Mechanical Systems and Signal Processing (1992) 6(2), 177–189

SHORT PAPER

MACHINERY CONDITION MONITORING BY INVERSE FILTERING AND STATISTICAL ANALYSIS

YUBAO CHEN
Department of Industrial and Systems Engineering, University of Michigan-Dearborn, Dearborn, MI 48128, U.S.A.

(*Received* 4 *May* 1990, *accepted* 4 *July* 1990)

Data used for machinery condition monitoring contains mainly the same information as that obtained under normal operation conditions. The traditional practice of feature extraction, which uses such data directly, suffers from low signal-to-noise ratio. This paper presents a method that uses an inverse filter to separate the information contents of the data, so that the feature extraction can be done by statistical analysis algorithms, which would otherwise be difficult. It is shown that the inverse filtering process is equivalent to that of prediction error estimation based on a signal model in the form of an autoregressive moving-average (ARMA) model. The construction of the inverse filter can therefore be carried out by ARMA modeling. An application example of this method for the monitoring of a paper handling system is also given.

1. INTRODUCTION

Machinery condition monitoring is generally performed by evaluating the characteristic changes of the system at different operation periods. This change, if any, is usually revealed by detecting variations in its signature. Figure 1 is a schematic flow-chart of a typical monitoring process, which involves feature extraction under both normal and operating conditions, and then a comparison between them in decision making. Many sensing devices, such as vibration, force, temperature, etc. and several signal processing algorithms have been developed [1, 2]. The increased investment and improved productivity, however, dictates a need for a monitoring system that is capable of detecting a possible abnormal condition at its earliest stage, and should be fast enough for on-line implementation. That is to say, the features extraction algorithm should be simple to implement, yet should also be sophisticated enough to reveal any change at the earliest moment. While these requirements sound contradictory to each other, there are ways to accommodate these demands.

A careful examination of the monitoring procedure shown in Fig. 1 reveals a drawback to this approach: there are a lot of redundant processing efforts in signal processing, due to the fact that signatures at different operating periods contain essentially the same information. Let us assume that x_0 is the signal representing normal condition, and x_t the current measurement. The signature acquired in monitoring process, x_t, contains two portions of information: the one representing the same characteristics of normal condition (identical portion), and the other containing the differences from the normal condition (different portion). In the early stage of failure, the different portion of information is embedded in signature x_t, where the identical portion dominates. In other words, the

0888-3270/92/020177+13 $03.00/0

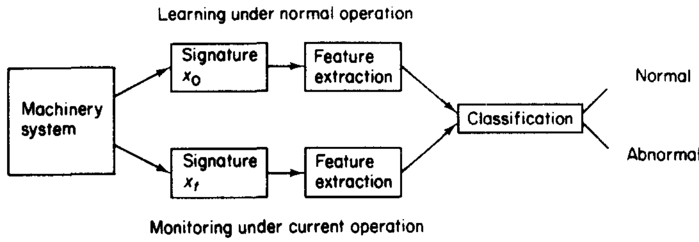

Figure 1. Schematic signal processing flow-chart of a typical monitoring process.

information carrying the difference between x_0 and x_t is so small that it is difficult to apply simple algorithms to extract features that are sensitive to this change. The purpose of monitoring, however, is to detect any change in a system. Only the different portion of the signal is really useful, and others, including the identical portion, are just 'noise' in signal processing. It is easy to see from Fig. 1 that in the process of feature extraction, very low signal-to-noise ratio can be expected. A natural question may be: Is there a way to suppress the identical portion so as to improve the signal-to-noise ratio before the feature extraction during monitoring process?

This paper presents a practical scheme to improve the signal-to-noise ratio in signal processing for machinery condition monitoring. As shown in Fig. 2, the proposed scheme employs an inverse filter to separate the two portions (identical and different) of the monitoring signal before feature extraction. The formation of the inverse filter is based on the prediction error analysis. A signal model representing the machinery characteristics is first constructed from the measured signal under normal operating condition. Then, data under both normal condition and current operation period will be passed inversely through this signal model, which yields a new process: prediction error series (or residual series, innovation process [3-5]). In this way, the identical portion of the signal will be retained in the filter, while only the difference portion of the signal will go with the prediction error series. Further feature extraction will use the prediction error series instead of the original data.

The linear prediction and inverse filtering (or pre-whiting technique [6]) is a tool which is widely used in many aspects of signal processing, such as speech analysis [7], spectral estimation [8], adaptive filtering [5], and EEG signal processing [6]. The problem, however, is the construction of the inverse filter. Most of them are based on the 'least square error (LSE)' criterion, which is not the exact inverse, but rather an approximate inverse of the system. It will be shown in this paper that an autoregressive moving-average (ARMA) model obtained directly from the measurement of a physical system can be used to construct the inverse filter, and the inverse filtering process is equivalent to the one-step prediction based on this ARMA model. The inverse filter can then be used in

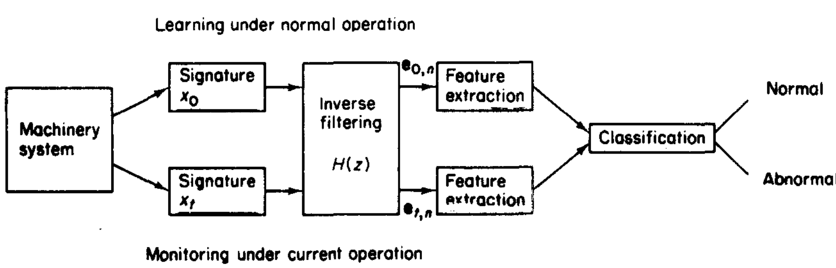

Figure 2. Proposed schematic signal processing flow chart for condition monitoring.

separating the signal for the purpose of condition monitoring. The feature extraction scheme, which evaluates the statistical properties of the prediction error series, can then be applied to the prediction error series, instead of the original measurement. In this way, the signal-to-noise ratio can be significantly improved and the feature extraction algorithm in monitoring can be made relatively simple, without sacrifice in reliability.

2. SIGNAL MODEL OF A MECHANICAL SYSTEM

A mechanical system in normal operation condition can be described as a dynamic system whose output or state variable can be represented by the stochastic differential equation [3]. While the analytic derivation of the stochastic differential equation is difficult, if not impossible, the dynamic model is often estimated from the measured signals. Such a signal model possesses physical properties and dynamic characteristics of the mechanical system, and can be used for the purpose of inverse filtering.

2.1. ARMA MODEL

The differential equation governing a linear continuous process is given as

$$\frac{\mathrm{d}^n \mathbf{x}(t)}{\mathrm{d}t^n} + \alpha_{n-1} \frac{\mathrm{d}^{n-1}\mathbf{x}(t)}{\mathrm{d}t^{n-1}} + \cdots + \mathbf{x}(t) = \mathbf{f}(t) \tag{1}$$

where $\mathbf{x}(t)$ is the stochastic response vector, $\mathbf{f}(t)$ is the stochastic input excitation vector, and α's are the coefficients. If the continuous process is sampled uniformly at a proper sampling interval, Δ, the corresponding discrete stochastic model representing the response of the system will be [3]

$$\mathbf{x}_t = \Phi_1 \mathbf{x}_{t-1} + \cdots + \Phi_n \mathbf{x}_{t-n} + \mathbf{a}_t - \Theta_1 \mathbf{a}_{t-1} - \cdots - \Theta_m \mathbf{a}_{t-m} \tag{2}$$

where $\mathbf{a}_t$ is the residual series that is a discrete white noise process (i.e. independent, Gaussian distribution with zero mean and variance σ_a^2), $\mathbf{x}_t$ is the sampled response vector, and Φ, Θ are the discrete coefficients matrices. The model given by equation (2) is called autoregressive moving average vector model (ARMAV). For simplicity, but not lost generality, a univariate response model is considered here as ARMA (n, m):

$$x_t = \phi_1 x_{t-1} + \cdots \phi_n x_{t-n} + a_t - \cdots \theta_m a_{t-m} \tag{3}$$

where n, m represent the orders of autoregressive and moving average part respectively. Equation (3) is indeed a stochastic difference equation, which can be used as the signal model of a mechanical system with x_t as the output time series and a_t as the input excitation.

The estimation of the model parameters, namely ϕ and θs, can be found in many references, e.g., references [3, 8]. Though many criteria exist regarding the 'best fit' of the model, the fundamental principle is based on the fact that the residual series a_t should be an independent and Gaussian process with minimum variance. The adequate model of a mechanical system contains pertinent dynamic information about the physical system. For instance, the frequency response is given by

$$s(f) = \frac{s_a(f) \left| 1 - \sum_{i=1}^{m} \theta_i \exp\left[-\left(\frac{i2\pi i f}{f_s} \right) \right] \right|^2}{\left| 1 - \sum_{i=1}^{n} \phi_i \exp\left[-\left(\frac{j2\pi i f}{f_s} \right) \right] \right|^2} \tag{4}$$

where $S_a(f)$ is the spectral of the residual time series a_t, and f_s is the sampling frequency. The natural frequency f_n and damping ratio ζ_n of the corresponding mode can be obtained as

$$f_n = \frac{\pi}{\Delta} \sqrt{[\ln \lambda\lambda^*]^2 + 4\left[\cos^{-1}\left(\frac{\lambda+\lambda^*}{2\sqrt{\lambda\lambda^*}}\right)\right]^2} \tag{5}$$

$$\zeta_n = \frac{\ln(\lambda\lambda^*)}{\sqrt{[\ln(\lambda\lambda^*)]^2}} + 4\left[\cos^{-1}\left(\frac{\lambda+\lambda^*}{2\sqrt{\lambda\lambda^*}}\right)\right]^2 \tag{6}$$

where λ, λ^* are the characteristic roots of the autoregressive part which appear in complex conjugate pairs.

2.2. INVERSE FILTERING AND PREDICTION ERROR SERIES

An ARMA model can be treated as an IIR filter with a_t as the input and x_t as the output. The discrete transfer function of this filter is given by

$$H(z) = \frac{1 - \theta_1 z^{-1} - \cdots \theta_m z^{-m}}{1 - \phi_1 z^{-1} - \cdots - \phi_n z^{-n}}. \tag{7}$$

The output x_t can be represented as

$$x(z) = H(z)A(z) \tag{8}$$

where $X(z)$, $A(z)$ are the Z-transforms of x_t and a_t respectively. For a minimum phase system [3, 9], an inverse filter, $G(z)$, can be defined as

$$G(z) = 1/H(z) \tag{9}$$

such that

$$A(z) = G(z)X(z). \tag{10}$$

It is easy to see from equation (3) that the input series a_t can be calculated recursively by

$$a_t = x_t - \left(\sum_{i=1}^{n} \phi_i x_{t-1} - \sum_{j=1}^{m} \theta_i a_{t-j}\right). \tag{11}$$

On the other hand, the ARMA (n, m) is a state-space equation that represents the relationship of the measurement (response) at different sampling instances. Specifically, the current measurement x_t is a function of the past $n-1$ measurements, $x_{t-1}, \ldots, x_{t-n}$, and the noise disturbance $a_{t-1}, \ldots, a_{t-m}$. The one-step prediction at time $t-1$ is, therefore, defined as

$$x_t|_{t-1} = x_{t-1}(1) = E(x_t \,|\, \mathbf{x}_{t-1}).$$

From equation (2) it follows that

$$x_t|_{t-1} = \phi_1 x_{t-1} + \cdots + \phi_n x_{t-n} - \theta_1 a_{t-1} - \cdots - \theta_m a_{t-m} \tag{12}$$

which is based on the fact that at time $t-1$, the values of $x_{t-1}, \ldots, x_{t-n}$ and $a_{t-1}, \ldots, a_{t-m}$ are known constants.

The prediction error $e_t(1)$, or simply e_t, is given by

$$e_t = x_t - x_t|_{t-1} \tag{13}$$

which is the difference between the true measured value x_t and its one-step prediction $x_t|_{t-1}$. The process e_t is usually termed as a prediction error series or innovation process [3, 8]. Combining equations (11)-(13) yields

$$e_t = x_t - \left(\sum_{i=1}^{n} \phi_i x_{t-1} - \sum_{j=1}^{m} \theta_i a_{t-j} \right)$$
$$= a_t. \tag{14}$$

Therefore, the calculation of prediction error series e_t defined by equation (11) is actually the same as passing x_t through its inverse-filter $G(z)$.

3. CONDITION MONITORING SCHEME

3.1. PRINCIPLE

As mentioned earlier, the basic criterion for a 'best fit' of a signal model $H(z)$ to a physical system is that the residual, or prediction error series, should be an independent, Gaussian process with minimum variance. In other word, if the system response x_t is passed through its inverse filter $G(z)$, the resulting prediction error series should be an independent, Gaussian process with minimum variance. Suppose x_0 is the data obtained in a known normal condition, and x_t is the current measurement. The condition monitoring task is done by evaluating the difference between x_0 and x_t. Instead of comparing x_0 and x_t directly, a method is proposed to first pass the two time series, x_0 and x_t, through the inverse filter $G(z)$ of the system, and then to evaluate the difference between their prediction error series, $e_{0,n}$ and $e_{t,n}$. This process is shown in Fig. 2, where the inverse filter $G(z)$ is constructed based on the ARMA model $H(z)$ obtained according to the normal operating condition of the system. In principle, if there is nothing changed in the system and the current condition is normal, the $H(z)$ will still be an adequate model for the system and the statistical properties of the $e_{t,n}$ will be the same as $e_{0,n}$. However, by contrast, if there is any change in the system away from the normal condition for any reason, the previously obtained model $H(z)$ will no longer be adequate, leading to a change of the statistic properties of $e_{t,n}$ away from that of $e_{0,n}$. It is this variation that can formulate a simple, yet sensitive feature for condition monitoring.

This approach possesses several advantages from the viewpoint of signal processing. First of all, as shown in Fig. 2, the dynamic characteristics of the normal system will be 'filtered' out and retained in the inverse filter $G(z)$, and only the different portion of the information will go into $e_{t,n}$, which fulfills the demand of information separation before feature extraction. The comparison of statistical properties of $e_{t,n}$ with that of $e_{0,n}$ is relatively easier than that of x_t and x_0 since, theoretially, $e_{0,n}$ is a white noise process. This is a model-based approach, yet in the monitoring stage where timing is critical, no model parameter estimation is involved. The normal model can be determined in advance either on-line or off-line. Therefore, this scheme is suitable for on-line implementation where the signal processing time is a critical factor. The limitation, however, is that the normal operation process of the system should be stable or stationary. Otherwise, more than one normal model may be needed to commentate the different normal conditions.

3.2. FEATURE EXTRACTION AND CLASSIFICATION

To evaluate if the prediction error series $e_{t,n}$ is still an independent Gaussian process with minimum variance, a set of feature including the normalized variance (NV), kurtosis (KT), and the autocorrelation (AC) is proposed.

Normalized variance (*NV*). The power (or variance) of the prediction error will indicate the closeness of the current data to the model obtained under normal condition. The variance of $\mathbf{e}_t$ can be estimated by

$$\mathrm{Var}(\mathbf{e}_t) = \sum_{t=1}^{N} e_t^2/N \tag{15}$$

where N is the data number. In order to suppress the influence of the other factors such as instrument gains or variation of the machine load, the variance of equation (12) is normalised by dividing the variance of $\mathbf{x}_t$ [10]:

$$\mathrm{NV} = \frac{\mathrm{Var}(\mathbf{e}_t)}{\mathrm{Var}(\mathbf{x}_t)}. \tag{16}$$

Kurtosis (*KT*). The kurtosis of a random variable $\mathbf{x}$ with a probability density function (PDF) $p(x)$ is defined as [11]

$$\mathrm{KT} = \frac{M_4}{(M_2)^2} - 3 \tag{17}$$

where M_4 and M_2 represent the fourth and second moments, and

$$M_k = \int_{-\infty}^{+\infty} x^k p(x)\,\mathrm{d}x. \tag{18}$$

Geometrically, KT is a statistical concept related to the 'flatness' of the distribution of the vibration waveform, and is a good measure of normality of a random process.

Autocorrelation (*AC*). The autocorrelation coefficients of random data describe the general dependence of the values of data at one time on the data at another time. For an independent, or white, process, the AC should approach to zero. Therefore, AC can be used to evaluate a process to see if it is a white process. The AC can be estimated by

$$\mathrm{AC} = \frac{\sum_{t=2}^{N} a_t a_{t-1}}{\sum_{t=2}^{N} a_t^2}. \tag{19}$$

4. APPLICATION IN MONITORING OF A PAPER HANDLING SYSTEM

Paper jam is the most prominent failure mode in a recirculating document feeder (RDF). It is desired to have a monitoring system that can detect any possible malfunctions of RDF which will cause paper jam. Such a system has been developed, and the inverse filter has been used in monitoring the condition of one of the most important components—the nip roller structure—of the RDF system. A schematic diagram of a nip roller and its working mechanism is given in Fig. 3. When the paper is fed through this structure, an appropriate force is applied to the paper through the roller, which is provided by a preloaded nip spring. Paper jam will most likely occur under the conditions of (1) lower force due to a softening-spring, (2) higher force due to a stiffening-spring, (3) force fluctuation due to looseness of the structure, and (4) bad paper. As shown in Fig. 3, the pre-load of the spring can be adjusted by turning the adjusting screw in a loosening or fastening direction.

To make sure that the nip roller structure works at a pre-set condition, a non-contact vibration sensor (eddy current type) is used to pick up the motion of the leakage at the

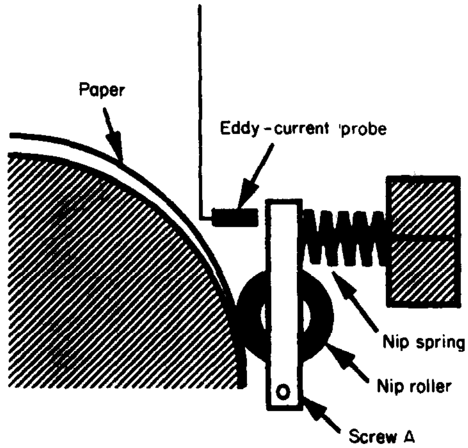

Figure 3. Schematic of the nip roller-spring structure.

location as shown in Fig. 3. Such a system can be modeled as a mass-spring-damper system. Figure 4 is a plot of raw data under various conditions. With 20 sets of data cathered under normal operation condition, an ARMA (6, 4) model was found to be adequate following the procedures outlined in reference [3]:

$$\begin{aligned} &x_t + 0{\cdot}6233x_{t-1} - 0{\cdot}1552x_{t-2} + 0{\cdot}2516x_{t-3} + 0{\cdot}0398x_{t-4} - 0{\cdot}0402x_{t-5} - 0{\cdot}1409x_{t-6} \\ &\quad = a_t + 0{\cdot}0215a_{t-1} + 0{\cdot}1916a_{t-2} + 0{\cdot}0372x_{t-3} + 0{\cdot}1542a_{t-4}. \end{aligned} \tag{20}$$

Then, data under each of the following conditions was acquired by (1) loosening spring by turns of 2, 4, 7; (2) fastening spring by turns of 2, 4, 5; (3) loosening screw A by 2, 4 turns; (4) adding one bad paper.

A digital band-pass filter with a passing frequency range of 80-200 Hz was first applied to the data in order to suppress the noise unrelated to the nip roller structure. The signals were then passed inversely through the filter defined by equation (20), which was done simply by applying equation (14) recursively. In the final decision-making stage, a multiple-voting scheme was employed [15]. The monitoring results are given in Table 1 and Figure 5. It is shown that there is a clear distinction between normal and abnormal conditions, as seen from the indices of NV, KT and AC of the prediction error series.

5. DISCUSSION

As shown in Table 1, as long as the system is under normal operating conditions, the values of the feature are bounded within a normal range. There are clear changes in the features after inverse filtering corresponding to the variation of the system conditions. For comparison, the same statistical features of the raw data before inverse filtering are also listed in Table 1 and depicted in Fig. 5, which showed less coherence to changes of operation conditions. For instance, Figs 5(c) and (e) show that the features of KT and AC are good for the prediction error series to identify the abnormal condition, while Figs 5(d) and (f) suggest that they are poor if used for the data before inverse filtering. The reason is that the system characteristic information dominates the data before inverse filtering, and the variation portion is too small to be identified directly from them. The similarity among the spectra of the raw data, shown in Fig. 6, further verifies this point.

Figure 7 is the plots of the spectra of the prediction error series after inverse filtering for different conditions. For normal condition, as shown by Fig. 7(a), the spectrum of

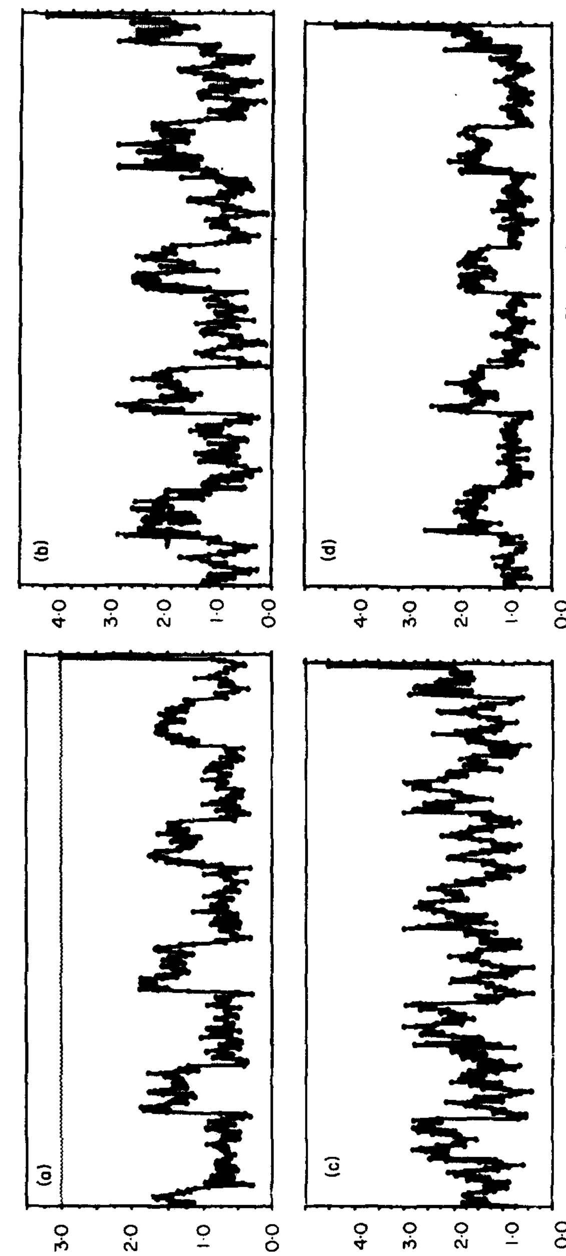

Figure 4. Plot of raw data under different conditions. (a) Normal; (b) spring loosening; (c) structure loosening; (d) bad paper.

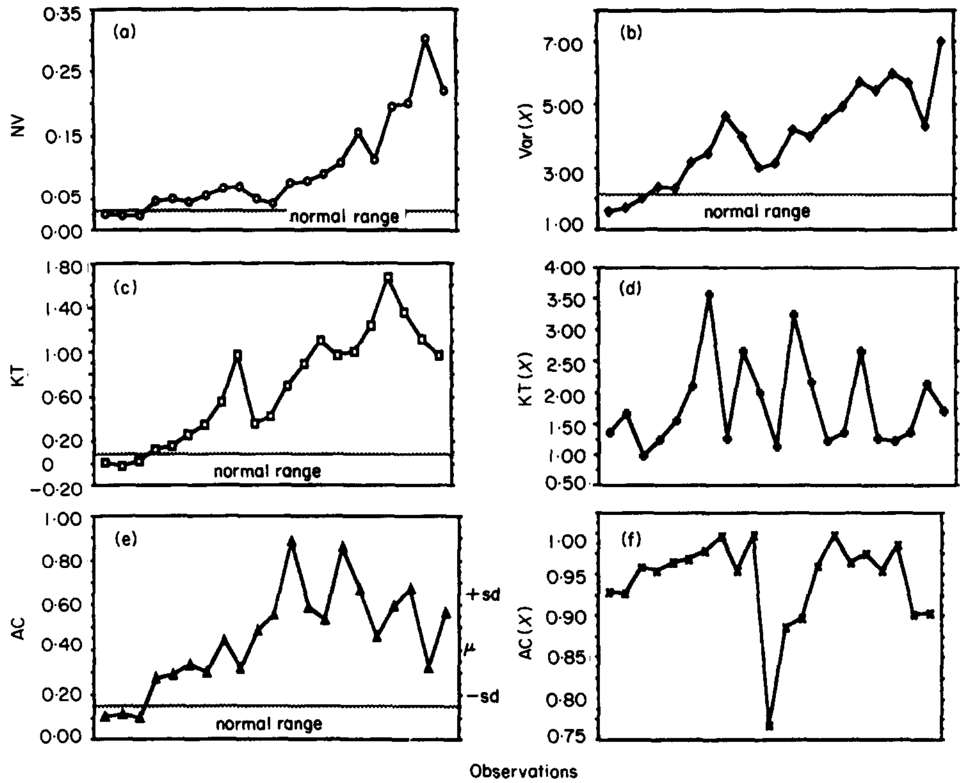

Figure 5. Plot of the indices under different conditions. (a) NV of prediction errors; (b) variance before inverse filtering; (c) KT of prediction errors; (d) KT before inverse filtering; (e) AC of prediction errors; (f) AC before inverse filtering.

the prediction series appears to be flat since, ideally, the prediction error under normal condition should be a white noise process. It is relatively easy to check changes of any spectrum against a flat (white noise) one. For instance, Figs 7(b)-(d) all show some peaks in their spectral plots, which suggests that some dynamics in the signal leaked into the prediction error series. This could occur only when the normal model is no longer adequate for the current condition. From equation (4), we have

$$s_a = \frac{|s(f)|^2}{|H(f)|^2}. \tag{21}$$

It is clear that the inverse filtering process is actually a model comparison process: the power spectrum of current measurement is compared against the standard spectrum of the normal model $|H(\omega)|^2$. They are the same, i.e. there is no change in system characteristics, the resulting ratio would tend to be flat. Otherwise, peaks or valleys will appear in a certain band, as shown in Fig. 7(b)-(d). Actually, the prediction error series can be treated as a new (innovation) process, and many signal processing methods, including modeling, could be applied to reveal any dynamics retained in it.

It should be mentioned that in the monitoring process, it is relatively easy to distinguish normal condition from the abnormal conditions, if any. It is, however, difficult to isolate what causes the abnormal condition. Further classification, or diagnosis, needs more sophisticated algorithms, which usually take a longer processing time. Most time-critical monitoring tasks require stopping the operating process as long as an abnormal condition

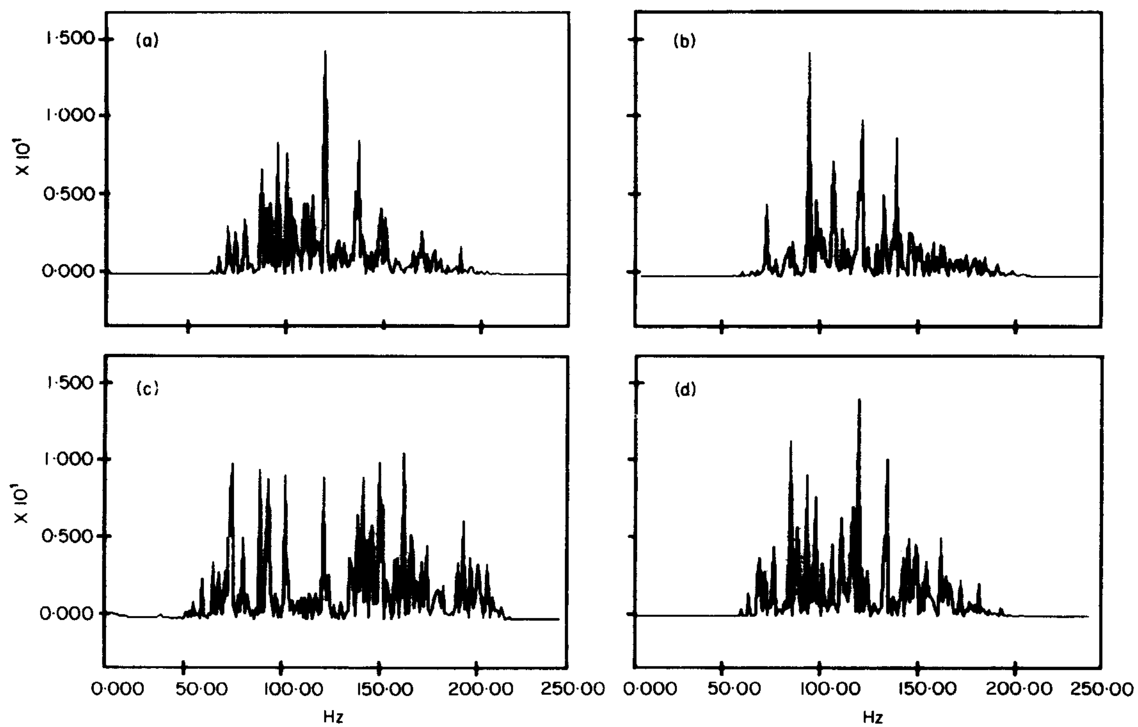

Figure 6. Spectra of data before inverse filtering. (a) Normal; (b) spring loosening; (c) structure loosening; (d) bad paper.

TABLE 1

Result of monitoring for the nip roller structure

Conditions	NV	KT	AC	Var (X)	KT(X)	AC(X)
1. Normal	0·0244	0·0112	0·1030	1·5684	1·3687	0·9290
2. Normal	0·0236	0·0254	0·1150	1·6698	1·6698	0·9271
3. Normal	0·0239	0·0211	0·0980	1·9863	0·9875	0·9590
4. Spring loosening 2	0·0425	0·1320	0·2740	2·3685	1·2369	0·9550
5. Spring loosening 2	0·0495	0·1560	0·2890	2·3398	1·5568	0·9650
6. Spring loosening 4	0·0435	0·2560	0·3360	3·1756	2·1077	0·9690
7. Spring loosening 4	0·0553	0·3450	0·2980	3·4468	3·5587	0·9790
8. Spring loosening 7	0·0665	0·5560	0·4450	4·6325	1·2568	0·9970
9. Spring loosening 7	0·0695	0·9690	0·3150	3·9687	2·6542	0·9538
10. Spring fastening 2	0·0489	0·3544	0·4850	2·9975	1·9983	0·9986
11. Spring fastening	0·0421	0·4187	0·5590	3·1451	1·1256	0·7687
12. Spring fastening	0·0745	0·6980	0·8870	4·2153	3·2258	0·8865
13. Spring fastening	0·0782	0·8880	0·5890	3·9981	2·1547	0·8974
14. Spting fastening	0·0900	1·1000	0·5360	4·5682	1·2258	0·9597
15. Spring fastening	0·1080	0·9680	0·8580	4·9573	1·3695	0·9982
16. Screw loosening 2	0·1540	0·9980	0·6650	5·6875	2·6574	0·9655
17. Screw loosening 2	0·1120	1·2350	0·4580	5·4327	1·2659	0·9758
18. Screw loosening 4	0·1950	1·6690	0·5950	5·9683	1·2256	0·9539
19. Screw loosening 4	0·2010	1·3510	0·6720	5·6784	1·3654	0·9856
20. Bad paper	0·3020	1·1120	0·3250	4·3258	2·1452	0·9024
21. Bad paper	0·2191	0·9650	0·5680	6·9984	1·6984	0·9038

is pending, no matter what it it. Further answer to 'what it is' could be sought after the alarm is sent, and the process is stopped.

The implementation of the monitoring scheme outlined above requires learning the adequate signal model for the machinery system, which could be time consuming. However, with the advent of computing technology, this becomes less of an obstacle. It should also be pointed out that the system is assumed to be stable under normal operating conditions so that single normal model could be used to represent the normal condition. Otherwise, several normal signal models may be needed. In the worst case when there is a slow variation even under normal operating conditions, an adaptive filter can still feasibly be constructed [5].

6. CONCLUSION

The signals for machinery condition monitoring basically carry two portions for information: the one which represents the same characteristics of normal condition, and the other which represents the difference from the normal condition. It is appropriate to separate these two portions before feature extraction in order to improve the signal-to-noise ratio, which can be done by the inverse filtering method. It was shown that the inverse filtering process is equivalent to the estimation of prediction errors based on a signal model obtained for a physical system. Thus the construction of the inverse filter can be carried out by ARMA modeling, provided the system response can be measured. Application of this algorithm to a paper handling system showed that the separability of features using statistical analysis from data after inverse filtering can be improved significantly against those without inverse filtering. In this way, it is feasible to apply simple statistical analysis algorithms for machinery condition monitoring where processing time is critical.

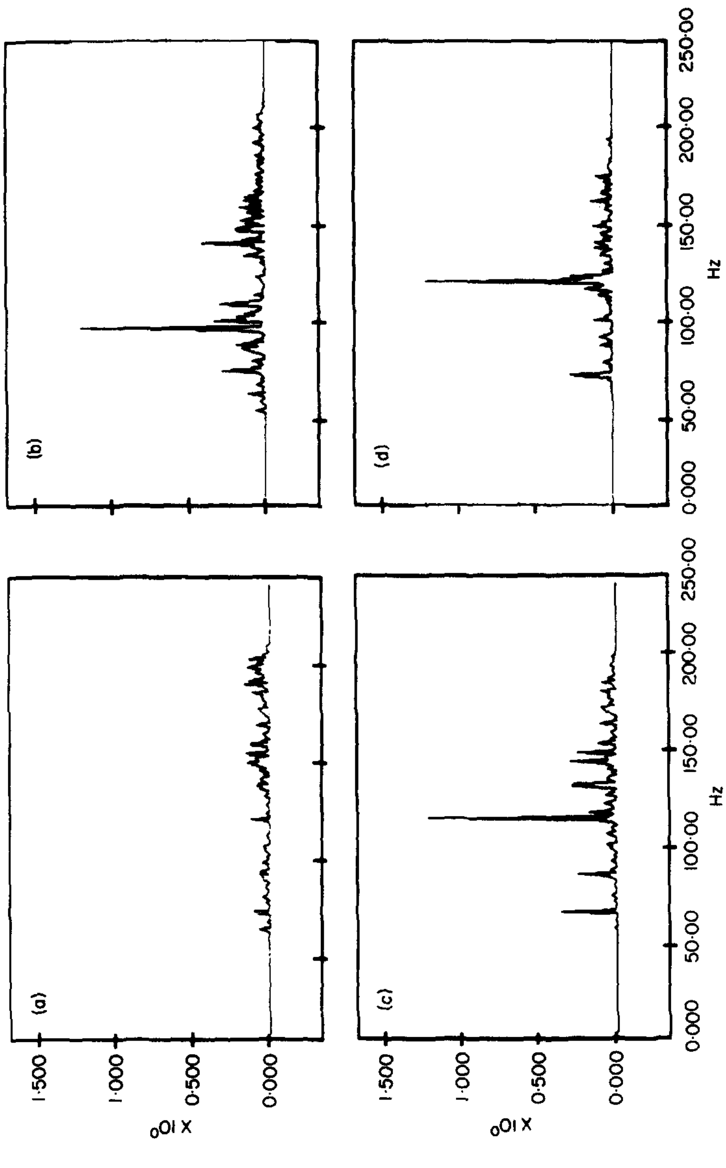

Figure 7. Spectra of prediction error series. (a) Normal; (b) spring loosening; (c) structure loosening; (d) bad paper.

REFERENCES

1. S. M. WU and T. H. TOBIN 1980 *Journal of Mechanical Design* **102**, 217-221. Signature analysis for mechanical system via dynamic data system (DDS) monitoring technology.
2. M. WECK 1986 *International Journal of Materials and Product Technology*, **1**, 195-210. Sensors, diagnostic methods and systems for application in manufacturing systems.
3. S. M. PANDIT and S. M. WU 1983 *Time Series and System Analysis with Applications*, pp. 5-7, 164-167, 177-192. New York: John Wiley.
4. N. MIYOSHI and Y. KANEDA 1988 *IEEE Transactions on Acoustics, Speech, and Signal Processing* **36**, 145-152. Inverse filtering of room acoustics.
5. D. GRAUPE 1984 *Time Series Analysis, Identification and Adaptive Filtering*, pp. 166-178. Malabar, Florida: Rober E. Krieger.
6. G. E. BIRCH, P. D. LAWRENCE and J. C. LIND 1988 *IEEE Transactions on Biomedical Engineering* **35**, 640-645. Application of prewhitening to AR spectral estimation of EEG.
7. J. MAKHONL 1975 *Proceedings IEEE* **63**, 561-580. Linear prediction: a tutorial view.
8. S. M. KAY 1988 *Modern Spectral Estimation Theory and Application*, pp. 356-364. Englewood Cliffs, NJ: Prentice Hall.
9. S. A. TRETTER 1976 *Introduction to Discrete-time Signal Processing*, pp. 174-182. New York: John Wiley.
10. C. LI and WU S. M. 1982 *ASME Computer Conference*, 215-218. A scheme of monitoring and diagnosing bearing malfunction by microprocessor.
11. D. DYER and R. V. STEWART 1978 *Journal of Mechanical Design* **100**, 229-235. Detection of rolling element bearing damage by statistical vibration analysis.
12. J. S. BENDAT and A. G. PIERSOL 1971 *Random Data: Analysis and Measurement Procedures*, pp. 18-22. New York: John Wiley.
13. R. H. LYON 1987 *Machinery Noise and Diagnostics*, pp. 221-228. Boston: Butterworth.
14. B. PICINBONO and J. KERLIS 1988 *IEEE Transactions on Acoustics, Speech, and Signal Processing* **36**, 525-531. Some properties of prediction and interpolation errors.
15. G. HAYWARD and J. E. LEWIS 1989 *IEEE Transactions on Ultrasonics, Ferroelectrics, and Frequency Control* **36**, 356-361. A theoretical approach for inverse filter design in ultrasonic applications.
16. Y. B. CHEN, J. L. SHA and S. M. WU 1989 *ASME Symposium of Advances in Manufacturing Systems Engineering*, 195-207. Diagnosis of tapping processes by information measure and probability voting approach.