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Development of Software for Machinery Diagnostics by Adaptive Noise Cancelling Method (1st: Cepstrum Analysis)

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ABSTRACT

Many kinds of conditioning monitoring technique have been studied, so this study has investigated the possibility of checking the trend in the fault diagnosis of ball bearing, one of the elements of rotating machine, by applying the cepstral analysis method using the adaptive noise cancelling (ANC) method. And computer simulation is conducted in oder to identify obviously the physical meaning of ANC.

The optimal adaptation gain in adaptive filter is estimated, the performance of ANC according to the change of the signal to noise ratio and convertgence of LMS algorithm is considered by simulation. It is verified that cepstral analysis using ANC method is more effective than the conventional cepstral analysis method in bearing fault diagnosis.

1. Introduction

In monitoring the faults within a rotating machine, using vibration signal, various kinds of analysis method have been used. Generally, these analysis mehtods can be divided roughly into two main classes, namely the handiness diagnosis and the precision diagnosis. The handiness diagnosis is the method that measure the change of RMS level, peak level, crest factor, and kurtosis value in vibration signal. And another method, the precision diagnosis, is to use the power spectrum and the power cepstrum.

The main objective of vibrational signature analysis is to extract suitable features from a diagnostic signal which can discriminate between the good and defective states of components within a machine. However, if, when the above analysis method is applied to detection of faults, one is confronted with a situation in which the diagnostic signal is embedded in a high background noise, the signal to noise ratio (SNR) will be aggravated and then it will show that these analysis methods are not available to detect and diagnose faults. In order to these situations, a substantial improvement in SNR must be achieved.

In the work reported here the conventional analysis methods which fail to detect and diagnose faults because of a poor SNR can be made to be effective by using the adaptive noise cancelling (ANC) method. Essentially, the ANC is method of estimating signal corrupted by additive noise or interference. This method makes use of two inputs: a primary input which contains the corrupted signal and a reference input containing noise correlated in some unknown way with the primary noise. The reference input is suitably filtered and subtracted from the primary input to obtain the signal estimate. The filtering process is based on the least mean square algorithm.

2. THEORETICAL ANALYSIS

2.1 THE GENERAL CONCEPTS OF ANC

The basic adaptive noise cancelling situation is illustrated in Fig.1. A signal is transmitted over a channel to a sensor that receives the signal plus an uncorrelated noise, n_0. The combined signal and noise, $s+n_0$, form the primary input to the canceller. A noise n_1 which is uncorrelated with the signal but correlated in some unknown way with the noise n_0 forms the reference input to the canceller.

Assume that s, n_0, n_1, and y are statistically stationary and s is uncorrelated with n_0 and n_1, and suppose that n_1 is correlated with n_0.
The output is

$$\varepsilon = s + n_0 - y \qquad (1)$$

Squaring, one obtains

$$\varepsilon^2 = s^2 + (n_0 - y)^2 + 2s(n_0 - y) \qquad (2)$$

Taking expectations of both sides of (2), and realizing that s is uncorrelated with n_0 and with y, yields

$$E[\varepsilon^2] = E[s^2] + E[(n_0 - y)^2] \qquad (3)$$

Accordingly, the minimum output power is

$$\min E[\varepsilon^2] = E[s^2] + \min E[(n_0 - y)] \qquad (4)$$

when the filter is adjusted so that $E[s^2]$ is minimized, $E[(n_0 - y)^2]$ therefore also minimized. The filter output y is then a best least-squares estimate of the primary noise n_0. Moreover, when $E[(n_0-y)^2]$ is minimized, $E[(\varepsilon-s)^2]$ is also minimized, since, from (1)

$$(\varepsilon - s) = (n_0 - y) \qquad (5)$$

Adjusting or adapting the filter to minimize the total output power is thus tantamount to causing the output ε to be a best least-squares estimate of the signal s.

The output ε will generally contain the signal s plus some noise. From (1), the output noise is given by (n_0-y). Since minimizing $E[\varepsilon^2]$ minimizes $E[(n_0-y)^2]$, minimizes the output noise power and, since the signal in the output remains constant, minimizing the total output power maximizes the output signal to noise ratio.

2.2 LMS ALGORITHM ANALYSIS

LMS algorithm is important algorithm which can be implemented in a practical system of the noise canceller in the noise cancelling problem, because it is elegant in its simplicity and efficiency. In this study, the single-input adaptive transversal filter, using LMS algorithm, is used. The principal component of most adaptive system is the adaptive linear combiner shown in Fig.2. The combiner weights and sums a set of input signals to form an output signal. The input signal vector is defined as

$$\mathbf{X}_k = [x_k \quad x_{k-1} \quad \cdots \quad x_{k-L}]^T \qquad (6)$$

The weight vector is

$$\mathbf{W}_k = [w_{0k} \quad w_{1k} \quad \cdots \quad w_{Lk}]^T \qquad (7)$$

The kth output signal is

$$y_k = \sum_{l=0}^{L} w_{lk} x_{k-l} \qquad (8)$$

This can be written in vector notation

$$y_k = \mathbf{W}_k^T \mathbf{X}_k = \mathbf{X}_k^T \mathbf{W}_k \qquad (9)$$

Denoting the desired response for the kth set of input signals as d_k, the error at the kth iteration time is

$$\varepsilon_k = d_k - y_k = d_k - \mathbf{W}_k^T \mathbf{X}_k \qquad (10)$$

The square of this error is

$$\varepsilon_k^2 = d_k^2 - 2d_k \mathbf{X}_k^T \mathbf{W}_k + \mathbf{W}_k^T \mathbf{X}_k \mathbf{X}_k^T \mathbf{W}_k \qquad (11)$$

The mean-square error, the expected value of ε_k^2, is

$$E[\varepsilon_k^2] = E[d_k^2] - 2E[d_k \mathbf{X}_k^T]\mathbf{W}_k + \mathbf{W}_k^T E[\mathbf{X}_k \mathbf{X}_k^T]\mathbf{W}_k \qquad (12)$$

where the vector of cross-correlation between the input signals and the desired response is defined as

$$E[d_k \mathbf{X}_k^T] \triangleq \mathbf{P} \qquad (13)$$

The input correlation matrix is defined as

$$E[\mathbf{X}_k \mathbf{X}_k^T] \triangleq \mathbf{R} \qquad (14)$$

It is clear from (12) that the mean-square error is precisely a quadratic function of the component of the weight vector $\mathbf{W}$, so the error can be pictured as a concave hyperparaboloidal surface. Adjusting the weights to minimize the error is to seek the minimum of this surface. Gradient methods are commonly used for this purpose. The gradient at any point on this surface may be obtained by differentiating (12) with respect to the weight vector.

$$\nabla[\varepsilon_k^2] = -2\mathbf{P} + 2\mathbf{R}\mathbf{W}_k \qquad (15)$$

To find the optimal weight vector $\mathbf{W}^*$ that yields the least mean square error, set the gradient to zero. Accordingly

$$\mathbf{P} = \mathbf{R}\mathbf{W}^*, \quad \mathbf{W}^* = \mathbf{R}^{-1}\mathbf{P} \qquad (16)$$

This equation is the Wiener-Hopf equation in matrix form. The LMS adaptive algorithm is a practical method for finding close approximate solutions to (16) in real time. According to this method, the 'next' weight vector $\mathbf{W}_{k+1}$ is equal to the 'present' weight vector $\mathbf{W}_k$ plus a change proportional to the negative gradient.

$$\mathbf{W}_{k+1} = \mathbf{W}_k - \mu \nabla_k \qquad (17)$$

The paramenter μ is the factor that controls stability and rate of convergence. The true gradient at the kth iteration is represented by ∇_k. The estimated gradient is related to the partial derivative of the instantaneous error with respect to the weight component. And the relationship between the true gradient and the estimated gradient is defined as follows

$$\hat{\nabla}_k = \nabla[\,\varepsilon_k^2\,] = 2\varepsilon_k \nabla[\,\varepsilon_k\,] \qquad (18)$$

According to the above definition, the estimated gradient is

$$\hat{\nabla}_k = -2\varepsilon_k \mathbf{X}_k \qquad (19)$$

Using the estimate in place of the true gradient in (17) yields the next equation.

$$\mathbf{W}_{k+1} = \mathbf{W}_k + 2\mu\varepsilon_k \mathbf{X}_k \qquad (20)$$

This equation is the Widro-Hoff equation. This algorithm is simple and generally easy to implement, because it does not even require squaring, averaging, or differentiation in order to make use of gradients of mean-square- error functions. Starting with an arbitrary initial weight vector, the algorithm will converge in the mean and will remain stable as long as the paramenter μ is greater than 0 but less than reciprocal of the largest eigenvalue λ_{max} of the matrix $\mathbf{R}$.

$$0 < \mu < 1/\lambda_{max} \qquad (21)$$

An appropriate value of μ, the scalar constant which controls the stability and rate of convergence, has to be chosen when implementing ANC method. Small values of μ result in very slow adaptation and large values introduce instability.

3.CONSIDERATION OF COMPUTER SIMULATION

A computer simulation of ANC has been carried out by following equation consisted of direct wave and reflect wave.

$$x(t) = e^{-180t}\,\sin(2\pi f t)\{\,\delta(t) + a\delta(t-\tau)\} \qquad (22)$$

where f is the fundamental frequency, $\delta(t)$ is the unit pulse function, X(=1)is constant, and τ is the time delay (an arrival time of reflect wave).

3.1 ESTIMATION OF OPTIMAL ADAPTATION GAIN

ANC method, using LMS algorithm, is considerably effected on the stability and rate of convergence by the value of adaptation gain μ. In order to estimate the optimal value of adaptation gain μ, the primary input has been used as a wave which consists of a fundamental wave in (22) plus a vibration signal of an actual rotating machine, and the reference input has been used as a vibration signal of an actual rotating machine. A fundamental wave is characterized by following parameters: fundamental frequency, 500Hz; time delay of reflect wave, 25msec.

After calculating the upper bound of μ given in (21), ANC has been implemented into several values of μ below the upper bound. The error percentages by RMS ratio between the fundamental wave and the estimated fundamental wave at the output of noise canceller is illustrated in Table 1 and Fig.3. In this case, the value of μ with the smallest error percentage can be estimated as the optimal value of μ. Fig.4 shows the estimated fundamental wave at the output of noise canceller. The result of Table 1 and Fig.4 represent the optimal value of μ=0.1 in this simulation.

3.2 COMPARISON OF ANC PERFORMANCE CAUSED BY THE CHANGE OF SNR

In order to compare ANC performance caused by the change of SNR, the primary input has been used as a wave which consists of a fundamental wave as in section 3.1 plus additive random noise. The random noise was generated on using the RND function in micro computer.

When SNR are -10dB, -5dB, 0dB and 5dB, the results in the power cepstrum before and after implementing ANC is shown in Fig.5 and Fig.6. As one can see in Fig.5 and Fig.6, the result of the power cepstrum, after implementing ANC, shows that it is possible to obtain the definite signal analysis even in the case of a poor SNR.

3.3 CONVERGENCE PERFORMANCE ACCORDING TO THE NUMBER OF DATA

In LMS algorithm, the value of mean-square-error becomes smaller when the iteration number of adaptation is proportional to the number of data, the mean-square-error becomes smaller as the number of data increase. Fig.7 illustrate the convergence performance according to the number of data.

4. CONSIDERATION OF RESULT IN APPLYING ANC TO BALL BEARING

The ANC method has been utilized in the fault diagnosis of ball bearing, one of the elements of rotating machine, by using the result obtained by computer simulation. The ball bearing used in this experiment was type 6207zz, manufactured by KBC.

The vibration signal in good state was measured by fixing outer race and rotating at 4,000 rpm. And also the vibration signal was measured same as above, with outer race in defective state caused artificially.

Fig.8 illustrates the vibration characteristics of the ball bearing in good state and Fig.9 illustratesthe defective state. Fig.10 shows the vibration characteristics of the ball bearing after implementing ANC with good state as the reference input and defective state as the primary input. In time signal and the power spectrum, it is difficult to estimate the component of faults, however, in the power cepstrum, it is possible to interpret the faults with distinct peak value when the faults occur in bearing.

In observing the result of the power cepstrum after implementing ANC, the gamnitude of a1 at quefrency 16.5msec and of a2 at quefrency 33msec are rahmonics which are cause by side band coinciding with the 4th harmonics of the rotating frequency 240Hz of outer race due to the fault of outer race. The gamnitude of b1 at quefrency 28.5msec and of b2 at quefrency 53msec are rahmonics which are caused by side band coinciding with the 9th harmonics of rotating frequency 320Hz of ball due to the fault of ball. And the gamnitude of c1 equals to the 3rd harmonic of shaft speed 4,000 rpm (66.6Hz).

From these results, we can see artificial fault of outer race and fault arising out of ball contacting with outer race after implementing ANC.

5. CONCLUSION

In this study, we obtained the following conclusions by computer simulation and application of ANC method to the ball bearing fault diagnosis.

(1) It can be finded that it is important to estimate the adaptation gain appropriately when applying ANC method.

(2) By applying ANC method, it is possible to practically improve the signal to noise ratio of input signal.

(3) In the fault diagnosis, applying ANC method in cepstrum analysis is more effective compared to the conventional cepstrum anslysis.

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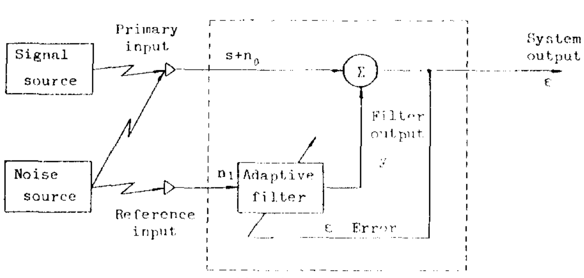

Fig. 1 Adaptive linear cancelling applied to a simplified model of a machine.

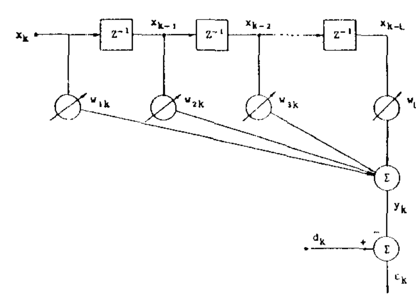

Fig. 2 Adaptive linear combiner in the forms of single-input adaptive transversal filter.

Table 1 RMS error percentage according to the change of μ value.

μ	Error(%)	μ	Error(%)
0.01	21.52	1.5	-47.18
0.05	7.09	2.0	-50.06
0.1	- 0.68	2.5	-52.85
0.5	-26.60	3.0	-53.26
1.0	-40.20	3.5	-53.67

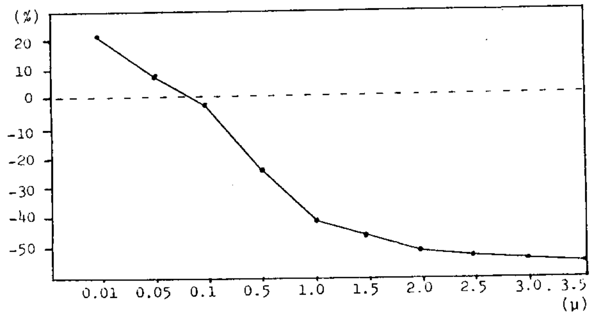

Fig.3 RMS error percentage according to the change of μ value.

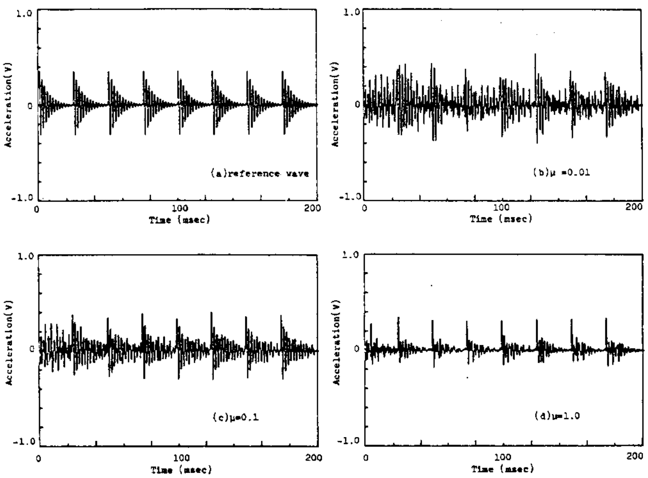

Fig.4 Variation of the output wave at the noise canceller according to the change of μ value.

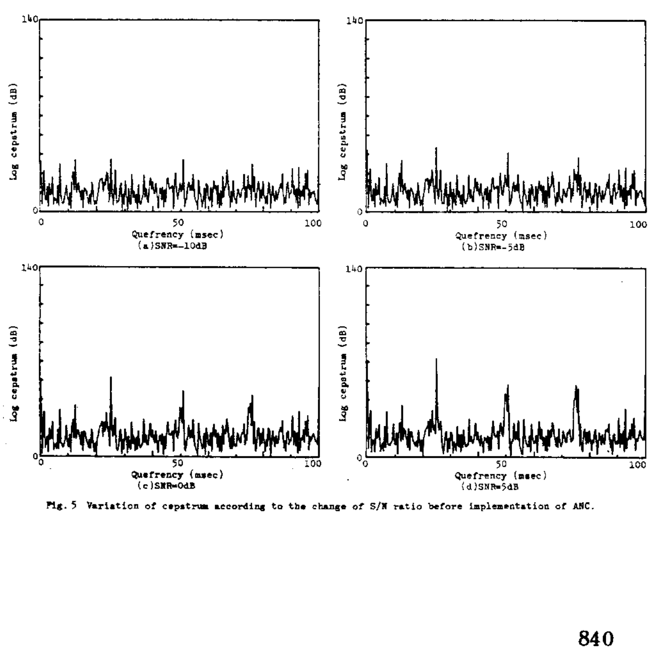

Fig.5 Variation of cepstrum according to the change of S/N ratio before implementation of ANC.

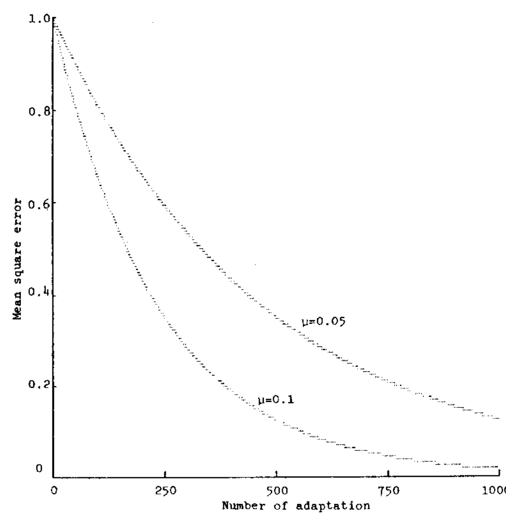

Fig.7 Typical learning curves for the LMS algorithm.

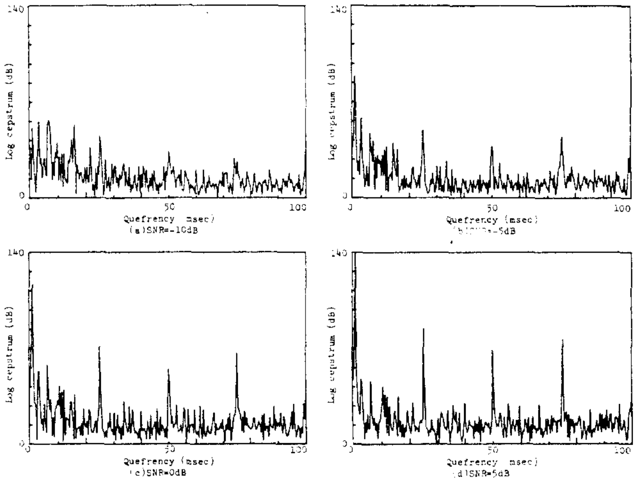

Fig.6 Variation of cepstrum according to the change of S/N ratio after implementation of ANC.

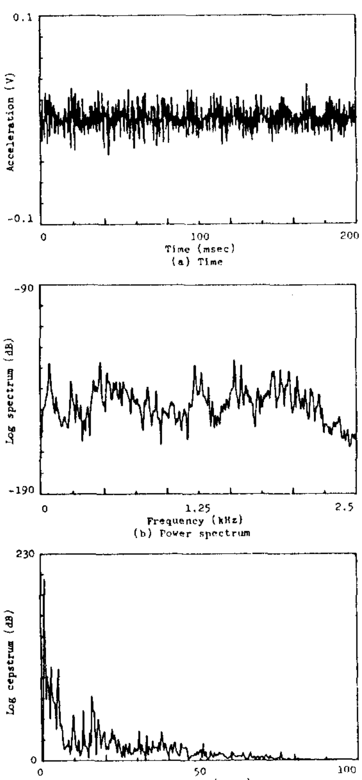

Fig.8 Vibration characteristics of ball bearing in good condition.

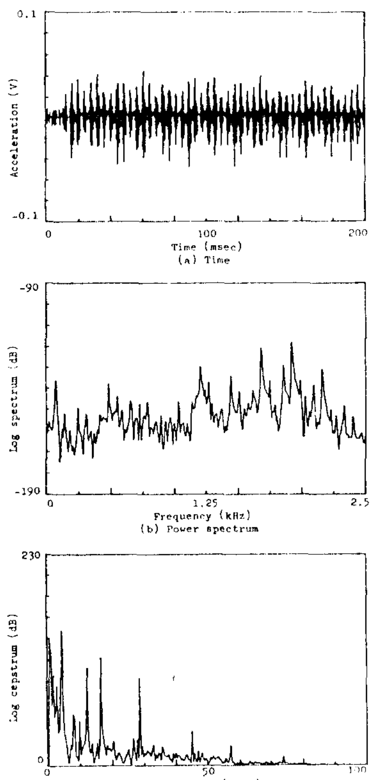

Fig.9 Vibration characteristics of ball bearing in bad condition.

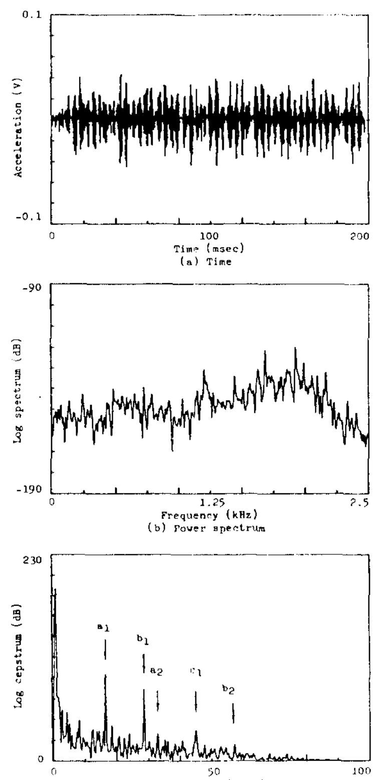

Fig.10 Vibration characteristics of ball bearing after implementation of ANC.