results. To check the effectiveness of the ANC system spectrum

analysis was applied to different signals in the system. As shown in Figure 10, the error signal spectra are presented when the system using sinusoidal signals and mixed signals as the primary inputs.

(a) 80Hz ANC off

(b) 80Hz ANC on

(c) 120Hz ANC off
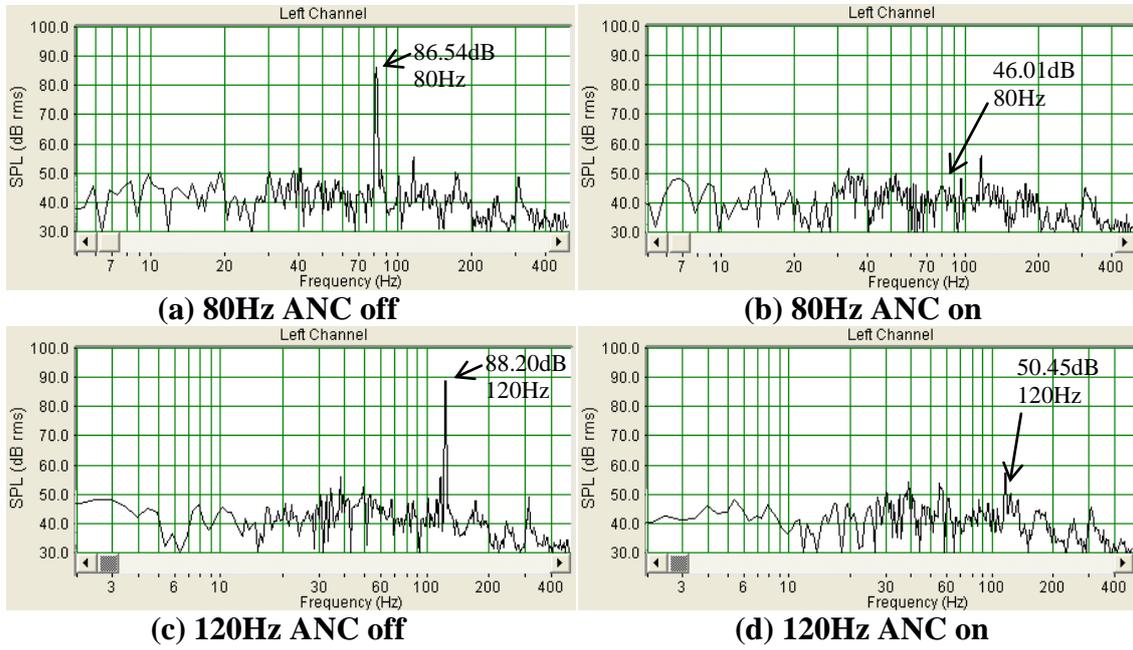
(d) 120Hz ANC on

Figure 10 Experimental results for sinusoidal signals

Figure 10(a) and (c) show spectrum of error signal before applying ANC algorithm when the primary noise is 80Hz and 120Hz. Figure 10(b) and 10(d) illustrate frequency spectrum of error signal after implementing ANC algorithm. The experimental results show that the ANC system can reduce the periodic components effectively from more than 80dB to almost the same level as other components. In this experiment, the noise attenuation is about 40dB for signal with single frequency and 30dB for mixed signal of 100Hz sinusoidal and weak noise, respectively.

(a) Weak signal extraction

(b) Transient signal extraction

Figure 11 Experimental results for a mixed signal

Figure 11(a) shows the experimental result when the primary noise is 100Hz sinusoidal signal mixed with small white noise in the time domain. Figure 11(b) illustrates the

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result for 100Hz sinusoidal signal including transient signal. The weak noise and transient signal are extracted from the primary noise obviously.

(a) ANC off   (b) ANC on
Figure 12 Experimental results for engine signal

Figure 12(a) shows a noise signal measured from a diesel engine in the time domain. It can be seen that the signal consists of not only of stationary contents with high amplitude but also distinctive non-stationary contents due to the reciprocating operating process of the engine. After applying ANC process, the amplitude of stationary contents are reduced greatly while the non-stationary contents are remained as illustrated in Figure 12(b). It means that non-stationary contents are enhanced in comparison to stationary contents.

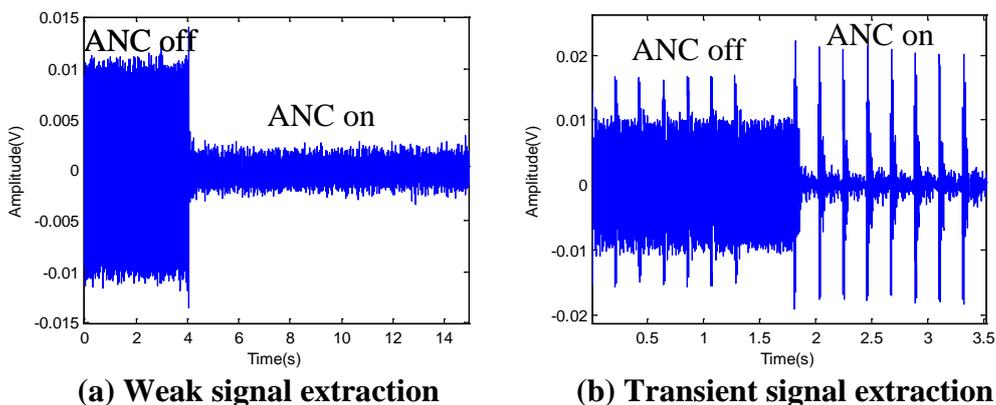From the experiment results, the sinusoidal signal components can be significantly reduced. This is similar with the simulation study. Therefore, the weak and transient signals that contain diagnosis features mixed in the noise are relatively enhanced. This achievement is useful for extracting reliably diagnostic features in machine condition monitoring.

6. Conclusion

In this paper, a weak transient content extraction approach has been explored based on an ANC system using both numerical simulation and experimental studies. The feed-forward FXLMS algorithm has been evaluated to attain attenuation as high as 30dB for stationary signals in the low frequency range. This attenuation then makes the non-stationary transient contents to be intensified significantly, which paves the fundamental for reliable feature extraction and machine condition monitoring.

References

1. G. K. Chaturvedi and D.W. Thomas, 'Bearing Fault Detection using Adaptive Noise Cancelling', Transactions of the American Society of Mechanical Engineers, Journal of Mechanical design, Vol. 104, pp 280-289, April 1982.

2. R. H. Bannister, 'A review of rolling element bearing monitoring techniques', I.MECH.E Conference on Condition Monitoring of Machinery and Plant, pp 11-24, 1985.

3. C. C. Tan, 'Adaptive noise cancellation of acoustic emission noise in ball bearings'. Proceedings of the Asia-Pacific Vibration Conference, Monash University, Melbourne, Australia, pp 5.28-5.35, November 1991.

4. S. J. Elliot, 'Signal processing for active control', pp 77, 2001.

5. D. Zhen, Y. Fan, F. Gu and A. Ball, 'A Study of Sound Source Characteristics in Active Noise Control and Fault Diagnosis', in: Inter noise 2010-39th International congress on Noise Control Engineering, Lisbon, Portugal, June 2010.

6. S. M. Kuo and D. R. Morgan, 'Active Noise Control Systems - Algorithms and DSP Implementations', 1996, pp 62-65.

7. D. R. Morgan, 'An analysis of multiple correlation cancellation loops with a filter in the auxiliary path', IEEE Transactions on Acoustics Speech and Signal Processing, ASSP-28, 454-467, 1980.

8. B. Widrow, D. Shur, and S. Shaffer, 'On adaptive inverse control', in Proc. 15th Asilomar Conference Circuits, Systems and Computers, pp 185-189, 1981.

9. J. C. Burgess, 'Active adaptive sound control in a duct: A computer simulation', Journal of Acoustical Society America, Vol 70, pp 715-726, Sept. 1981.