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Discussion

Authors' reply ☆

Li Li*, Liangsheng Qu

Research Institute of Diagnostics and Cybernetics, Xian Jiaotong University, 710049 Xi'an, P.R. China

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The paper [1] presents a demodulation method based on second-order cyclic statistic and its application in engineering diagnosis. The aim is to find faulty mechanical parts by their fault characteristic frequency. This estimation method is commonly used in machine diagnosis and accords with engineering conditions. Undoubtedly, the stochastic model of Ref. [2] is helpful in analyzing the motion mechanism of the faulty rolling bearing and maybe the model is more accurate in theory. But it is really a pity that the structure and the motion forms of bearings differ in thousands of ways. To date, there has been no diagnostic method based on the stochastic model that is available in the actual world, especially in on-line monitoring of a real machine.

1. The signal model in Ref. [1] is suitable to engineering practice

It goes without saying that the cyclic statistic method can be used to extract the periodic components hidden in the statistic of a stochastic process. The model in Ref. [1] is the deterministic or modulating part, which expresses the faulty signal mixing in the stochastic signal of the faulty bearing. It is the deterministic part that decides the time-varying statistic characteristics of the bearing vibration signal. Generally, for the vibration data of the rolling bearing, the high sampling frequency results in a very short measuring time. For example, the sampling frequency in Ref. [1] is 20 kHz and the sampling points amount to 8192. Then the

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*Corresponding author.
E-mail address: Li7466@263.net (L. Li).

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measuring time is about 0.4 s. In addition, the model error caused by the fluctuation of model parameters is negligible and allowed in engineering. As a stochastic component, denoted by $n(t)$, it is a white stationary noise composed of a number of noise sources coming from mechanical parts. In general, the noise is also ergodic. The aim of the paper [1] is just to confirm the periodicities submerged in the noise in order to validate the characteristic frequency of the faulty bearing. Assumed that the deterministic component is $x(t)$, the statistic of $x(t)+n(t)$ (such as the average value, the autocorrelation function, etc.) should be calculated by the ensemble average of all realities related to time, i.e. $x(t)+n_1(t), x(t)+n_2(t), \ldots$. However, under the stationary assumption, the statistic can be replaced by the time average of a reality instead of the ensemble average. The stationary assumption commonly used in engineering also means the invariable working condition. This results from the fact that the change of operational conditions can be avoided. The time average in the paper [1] implied that the noise is stationary and ergodic.

Suppose the mean of $n(t)$ is zero, the autocorrelation function is $r_n(\tau)$, and both $n(t)$ and $x(t)$ are irrelevant. The first- and the second-order statistics of the stochastic signal $x(t)+n(t)$ are

$$m(t) = E\{x(t)+n(t)\} = E\{x(t)\} + E\{n(t)\} = x(t), \tag{1}$$

$$r_{xn}(t,\tau) = E\{[x(t)+n(t)][x(t+\tau)+n(t+\tau)]\} = x(t)x(t+\tau) + r_n(\tau), \tag{2}$$

where $E\{\cdot\}$ is the statistic average. It can be seen that the time-varying characters of the statistics are determined by $x(t)$. Fig. 1 also illustrates this argument. The signal in Fig. 1 is assumed to be $\cos(\omega_0 t+\theta)+n(t)$; Fig. 1(a), (b) and (c) are the time waveforms of one reality, the average of 2000 realities and the periodic part, respectively. We can see that the time-varying characters of both Fig. 1(b) and (c) are basically identical.

Since the statistic character of the stochastic signal is determined by the deterministic part, when using the second-order cyclic statistic method it is unnecessary for the signal model of bearing to add the noise that does not affect the statistic character. Besides, since the sampling

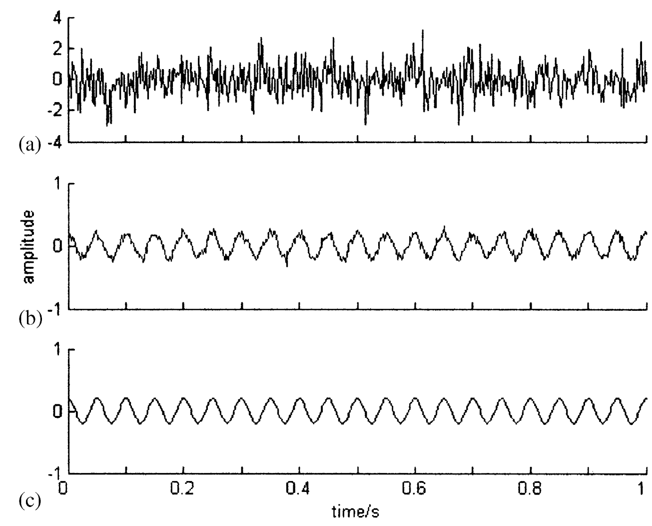

Fig. 1. The stochastic signal with a periodic part: (a) one reality, (b) the average of 2000 realities, (c) the periodic part.

time of the bearing signal is very short and the model error caused by model parameters is negligible in engineering, the model in the paper [1] is reasonable and conforms to objective practice. The demodulation based on the model is derived, which separates the modulators and carrier so that the modulators can be recognized and extracted more easily; it is impossible for the analysis using the power spectra to achieve such results.

Figs. 2–5 are Fourier spectra and cyclic spectra of several real mechanical signals, the preprocessing scheme ob both (a) and (b) in a figure are same. The real signals often contain unknown noises coming from other parts, the cyclic spectra have the de-noising capability better than Fourier spectra, which can be seen intuitively from Figs. 2 and 3. Moreover, on the extraction of mechanical characteristics, the cyclic spectra have the surprising power that Fourier transform with a short or long data cannot match with, such as the examples of Figs. 4 and 5. In conclusion, the cyclic spectrum has the advantage to detect periodic signals.

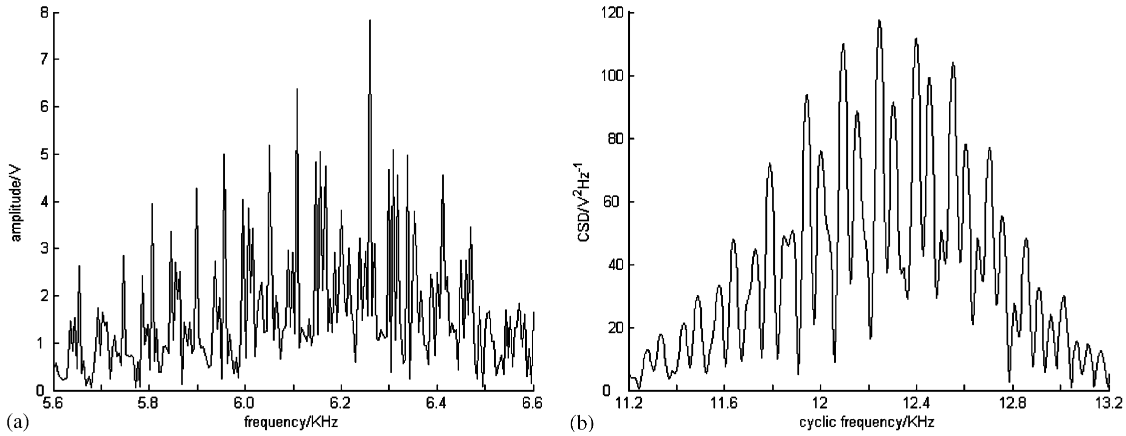

Fig 2. The vibration signal of faulty bearing in the water pump. (a) Fourier spectrum, (b) cyclic spectrum.

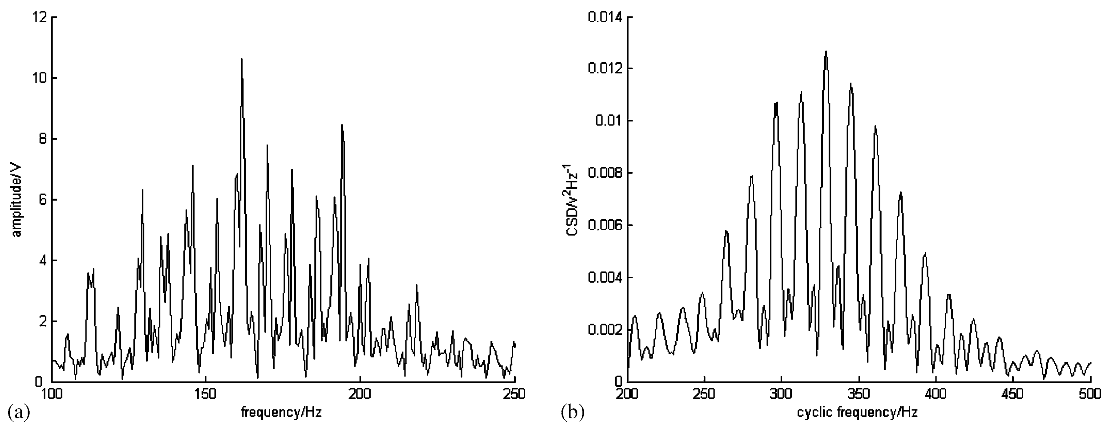

Fig. 3. The abnormal sound signal of mobile engine. (a) Fourier spectrum, (b) cyclic spectrum.

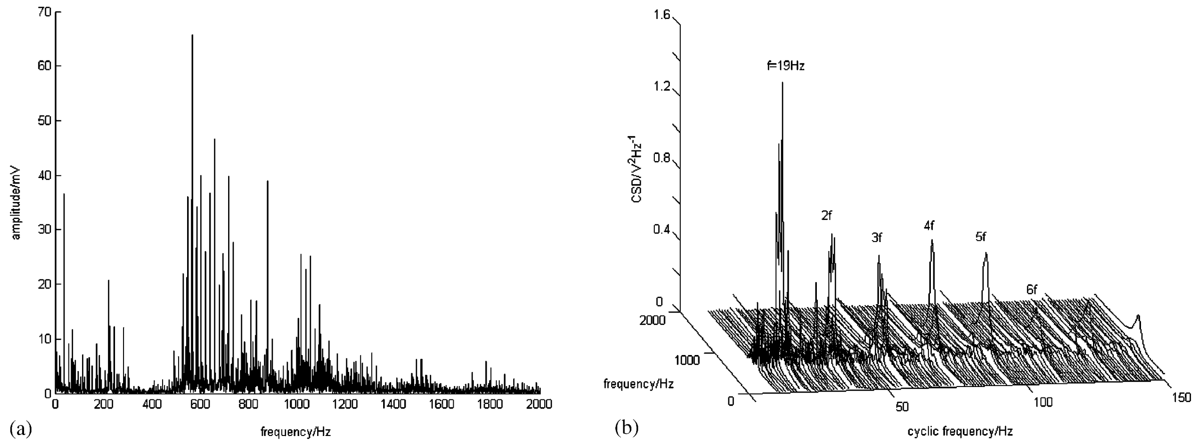

Fig. 4. The vibration signal of reciprocating compressor. (a) Fourier spectrum, (b) cyclic spectrum.

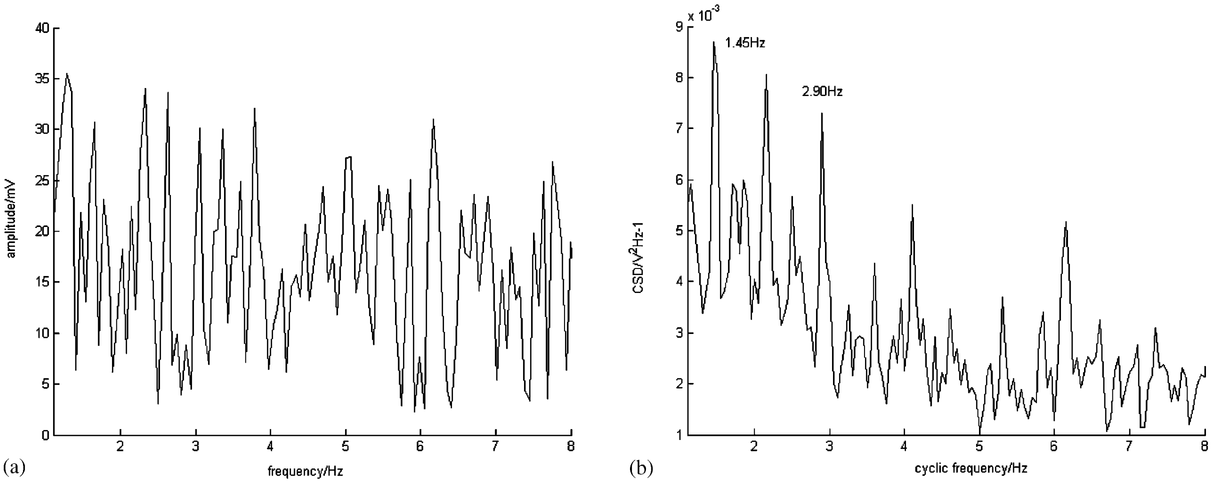

Fig. 5. The vibration signal of concrete injecting machine. (a) Fourier spectrum, (b) cyclic spectrum.

As there is a great diversity in the types of rolling bearings, the mechanical structures on which the bearings are mounted and the operating states, there are enormous differences in fault types, detecting means and diagnostic methods. Obviously, there is no method that can be used to diagnose all bearings. In these aspects, a lot of research has been performed by many scholars and various methods are presented, such as the diagnosis method based on the statistic index [3,4], the model diagnosis method [5,6], the continuous wavelet transformation diagnosis method [7] and the demodulation method using the complex shifted Morlet wavelet [8], etc. These methods with their own advantages and disadvantages have tackled many kinds of practical problems, but none of them was claimed by itself to be the best or the uniquely correct one.

2. Several explanations on the paper [1]

The paper [1] discussed the diagnostic application of the demodulation method based on the second-order cyclic statistic. In order to satisfy needs of the signal model, the routine filtering of band pass (3500 Hz, 4200 Hz) was used. Though not mentioning the above in the paper, its effect has been manifested clearly in the figures. Furthermore, since for engineering diagnosis it is only required to search the known fault characteristic frequencies, for the diagnosis results, other frequencies or whether or not there are cross items are not taken into consideration. Moreover, the discrete structure of the cyclic domain provides this advantage. In the paper [1], for the scanning of the cyclic domain in a selective way, the scanning range and the interval are listed in Table 3, and the example analytic graphs concerned express the diagnostic results truly.

As for envelope demodulation methods, whether they provide good results or not must be judged by taking into account numerous factors, such as bearing type, signal structures and so on, and they should not be treated as the same. A method should be evaluated based on its actual effect. A good method is applicable in most real situations. The resonance envelope demodulation has several disadvantages in processing mechanical signals. They are as follows: (1) the signal waveform must have the clear pulses in waveform (i.e. higher signal-to-noise ratio); (2) if the signal has no clear pulses, the suitable signal filtering operation should be performed; and (3) when there are more than two modulators, the modulating type of signal must be known to extract modulators.

Finally, I should like to thank the references mentioned in the letter. However, the research work in the paper [1] was finished at the end of 2001. It seems, undoubtedly, the work in Refs. [9–11] is helpful in analyzing the behavior of the faulty bearing. We will conduct further studies with regard to this aspect.

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