Hybrid Method Based on the Inverse of the Belonging Joint Probability and the PSD for Fault Diagnosis

BENABDELLAH YAGOUBI
Electrical Engineering Department
University of Mostaganem
ALGERIA
sbmsvy@gmail.com
yagoubibenabdellah@yahoo.com

Abstract: **-** The hybrid method presented in this paper, is based on the inverse of the belonging joint probability (IBJP) and the power spectral density (PSD) to detect new anomalous in a random signal representing normal state behavior of a given machine. We first compute the power spectral density (PSD) of the normal state signal and then represent this PSD signal by an adequate Gaussian white noise (GWN) model. The new changes or anomalous in the machine behavior are, usually, represented by new picks in the PSD curve. Since the latter is usually random, these picks may be, however, smeared out and thus, they will not be well detected. To overcome this problem, we propose, in this work a technique based on the belonging joint probability inverse (IBJP) combined with the PSD to detect these faults. We have, furthermore, performed a simulation to clarify this hybrid technique efficiency.

Key-Words: - Faults diagnosis; inverse of the belonging probability; power spectral density; Gaussian stationary white noise model.

1. Introduction

Faults diagnosis, in engineering and many other fields such as medical field, is very important for the control and supervision [1,…,7]. An early detection of a particular anomalous is crucial in any domain.

Many algorithms based on variety of statistical method have been proposed in the scientific literature for fault diagnosis and detection. Two common approaches, usually, mentioned in literature for machine fault (perturbation) diagnosis, in mechanical engineering, are; a) the analysis of the difference that may take place between the measured data and the expected results obtained by means of a mathematical model, b) the direct observation of sensor readings which may show a fault. Machine fault diagnosis is an important domain of seeking faults in a given signal provided by a machine vibrations sound. To detect the faults that may cause a machine failure, many mathematical methods were suggested for the machine data analysis. Among these methods we can name the time–scale analysis which deals with the continues wavelet transform (CWT)[8,9], the time-frequency analysis technique using short term Fourier transform (STFT) and the frequency space utilizing the Fourier Transform (FT). The latter method can be easily computed using the Fast Fourier Transform (fft) algorithm and it is, therefore, very commonly used in practice [10, 11]. The power spectral density (PSD), as it is named, represents the concentration of the power along the frequency axis, and hence it can localize the fault through its associated power. In certain cases the PSD curve is, however, very random leading to a hard and ambiguous fault detection.

To overcome this difficulty, we suggest in the following a simple hybrid technique based on the inverse of the belonging joint probability (IBJP) and the power spectral density (PSD)

2. Results and discussion

The free software Scilab5.5.0 was used to perform our analysis. To clarify the efficiency of our proposed hybrid technique for fault diagnosis, we have simulated a normal working state (before changes) of a machine by a random stationary ergodic Gaussian signal w, and the fault by an additive cosine vibration x. The resulting signal s with a fault taking place can be, thus, expressed as follows;

$$s(n) = w(n) + x(n) \qquad (1)$$

Where w and x can be generated using the Scilab functions $rand$ and $\cos$ respectively.

Figure (1) shows the normal working state signal (before changes) w , above and the signal s with the fault, below. The power spectral density of a given signal is defined as the Fourier transform of its autocorrelation $\phi(n)$;

$$psd(f) = F[\phi(n)] \qquad (2)$$

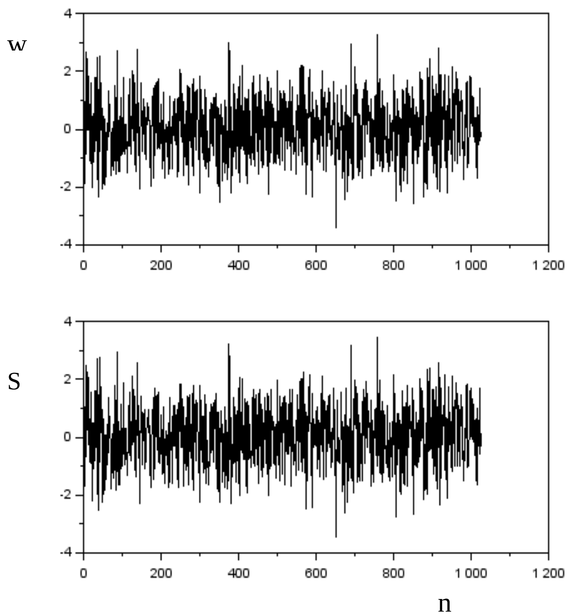

Fig.1. the normal working state signal w above and the signal with the fault s below (vs time n)

The PSD of both signals; the normal and with fault, can be estimated in decibel using the following expressions respectively

$$\hat{W}_{db} = 20\,Log_{10}(|W(f)|) - 10\,Log_{10}(N)$$
$$\hat{S}_{db} = 20\,Log_{10}(|S(f)|) - 10\,Log_{10}(N) \qquad (3)$$

The results of these two PSDs estimations are illustrated in figure (2). The PSD $\hat{W}_{db}$ of the normal state signal is shown above and that $\hat{S}_{db}$ of the signal with the fault is below.

The pick indicating the existence of a fault is shown by the arrow in the PSD curve at 0.3Hz in the frequency axis. It is clearly not easy to detect the pick representing the fault in this PSD curve. To overcome this problem, we suggest, therefore, in the following a new technique based on the inverse of the belonging joint probability (IBJP) to support the PSD observation.

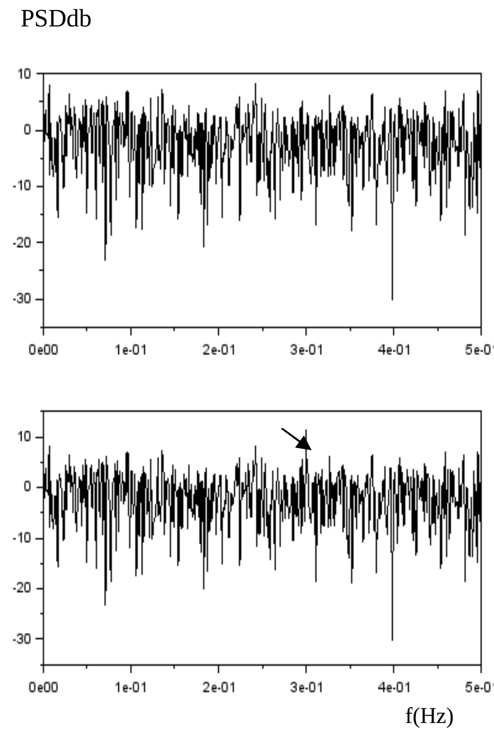

Fig.2. the normal PSD signal (vs frequency) above and with a fault (arrow) below

The IBJP technique

1- Divide the PSD $\hat{W}_{db}$ of the normal working state signal into short length stationary intervals and then model each of them as a Gaussian white noise model [12,…,14]. The average $\hat{m}_{in}$ and the variance $\hat{\sigma}^2_{in}$, of each interval is estimated using the following two well known expressions respectively [5].

$$\hat{m}_{in} = \frac{1}{L}\sum_{k=l-L}^{l-1} x_{in}(k) \qquad (4)$$

$$\hat{\sigma}^2_{in} = \frac{1}{L}\sum_{k=l-L}^{l-1} (x_{in}(k) - \hat{m}_{in})^2 \qquad (5)$$

Where $x_i(l-L),..., x_i(l-1)$ are the values of the n^{th} $(n = 1,2...N)$ interval, L is the interval length and $l = n.L$. If the PSD signal reconstruction is not acceptable, we reduce the interval length. We repeat this step till a reasonable reconstruction is achieved. The reconstructed version will constitute the mathematical model of the normal working state PSD signal. This PSD original signal (solid curve) and its corresponding reconstructed entire version (dotted curve) using the Gaussian white noise (GWN) model is shown in figure (3). We can see that the reconstruction is good enough with a segment length L=8 samples.

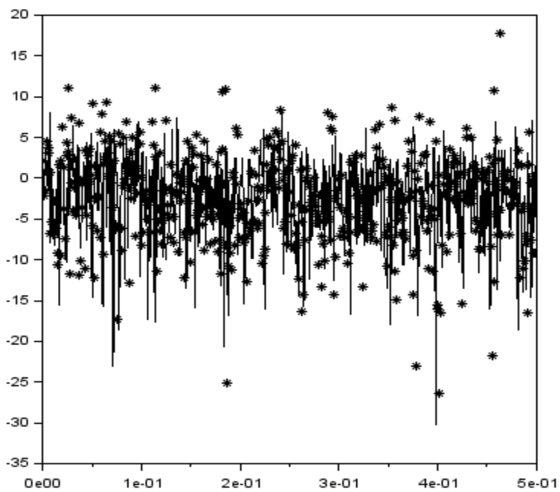

Fig.3. the original PSD signal (solid) and its reconstructed version with a GWN (dotted).

2-So, when a fault takes place within this PSD signal, compute the inverse of its belonging joint probability [5] using the previously estimated Gaussian parameters in the first step.

Figure (4A) shows the normal working state PSD signal and its corresponding IBJP in figure (4B). The same PSD signal but with a fault occurring at 0.3Hz is shown in figure (4A'), and its IBJP is shown if figure (4B').

The fault is indicated by the arrows in figure (4A') of the PSD signal and in figure (4B') of the IBJP. It can be seen that due to the nature of the PSD signal, the pick indicating the existence of a fault, is difficult to detect or to localize. However, since any new fault is deemed a rare event in the normal working state PSD signal, then its belonging probability to this PSD signal is very small. So by inversing these probabilities, the smallest values become the highest and, vice versa, the largest become the smallest, thus a fault will have a higher belonging probability inverse value $\frac{1}{\mathbf{P}}$ as illustrated by the arrow in figure (4B').

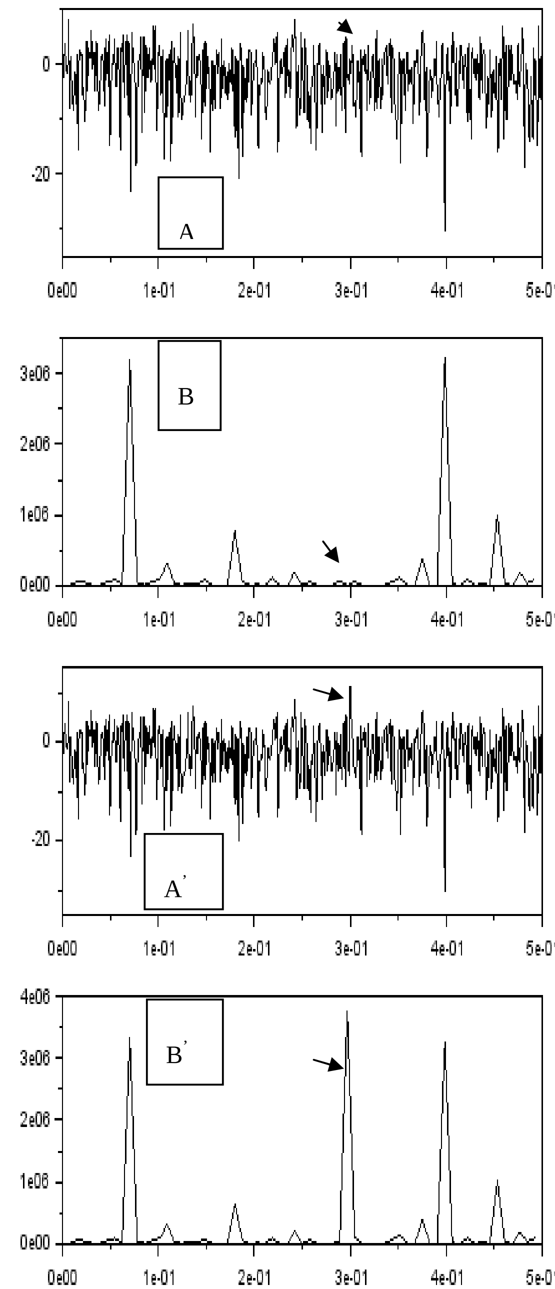

Fig.4. the PSD (A) and (A') of the normal working state and their corresponding IBJP ($\frac{1}{\mathbf{P}}$); (B) and (B') respectively

3. Conclusion

We have proposed a hybrid method based on the inverse of the belonging joint probability and the power spectral density to ease the fault detection in a machine behavior. We have shown that this procedure, for detecting faults or new changes in a normal working state signal, can be very useful for supporting a direct control and supervision of a normal working state signal of a given machine behavior.

References

[1] Riemer, P.L, J.W. Mitchell, and W.A. Beckman. 2002. The use of time series analysis in fault detection and diagnosis methodologies. ASHRAE Transactions 108(2).

[2] Patton, R.J., C. Fantuzzi, and S. Simani. 2003. Model-Based Fault Diagnosis in Dynamic Systems Using Identification Techniques. New York: Springer-Verlag.

[3] Patton, R.J., P. Frank, and R. Clark. 1989. Fault Diagnosis in Dynamic Systems, Theory and Application. Prentice Hall.

[4] F. Lafarge, X. Descombes., J. Zerubia.and S. Mathieu, (2007). Forest fire detection based on Gaussian field analysis, European Signal Processing Conference (EUSIPC

[5] S. Benkraouda, B. Yagoubi, M. Rebhi and A. Bouziane., Belonging probability inverse image approach for forest fire detection, Afr. J. Ecol. John Wiley & Sons Ltd, 2013

[6] Shi D.F., Wang W.J. and Qu L.S., 2004. Defect detection for bearing using envelope spectra of wavelet transform. ASME J of Vibration and Acoustics, Vol.120, pp. 567-574.

[7] R. F. M. Marcal, M. Negreiros, A. A. Susin, andJ. L. Kovaleski,"Detecting faults in rotating machines,"Instrumentation& Measurement., vol. 3, iss. 4, pp. 24-26, 2000

[8] Al-Raheem K.F, Roy. A, Ramachandran.K.P. 2006. Detection of rollingelement bearing faults using optimized – wavelet denoising technique

[9] Z. K. Peng, andF. L. Chu, "Application of the wavelet transform in machine condition monitoring and fault diagnostics,"Mechanical Systems and Signal Processing.,vol. 18,pp. 199-221, 2004.

[10] J. W. Cooley, and J. W. Tukey,"An algorithm for the machine calculation of complex Fourier series"Mathematics of Computing., vol. 19, pp. 297-301, 1965

[11] H. Ghaderi, and P. Kabiri, "Automobile independent fault detection based on acoustic emission using FFT," International NDT Conference &Exhibition, Singapore 2011.

[12] T. Hida, and M. Hitsuda, 1993. Gaussian Processes. AMS, Providence.

[13] Chan, S.C and Zhou. Y., 2010. On the Performance Analysis of a Class of Transform-domain NLMS Algorithms with Gaussian Inputs and Mixture Gaussian Additive Noise Environment Journal of signal processing systems, Springerlink, V61.

[14] K-M. Chang, and Liu. S-Hong., 2010. Gaussian noise filtering from ECG by Wiener filter and ensemble EMD, Journal of signal processing systems, Springerlink V61.