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Signal Recovery of the Corrupted Metal Impact Signal using the Adaptive Filtering in NPPs

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Abstract

Loose Part Monitoring System(LPMS) is one of the fundamental diagnostic tools installed in the nuclear power plants. In this paper, recovery process algorithm and model for the corrupted impact signal generated by loose parts is presented. The characteristics of this algorithm can obtain a proper burst signal even though background noise is considerably high level comparing with actual impact signal. To verify performance of the proposed algorithm, we evaluate mathematically signal-to-noise ratio of primary output and noise. The performance of this recovery process algorithm is shown through computer simulation.

1. Introduction

The LPMS has been recognized as a useful tool for on-line assessing the mechanical integrity of component in the primary loop of nuclear power plants. Therefore, the LPMS can be said as the fundamental diagnostic system installed in nuclear power plants. The main purpose of the LPMS is to detect and identify the location of metal pieces which may be present in the primary loop.

Most of the LPMSs are designed with the various types of signal filtering techniques as a part of signal conditioning for the impact detection system. A number of impact detection methods are used in different systems and by different vendors. The functions of detection system have an effect on LPMS sensitivity, response to different types of loose part events, incidence of false alerts, and analysis result of impact signal. The general method to improve the detection sensitivity of LPMS and to reduce the high-frequency transient noise response is the adaptation of band-pass filters. The metal impact signal is usually captured/recorded with the pre-triggered value. The triggered value can be set by signal amplitude after processing of the background noise signal. Some have simple fixed signal level setpoint, while the others have adjustable the setpoint according to the back ground level. Such an adjustable method for caption of impact signal has been used in the almost conventional system design. However, because of background noise fluctuation as a function of reactor power level, it is difficult to decide a relevant setpoint. Furthermore, it is hard to analyze the signal due to the reason that the impact signal can be corrupted by external/internal interference signal. If background noise appears high level, the accurate impact signal may not be identified.

In order to improve this drawback, recovery process algorithm for the corrupted impact signal generated by loose parts is presented. The characteristics of this algorithm can get a proper burst signal even though background noise is considerably high level comparing with actual impact signal. The performance of this recovery process algorithm is shown through computer simulation.

Following the introduction, In Section 2, adaptive filtering with noise canceler is introduced to apply it for recovery process algorithm. In Section 3, performance evaluation of noise canceler algorithm is derived mathematically. The computer simulation results of algorithm are illustrated in Section 4. Finally, conclusions are provided In Section 5.

2. Adaptive Filtering with Noise Cancelling

The usual method of estimating a signal corrupted by additive noise is to pass the composite signal through a filter that tend to suppress the noise while leaving the signal relatively unchanged. The design of such filters is the domain of optimal filtering, which originated with the pioneering work of Wiener and was extended and enhanced by the work of Kalman, Bucy, and others.

Noise cancelling is a variation of optimal filtering that is highly advantageous in many applications. It uses an auxiliary or reference input derived from one or more sensors located at point in the noise field where the signal is weak or undectable This input is filtered and submitted from a primary input containing both signal and noise. In noise canceling system of Fig. 1, the practical objective is to produce s system output, $s+n_o-y$, that is a best fit in the least squares sense to the signal s. This objective is accomplished by feeding the system output back to the adaptive filter and adjusting the filter through an adaptive algorithm to minimize the total system output power.

Assume that s, n_o, n, and y and statistically stationary and have zero mean. Assume that s is uncorrelated with n_o and n, and suppose that n is correlated with n_o. The output is

$$\xi = s + n_o - y, \tag{1}$$

squaring, one obtains

$$\xi^2 = s^2 + (n_o - y)^2 + 2s(n_o - y). \tag{2}$$

Taking expectation of both of Eq.(2), and realizing that s is uncorrelated with n_o and with y, yields,

$$\begin{aligned} E[\xi^2] &= E[s^2] + E[(n_o - y)^2] + 2E[s(n_o - y)] \\ &= E[s^2] + E[(n_o - y)^2]. \end{aligned} \tag{3}$$

Signal power $E[s^2]$ will be unaffected as the filter is adjusted to minimize $E[\xi^2]$. Accordingly, the minimum output power is

$$E_{min}[\xi^2] = E[s^2] + E_{min}[(n_o - y)^2]. \tag{4}$$

Since minimizing $E[\xi^2]$ minimizes $E[(n_o - y)^2]$, minimizing the total output power, and since the signal in the output remains constant, minimizing the total output power maximizes the output signal-to-noise ratio. We see from Eq.(3) that the smallest possible output power is $E_{min}[\xi^2] = E[s^2]$. When this is achievable, $E[(n_o - y)] = 0$. Therefore, $y = n_o$ and $\xi = s$. In this case, minimizing output power causes the output signal to be perfectly free of noise. These fundamental principle can readily be extended to reduce the noise in the corrupted metal impact signal.

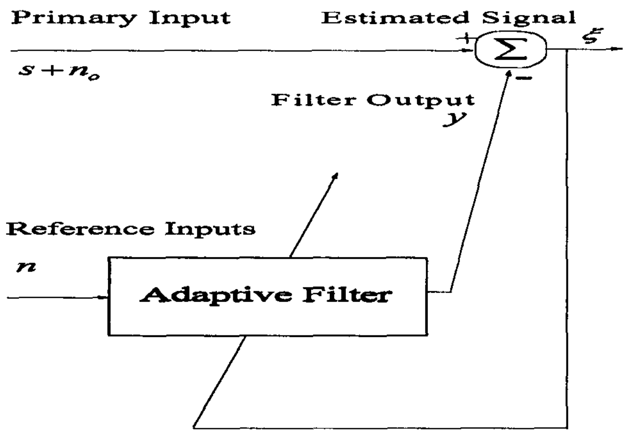

Fig.1 The Adaptive Noise Canceler Block Diagram

3. Performance Evaluation of Noise Canceling Algorithm

In this section, optimal Wiener solutions to certain stationary noise canceling problems are derived. Our purpose is to evaluate the increase in signal-to-noise ratio. In Fig. 1, filter input is x_k, external noise m_{ok} and m_{1k} are added in primary and reference input, respectively. The optimal filter transfer function can be presented as Eq.(5),

$$W^*(z) = \Phi_{xx}^{-1}(z)\Phi_{xd}(z). \tag{5}$$

This solution represents the unconstrained, noncausal solution to the Wiener filtering problem.

Let us consider how to apply the result in Eq.(5) in adaptive noise canceling. Filter input spectrum is

$$\Phi_{xx}(z) = \Phi_{m_1m_1}(z) + \Phi_{nn}(z)|H(z)|^2. \tag{6}$$

The cross power spectrum between the filter input and the desired response depends only on the mutually correlated primary and reference components, and is given by

$$\Phi_{xd}(z) = \Phi_{nn}(z)H(z^{-1}). \tag{7}$$

Using the results in Eq.(5), the Wiener transfer function is thus

$$W^*(z) = \frac{\Phi_{nn}(z)H(z^{-1})}{\Phi_{m_1m_1}(z) + \Phi_{nn}(z)|H(z)|^2}. \tag{8}$$

The performance of the single channel noise canceler can be evaluated more generally in terms of the ratio of the signal-to-noise power density ratio at the output, $\rho_{out}(z)$, to the signal-to-noise power density ratio at the primary input, $\rho_{pri}(z)$. Assuming that the signal spectrum is greater than zero at all frequencies and canceling out the signal power spectrum, we have

$$\frac{\rho_{out}(z)}{\rho_{pri}(z)} = \frac{\Phi_{nn}(z) + \Phi_{m_om_o}(z)}{\Phi_{output\ noise}(z)}, \tag{9}$$

where, the output noise power spectrum is

$$\begin{aligned}\Phi_{output\ noise}(z) &= \Phi_{m_om_o}(z) + \Phi_{m_1m_1}|W^*(z)|^2 \\ &\quad + \Phi_{nn}(z)|[1 - H(z)W^*(z)]|^2.\end{aligned} \tag{10}$$

By combining Eq.(8),(9), and (10), we can obtain the ratio of the primary to the output signal-to-noise power density ratio.

$$\frac{\rho_{out}(z)}{\rho_{pri}(z)} = \frac{[A(z)+1][B(z)+1]}{A(z) + A(z)B(z) + B(z)}, \tag{11}$$

where,

$$A(z) = \frac{\Phi_{m_om_o}(z)}{\Phi_{nn}(z)}, \quad B(z) = \frac{\Phi_{m_1m_1}(z)}{\Phi_{nn}(z)|H(z)|^2}. \tag{12}$$

For the small A(z) and B(z), in other words, as external noise is very small, Eq. (11) can be rewritten as Eq.(13),

$$\frac{\rho_{out}(z)}{\rho_{pri}(z)} \approx \frac{1}{A(z) + B(z)}. \tag{13}$$

In the Eq.(13), infinite improvement is implied by these relations when both A(z) and B(z) approach zero. In this case there is complete removal of noise at the system output, resulting in perfect signal reproduction. However, there are various factor to effect on the performance of noise canceler such as the finite length of adaptive filter, misadjustment and leaking of signal components to reference input.

4. Computer Simulation

The recovery process scheme is derived using the noise cancellation algorithm with the adaptive filtering which is Least Mean Square(LMS). Computer simulation for our study is based on the following assumptions :

- Two sensors are located in the plant; one is the primary sensor and the other is reference sensor(Fig. 1). Here, the primary input signals consist of desired signal and noise signal, reference signal is only noise signal.
- Background noise source is generated from one point, the noise source is transmitted to primary and reference sensor having delay time and attenuation.
- Between desired signal and background noise signal, there is no correlation.
- Reference signal is correlated with primary noise signal.

In order to evaluate the performance of noise canceler system proposed in this paper, the adaptive filter order is selected by 50 and the number of training is 10,000. Fig.2 and 3 present the corrupted impact signal and its frequency spectrum. We can not obtain any results, specially, in time domain from Fig. 2. The result after processing through the noise canceler system is shown in Fig. 4 and 5. Signal-to-noise ratio in output of noise canceler is improved as much as 23.2 dB. As a result, it is expected that the more accurate mass and location of loose parts can be identified through the proposed recovery algorithm.

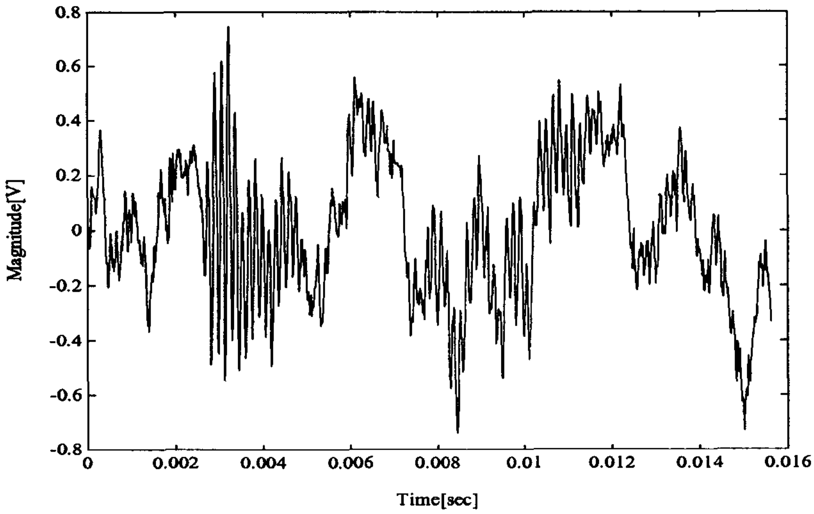

Fig.2 The corrupted impact signal

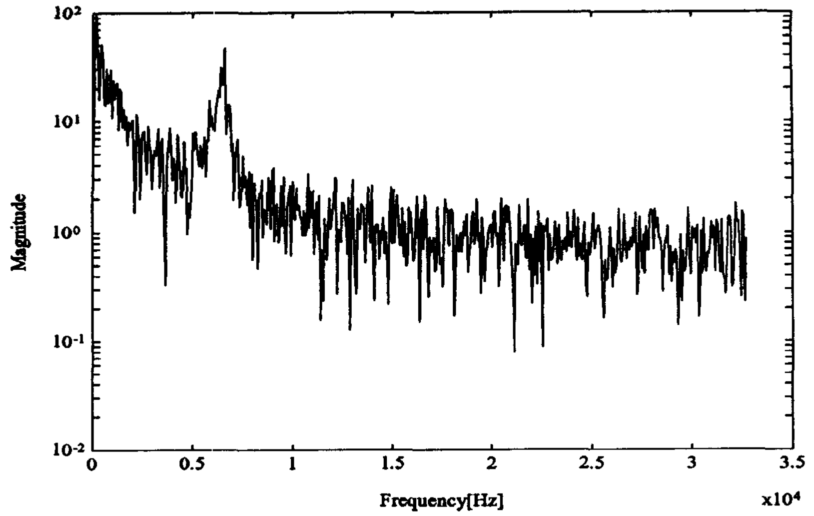

Fig.3 Frequency spectrum of the corrupted impact signal

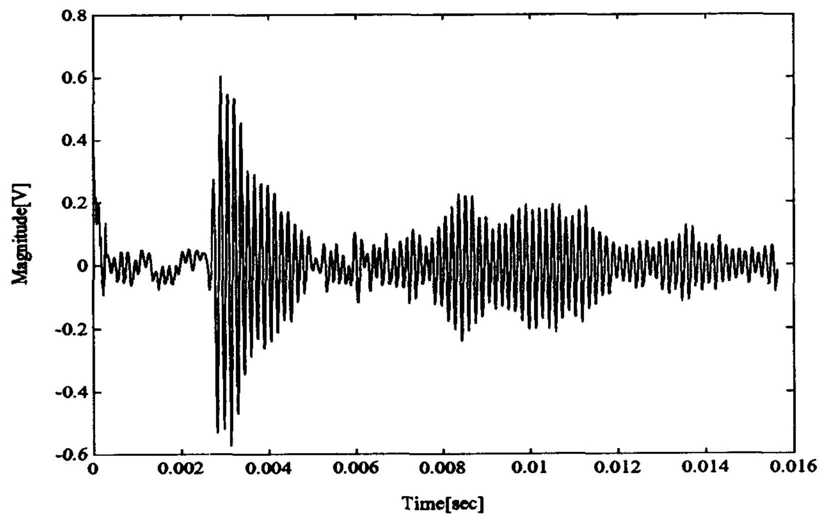

Fig.4 Recovery signal by adaptive noise canceler

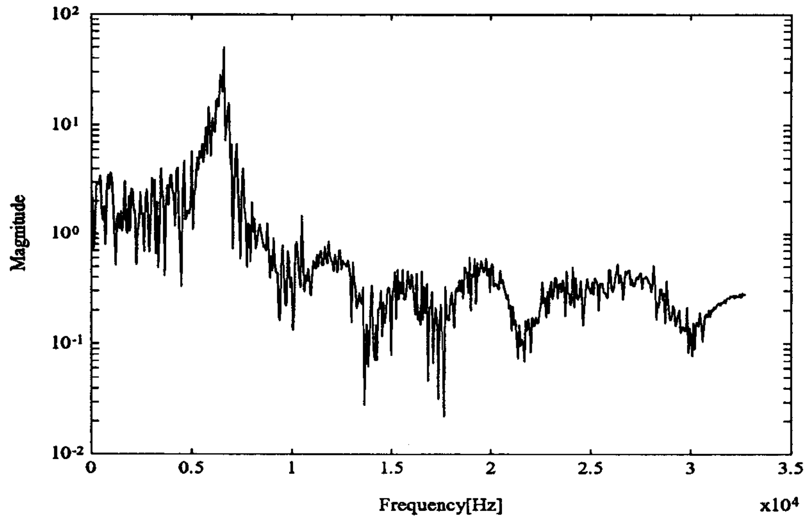

Fig.5 Frequency spectrum of recovery signal by adaptive noise canceler

4. Conclusions

In this paper, we have shown that recovery process algorithm of the corrupted metal impact signal is well suited method for the extraction of burst data from the captured signal. The characteristics of this algorithm can obtain a proper burst signal even though background noise is considerably high level comparing with actual impact signal. To validate the proposed algorithm and model, we simulated with orignal impact signal and simulated noise signal using the computer. The result after processing through the noise canceler system is shown in Fig. 4 and 5. Signal-to-noise ratio in output of noise canceler is improved as much as 23.2 dB. As a result, it is expected that the more accurate mass and location of loose parts can be identified through the proposed recovery algorithm. In further study, we will consider various factors such as the finite length of adaptive filter, misadjustment and leaking of signal components to reference input. Specially, leaking of signal component to reference input has greatly an effect on performance of algorithm.

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