Development of software for machinery Diagnosis by Adaptive Noise Cancelling Method (1st: Cepstrum Analysis)

Adaptive Noise Cancelling 법에 의한 기계 이상진단 소프트웨어 개발 (제 1 보 : Cepstrum 해석)

Jae Eung Oh*, Jong Kwan Kim,* Soo Hong Park*

오 재 응, 김 종 관, 박 수 홍

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 order to verify the usefulness 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 convergence of least mean square 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.

요 약

各種의 Conditioning Monitoring技術이 硏究되고 있는데 本 硏究에서는 Cepstrum 解析法에 Adaptive Noise Cancelling(ANC)法을 利用하여 回轉機械要素의 하나인 베어링의 缺陷을 管理하는 手段으로써의 可能性을 檢討하였으며 ANC의 物理的 意味를 正確히 把握하고자 컴퓨터 시뮬레이션을 行하였다.

컴퓨터 시뮬레이션에 依해 Adaptive filter에서의 最適한 適應利得을 推定하였으며 信號對雜音比에 따른 ANC의 性能과 LMS알고리즘의 收斂性을 考察하였다. 또한 ANC法을 Cepstrum 解析法에 利用한 베어링의 異常診斷은 旣存의 Cepstrum 解析法보다 有效함을 알았다.

* Department of Mechanical Engineering, University of Han-Yang, 17 Haeng Dang Dong Sung Dong Gu Seoul 133-792 Korea.
서울특별시 성동구 행당동 산17번지 한양대학교 기계공학과

I. INTRODUCTION

In monitoring the faults within a rotating machine, using vibration signal, various kinds of analysis method have been used. Generally, these analysis methods can be divided roughly into two main classes, namely the handiness diagnosis and the precision diagnosis. The handy 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 distinguish 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 dianose faults. In order to improve 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, ANC is the 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.

II. THEORETICAL ANALYSIS

2.1 Noise Cancelling Adaptive Filter

The general problem to be considered here is that of the noise cancelling adaptive filter shown in Fig.1. With time index k the primary input d_k consists of an information signal s_k contaminated by additive noise n_k ; the reference input x_k is a measureable noise signal derived from the same source as, and therefore correlated with s_k . All primary and reference inputs are assumed to be stationary and of zero mean, and it is further assumed that x_k is not correlated with s_k .

The adaptive filter attempts to cancel the primary noise by forming an estimate n_k which is then substracted from the primary input d_k to yield an error output e_k . It has been shown that best noise cancelling is equivalent to minimizing the mean square error (MSE)

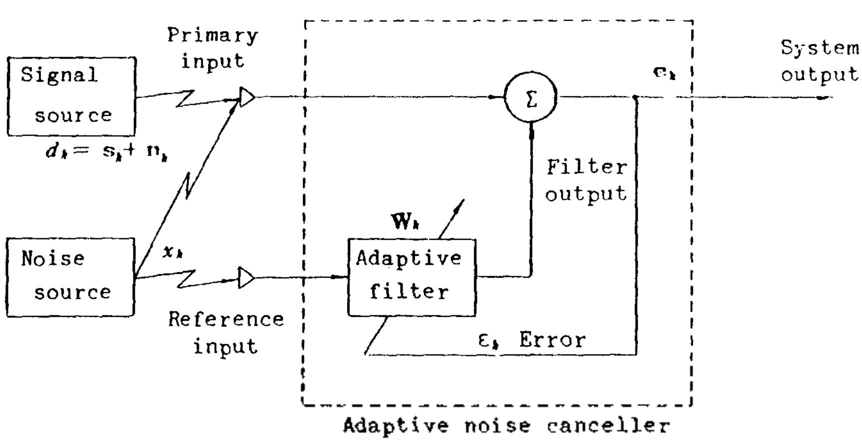


Fig. 1. Adaptive linear cancelling applied to a simplified model of a machine.

output.[5)]

Denoting the vector of reference noise samples by

$$X_K^T = [x_K,\ x_{K-1},\ \cdots,\ x_{K-n+1}] \tag{1}$$

and the weight vector of filter coefficients at time k by

$$W = [w_{0K},\ w_{1K},\ \cdots,\ w_{N-1K}] \tag{2}$$

We can express the MSE output as a function of W_K thus

$$\varepsilon(W_K) = E[e_K^2] = E[d_K^2] - 2W_K^T P + W_K^T R W_K \tag{3}$$

where E is the expectation operator.

$$R = E[X_K X_K^T] \tag{4}$$

is the reference noise covariance matrix, and

$$P = E[d_K X_K] \tag{5}$$

is the reference-primary covariance vector. Minimizing $\varepsilon(W_K)$ by setting the gradient $\nabla_W[\varepsilon(W_K)]$ equals to zero yields the optimum weight vector.

$$W^* = R^{-1}P \tag{6}$$

If ε^* represents the optimum MSE, then equation (3) may be rewritten in terms of the weight error vector

$$V_K = W_K - W^* \tag{7}$$

as

$$\varepsilon(V_K) = \varepsilon^* + J(V_K) \tag{8}$$

where the residual or excess MSE is given by

$$J(V_K) = V_K^T R V_K \tag{9}$$

If e^* is the error output for $W_K = W^*$, it may readily be shown that

$$e_K = e_K^* - V_K^T X_K \tag{10}$$

$$E[e_K^* X_K] = 0 \tag{11}$$

2.2 The LMS Algorithm

The adaptive system previously described must be provided with an algorithm such that, given an arbitrary starting weight vector V_K is forced to approach O in a least squares sense. If the statistical parameters R and P were known the gradient $\nabla_V[\varepsilon(V_K)]$ could be evaluated and the method of the speedest descent would give the following iterative procedure for computing the weight error vector :

$$V_{K+1} = V_K - \mu\nabla_N[\varepsilon(V_K)] \tag{12}$$

where the constant μ is greater than zero. The LMS algorithm replaces $\varepsilon(V_K)$ by its instaneous estimate e_K^2 to give the following approximation for the gradient :

$$\nabla_N[\varepsilon(V_K)] = 2X_K X_K^T V_K - 2e_K^* X_K \tag{13}$$

from equation (10). Substituting this into equation (12) we get the LMS algorithm in the following form :

$$V_{K+1} = (I - 2\mu X_K X_K^T)V_K + 2\mu e_K^* X_K \tag{14}$$

where I is the unit matrix.

Using previous results, equation (14) may be formulated in the more computationally efficient form

$$W_{K+1} = W_K + 2\mu e_K X_K \tag{15}$$

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 grdients 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 parameter μ is greater than 0 but less than reciprocal of the largest eigenvalue λ_{max} of the matrix R.

$$0 < \mu < 1 / \lambda_{max} \tag{16}$$

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 in very slow adaptation and large values introduce instability.

III. CONSIDERATION OF COMPUTER SIMULTION

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

$$x(t) = e^{-150t} \sin(2\pi f t) \{ \delta(t) + a\, \delta(t-\tau) \} \tag{17}$$

where f is the fundamental frequency, $\delta(t)$ is the unit pulse function, a(=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 (17) plus a vibration signal of an actual rotating machine, and the reference input has been used as a vibration signal of a simple 500 Hz simple wave. A fundamental wave is characterized by following parameters: fundamental frequency, 500 Hz; time delay of reflect wave, 25 msec.

After calculating the upper bound of 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.

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

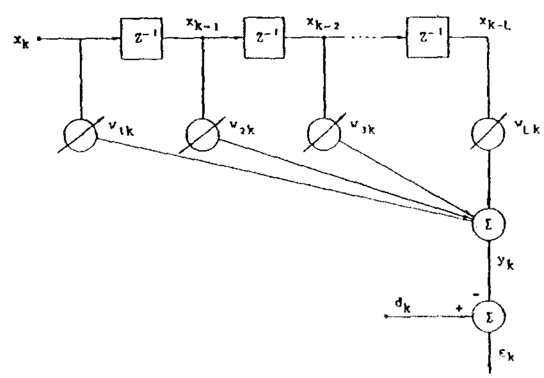


Fig. 2. Adaptive linear combiner in the forms of single-input adaptive transversal filter.

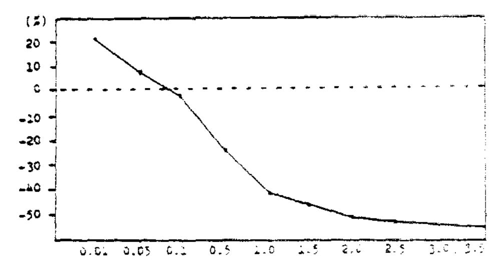


Fig. 3. RMS error percentage according to the change of μ value.

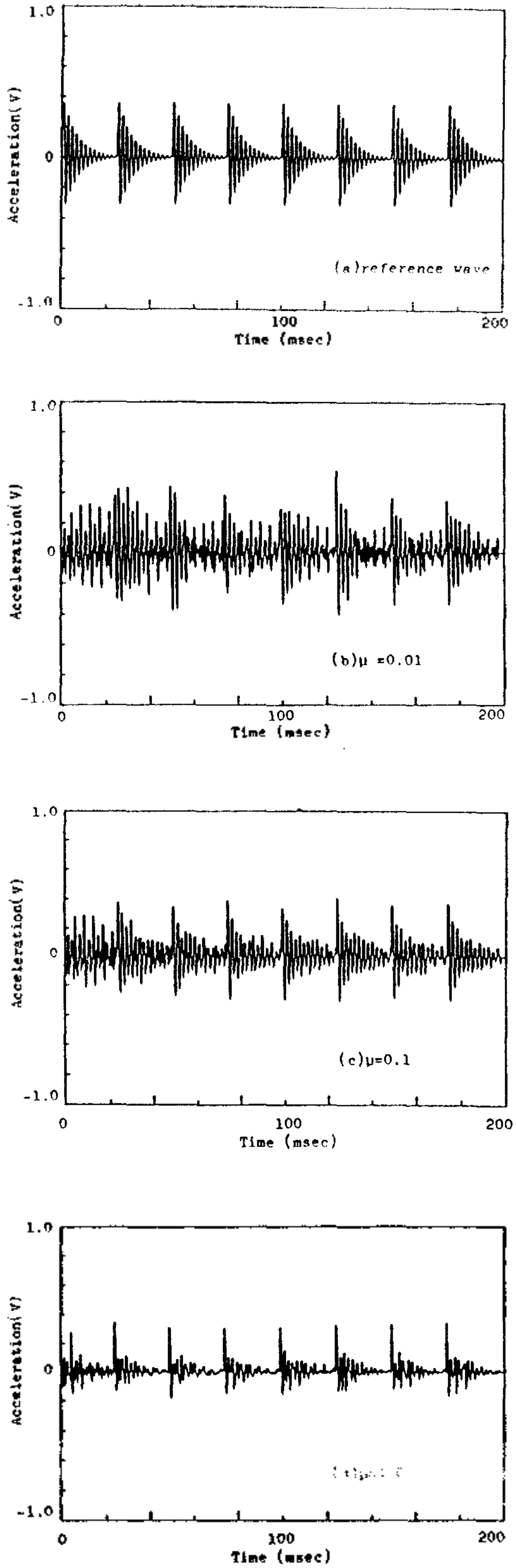
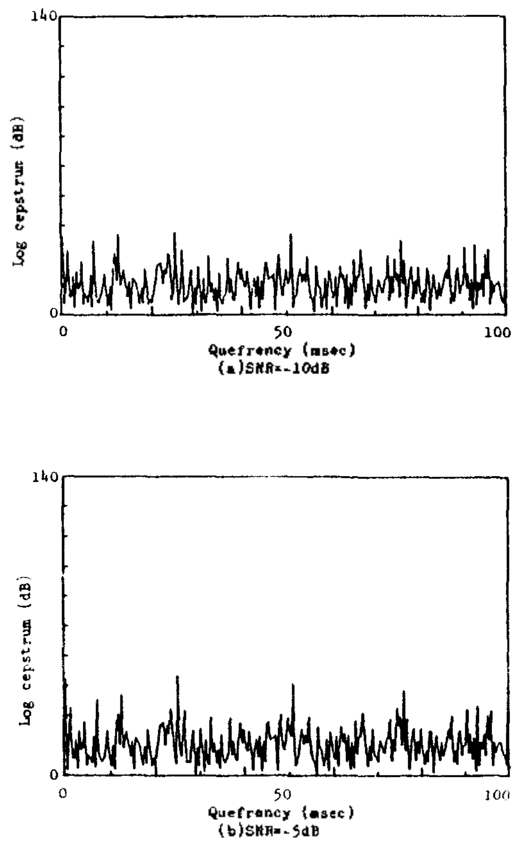


Fig. 4. Variation of the output wave at the noise canceller according to the change of μ value.

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 -10 dB, -5 dB, 0 dB and 5 dB, 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.



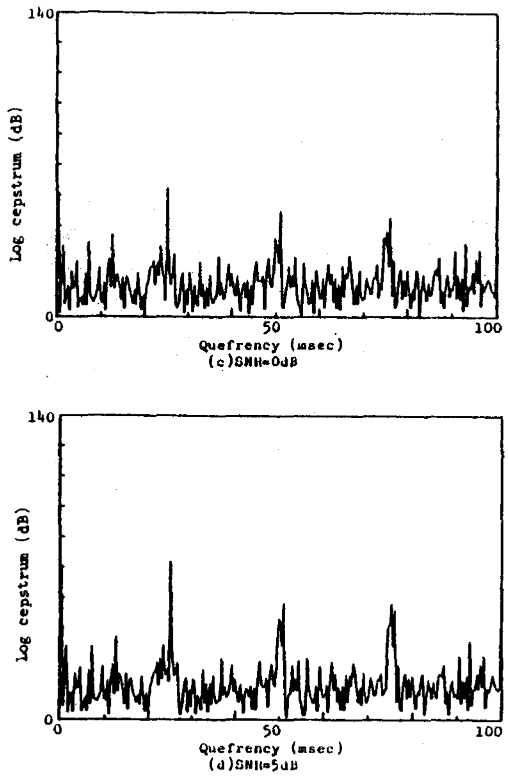
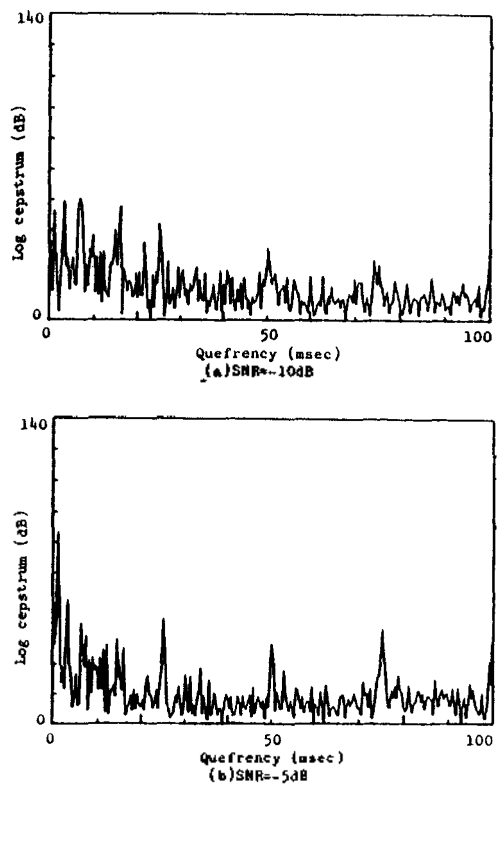


Fig. 5. Variation of cepstrum according to the change of S/N ratio before implementation of ANC.



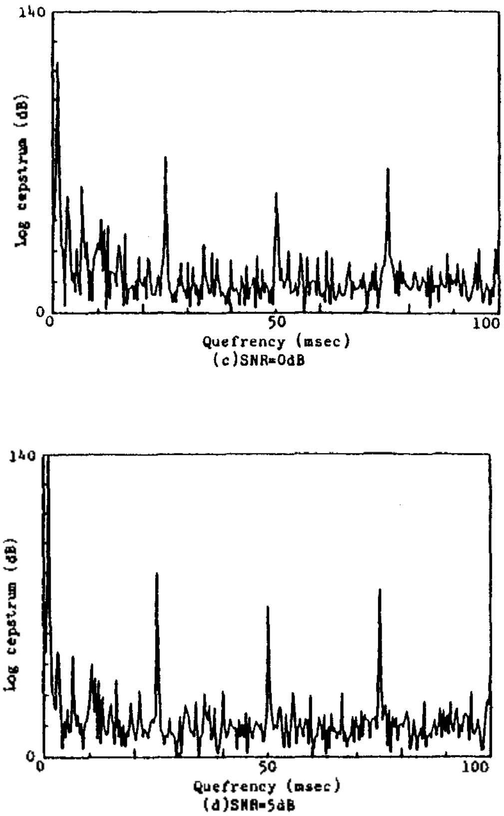


Fig. 6. Variation of cepstrum according to the change of S/N ratio after implementation of ANC.

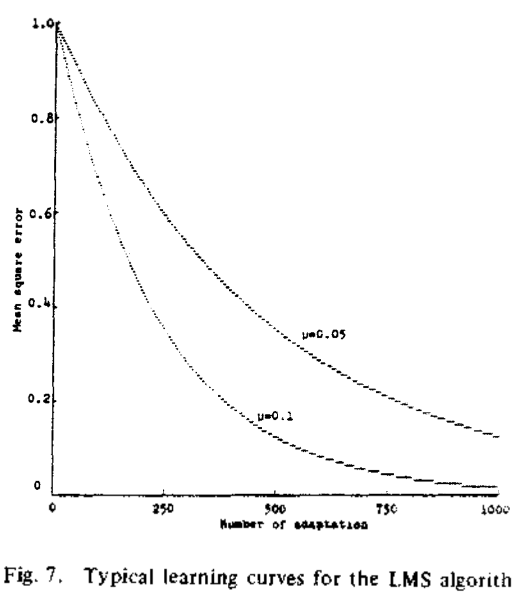


Fig. 7. Typical learning curves for the LMS algorithm

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 increases. As the iteration number of adaptation is proportional to the number of data, the mean-square-error becomes smaller as the number of data increases. Fig.7 illustrates the convergence performance according to the number of data.

IV. CONSIDERATION OF RESULT IN APPLYING AND 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 KMC.

The vibration signal in good state was measured by fixing outer race and rotating at 4,000 rpm. And also the vibration signal was measued 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 illustrates the 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 16.5 msec and of a2 at quefrency 33 msec are rahmonics which are caused by side band coinciding with the 4th harmonic of the rotation frequency 240 Hz of outer race due to the fault of outer race. The gamnitude of b1 at quefrency 28.5 msec and of b2 at quefrency 53 msec are rahmonics which are caused by side band coinciding with the 9th harmonics of rotating frequency 320 Hz of ball due to the fault of ball. And the gamnitude of c1 equals to the 3rd harmonic of shaft speed 4,000 rpm (66.6 Hz).

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

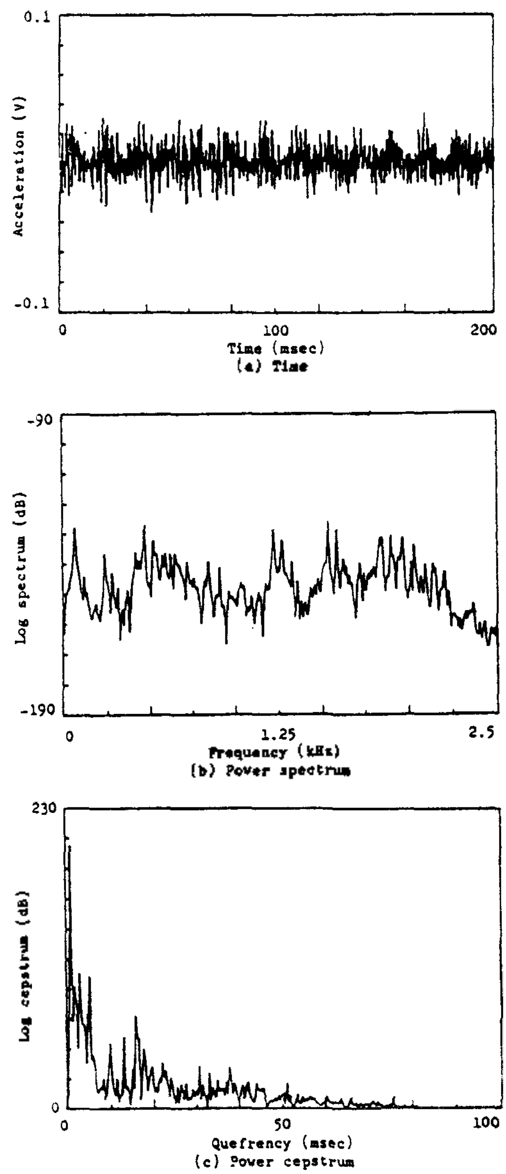


Fig. 8. Vibration characteristics of ball bearing in good condition.

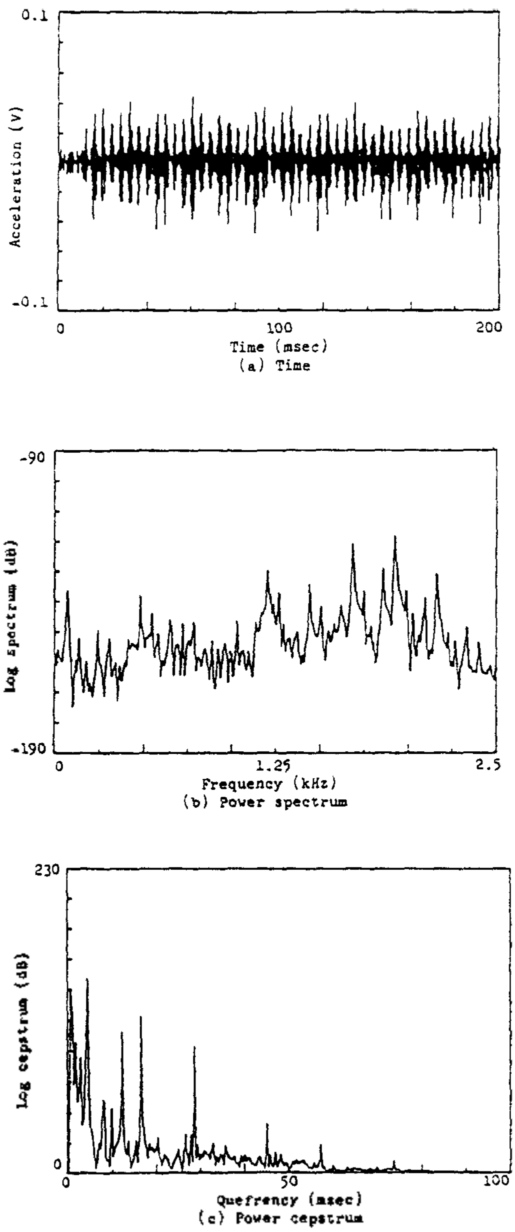


Fig. 9. Vibration characteristics of ball bearing in bad condition.

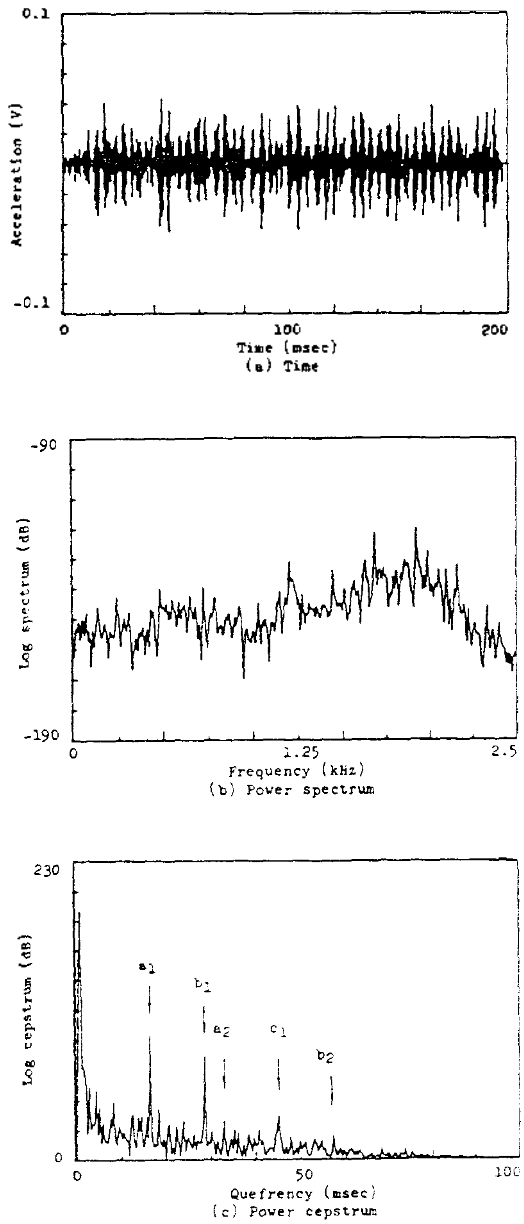


Fig. 10. Vibration characteristics of ball bearing after implementation of ANC.

V. 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 found 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 analysis.

ACKNOWLEDGEMENTS

The authors wish to express their gratitudes for the 1986 financial support of this study provided by the Korea Research Foundation.

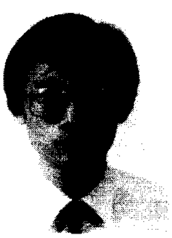
REFERENCES

1. D. Dyre and R.M. Stewart, "Detection of Rolling ELement Bearing Damage by Statistical Vibration Analysis," ASME Journal of Mechanical Design 100, 229-235, (1978).
2. J.E. Oh, E.S. Yoon, S.H. Yum and O.K. Kwon, "A Study on the Bearing Fault Diagnosis by Cepstral Analysis," Proc. of the International Conference on Rotordynamics, 397-401, (1986).
3. R.B. Randall, "Cepstrum Analysis and Gearbox Fault Diagnosis," B & K Application Note 13-150, (1974).
4. G.K. Chaturvedi and D.W. Thomas, "Adaptive Noise Cancelling and Conditioning Monitoring," Journal of Sound and Vibration, 76(3), 391-405, (1981).
5. B. Widrow, et al, "Adaptive Noise Cancelling: Principles and Application," Proc. of IEEE, Vol. 63, No.12, 1692-1716, (1975).
6. B. Widrow and D. Stearins, Adaptive Signal Processing, Prentice-Hall, Inc., Englewood Cliffs, New Jersey, (1985).
7. B. Widrow, J.M. McCool and C.R. Johnson, "Stationary and Nonstationary Learning Characteristics of the LMS Adaptive Filter," Proc. of IEEE, Vol.64, 1151-1162, (1976).

▲Name : Soo Hong Park

Date of Birth :
February 27, 1965
Position : Graduate Student of Precision Mechanical Engineering, Hanyang University
Education : * B.E. (Precision Mechanical Engineering, Hanyang University, Febraury 1987)

▲Name : Jong Kwan Kim



Date of Birth : March 13, 1961
Position : Graduate Student of Mechanical Engineering, Hanyang University
Education : * B.E. (Machine Design and Production Engineering Hanyang University February 1984
* M.S. (Machine Design and production Engineering Hanyang

▲Name : Jae Eung Oh

Date of Birth :
January 2, 1951
Position : Associate Professor of Mechanical Engineering, Hanyang University
Education :
* B.E (Mechanical Engineering, Hanyang University, February 1975)
* M.E (Safety Engineering, Yokohama National University, Japan, March 1980)
* Dr. E (Environmental Engineering, Tokyo Institute of Technology, Japan, March 1983)

Employment :
1975.3-1977.10 Engineer of Hyundai Co., Korea
1977.10-1980.3 Graduate School, Yokohama National University, Japan (M.E)
1980.4-1983.3 Graduate School, Tokyo Institute of Technology, Japan (Dr.E)
1984.4-1987.3 Assistant Professor, Dept. of Mechanical Engineering, Hanyang University, Korea
1984.3-present Editor of the Ministry of Education