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Acoustic Emission Monitoring of Mechanical Seals Using MUSIC Algorithm based on Higher Order Statistics

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Abstract

This paper presents the use of the MUSIC algorithm improved by higher order statistics (HOS) to extract key features from the noisy acoustic emission (AE) signals. The low signal-to-noise ratio of AE signals has been identified as a main barrier to the successful condition monitoring of pump mechanical seals. Since HOS methods can effectively eliminate Gaussian noise, it is possible in theory to identify a change in seal conditions from AE measurements even with low signal-to-noise ratios. Tests conducted on a test rig show that the developed algorithm can successfully detect the AE signal generated from the friction of seal faces under noisy conditions.

Introduction

As one of the most vulnerable parts in rotating machines, mechanical seals cost the oil and gas industry millions of dollars per annum due to their premature failure. Monitoring the condition of mechanical seals during their operation has attracted the attention of researchers for many years, yet to little avail. Acoustic emission (AE), the transient elastic wave that is spontaneously generated from a rapid release of strain energy caused by crack growth and wear, has been identified as one of the technologies with the potential to fulfil this purpose.

Studies on the AE monitoring of mechanical seals started in the 1960s. The pioneering work conducted by Orcutt [3] investigated the failure of mechanical seals using the AE method. Miettinen and Siekkinen [4] studied the AE response to the operation of a mechanical seal under different conditions and concluded that it was possible for AE measurement to detect leakage, dry running and cavitation in mechanical seals. Research [5] also reported that AE measurement successfully detected the problem of pump mechanical seals in a thermal power plant which was not optimised during commissioning. Fan et al [6, 7] found that the AE burst transients can be observed during the operation of mechanical seals, which have the same period as the rotation of the shaft. Further research has shown that the AE signal from a mechanical seal is modulated by the shaft frequency even when the AE burst transients cannot clearly be observed.

However, previous studies have shown that the technical barrier for a successful AE monitoring is the strong background noise generated from practical applications. As pointed out by Anderson et al [8], the main problem faced by AE techniques is the difficulty in distinguishing AE signals generated by the seal itself from those by other sources and from background noise.

The purpose of this research is to develop an effective algorithm to extract monitoring information from the AE signals measured from the friction of seal faces under very noisy conditions such as the presence of particles in pump fluids. High order statistics were integrated with the multiple signal classification (MUSIC) algorithm to improve the ability to suppress signal noises. The effectiveness of this improved algorithm was validated using the test data from a seal operating in water contaminated by sand particles.

MUSIC Algorithm based on Higher Order Statistics

The first-order and second-order measures are often used in statistics. For a zero-mean discrete signal *x(n)*, the first-order measure can be expressed as

$$M_{1x} = E\{x(n)\} \tag{1}$$

M_{1x} is also called the first-order moment of signal *x(n)*. Obviously the first-order moment is the mean of signal.
The second-order moment of signal *x(n)* can be expressed as

$$M_{2x}(k) = E\{x(n)x(n+k)\} \tag{2}$$

Obviously the second-order moment M_{2x} is the autocorrelation of signal *x(n)*.
Higher order statistics is the generalization of the first and second-order measures to higher orders. The third-order moment can be defined as

$$M_{3x}(k,l) = E\{x(n)x(n+k)x(n+l)\} \tag{3}$$

For mathematical convenience, the higher order measures are often expressed using cumulant defined as

$$C_{1x}(k) = E\{x(n)\} \tag{4}$$

$$C_{2x}(k) = E\{x^*(n)x(n+k)\} \tag{5}$$

$$C_{3x}(k,l) = E\{x^*(n)x(n+k)x(n+l)\} \tag{6}$$

$$\begin{aligned} C_{4x}(k,l,m) = {} & E\{x^*(n)x(n+k)x(n+l)x*(m+m)\} \\ & - C_{2x}(k)C_{2x}(l-m) - C_{2x}(l)C_{2x}(k-m) - M^*_{2x}(m)M_{2x}(k-l) \end{aligned} \tag{7}$$

Where *x** and *M** represent the complex conjugate. It can be found that the first-order cumulant is the mean; the second-order cumulant is the autocorrelation or the second-order moment of a real process; the third-order cumulant is the third-order moment of a real process; the fourth-order cumulant is a nonlinear combination of moments and cumulant up to fourth order.
The reason why HOS are developed is because the traditional second-order techniques can not identify the characteristics of non-Gaussian, non-linear signals while the HOS will change dramatically if there are non-Gaussian and non-linear components in signals. In normal signal processing the noises are more likely to be Gaussian signal. Therefore the HOS are very effective to characterise the non-Gaussian signal and get rid of the Gaussian noise.

The observed signal can be expressed as

$$y(n) = \sum_{k=1}^{p} a_k e^{j2\pi n f_k} + w(n) \qquad (8)$$

where:
a_k is the amplitude of one signal component;
f_k is the frequency of signal component;
w(n) is the additive noise.
The autocorrelation sequence of one signal observation defined by Eq. 8 is

$$R_{yy}(\tau) = \sum_{k=1}^{p} |a_k|^2 e^{j2\pi\tau f_k} + R_w(\tau) \qquad (9)$$

The conventional MUSIC algorithm detects the signal frequencies by performing an eigen decomposition on autocorrelation matrix R_{yy} of *M* observations of the signal. The signal subspace is defined by the eigenvectors corresponding to the *N* largest eigen values and the other eigenvectors form the noise subspace. Since the signal subspace, which contains the detected signals, is orthogonal to the noise subspace, the signals can be found from the peaks in the spectrum defined by

$$P_{yy}(f) = \frac{1}{\sum_{k=p+1}^{M} \left| V_k^H e(f) \right|^2} \qquad (10)$$

where:
p is the dimension of the signal subspace;
V_k is the k-th eigenvector;
e(f) is the signal vector.

The diagonal slice of the fourth-order cumulant of the signal given by Eq.8 can be calculated by

$$C_{4y}(m,m,m) = -\sum_{k=1}^{p} |a_k|^4 e^{j2\pi\tau f_k} + C_{4w}(m,m,m) \qquad (11)$$

It can be found that Eq.11 is similar to the autocorrelation sequence given by Eq.9. Therefore we can perform the eigen decomposition on the fourth-order cumulant and develop a modified MUSIC algorithm. The benefit of this modification is that $C_{4w}(m,m,m)$ is zero if the noise w(n) is Gaussian. Therefore the influence of Gaussian noise can be eliminated from the analysis.

Experimental Data

Figure 1 shows the test rig designed for the condition monitoring of mechanical seals at the University of Huddersfield. There is a pressure chamber at the non-driven end of the rig, which consists of two industrial pusher cartridge seals and a stainless steel drum. An auxiliary circulating system is connected with the chamber to pressurise the working fluid and take away the heat generated by the friction of mechanical seal. The load on mechanical seals is able to be changed by adjusting the pressure in the sealed chamber. The shaft of the test rig is driven by an electrical induction motor controlled by an inverter to allow the change of test speed.

For this research the seal was tested at 1560rpm and 0bar first to get the benchmark AE response. Then sand (80 grams) was added into the pressure chamber and the seal was run again at 1560rpm and 0bar. AE raw signals were recorded using a sampling rate of 2MB samples per second during both tests.

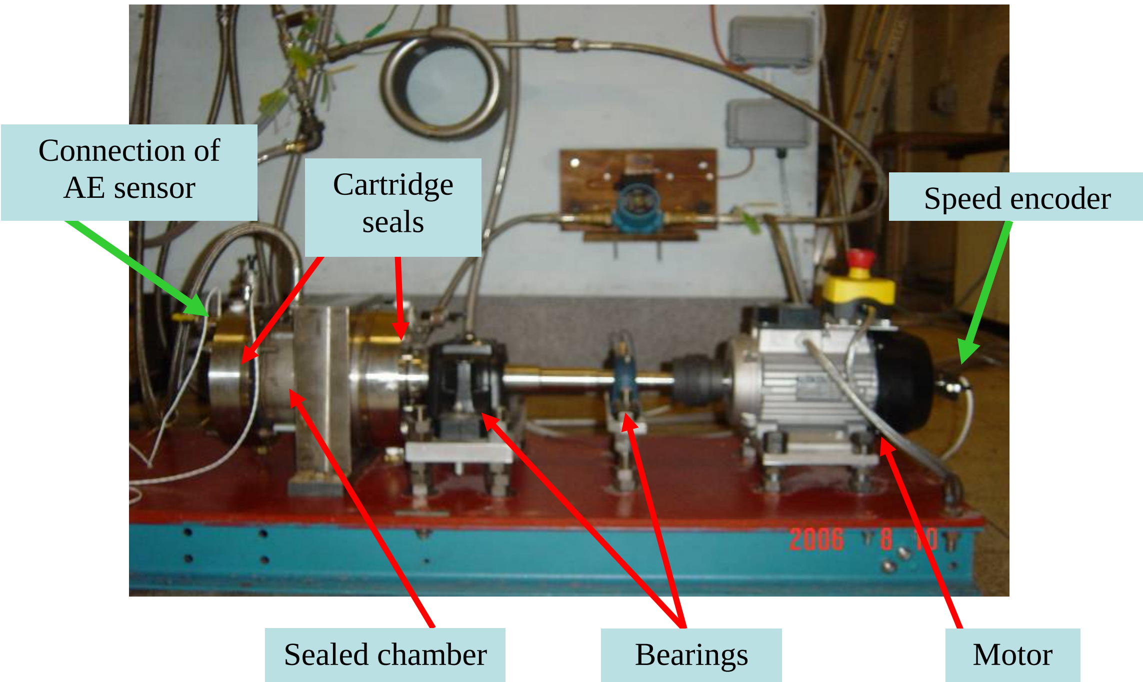

Figure 1 Layout of the Mechanical Seal Test Rig

Results and Discussions

To detect the modulation of the high frequency AE signal, the raw signal is converted to lower frequency by calculating a dynamic RMS value using

$$V_d(\tau) = [\frac{1}{T}\int_{\tau}^{\tau+T} V^2(t)dt]^{1/2} \qquad (12)$$

where:
V(t) is the measured AE raw signal;
T is the selected signal length.

Fig.2 gives the AE dynamic RMS under both experimental conditions. It can be observed that the AE amplitude increased and the signal became noisier because of the presence of sand.
The AE dynamic RMS was processed further using three different methods: conventional power spectrum, conventional MUSIC based on the autocorrelation function and the MUSIC based on higher order statistics.
The power spectra are shown in Fig.3. For the test with sand, the power spectrum could identify that the AE modulation caused by the friction of mechanical seal faces has the shaft frequency. However, this frequency merged into the background noises when sand was added into the fluid.
Fig. 4 gives the results of normal MUSIC. The AE modulation frequency due to seal friction could clearly be observed when the seal was tested without sand. The signal-to-noise ratio was also similar to that given by power spectrum. However, the conventional MUSIC again failed to find the modulation frequency from the noisy AE signal for the condition of the presence of sand. It can also be observed that the normal MUSIC results introduced a frequency component near 0Hz caused by the Gaussian noise within the AE signal.

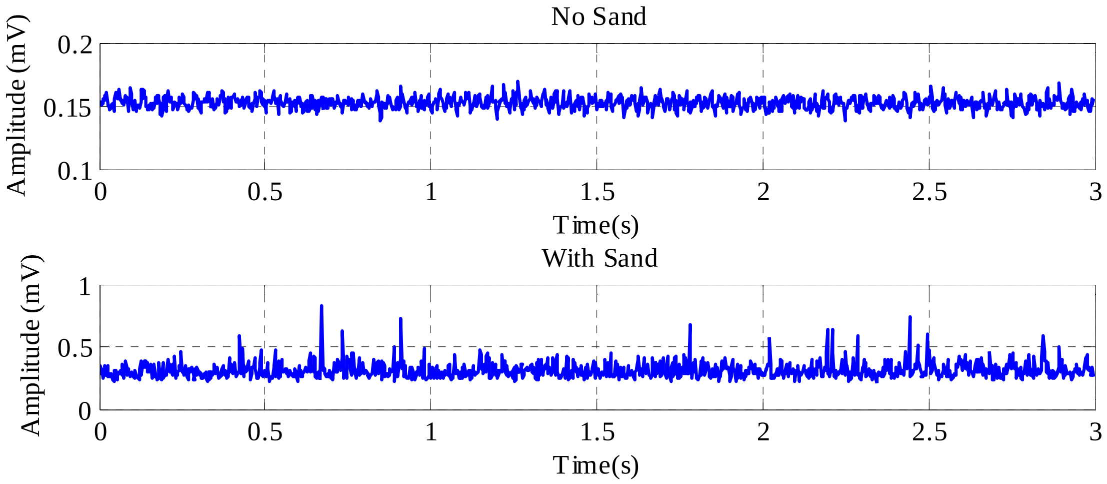

Figure 2 AE Dynamic RMS

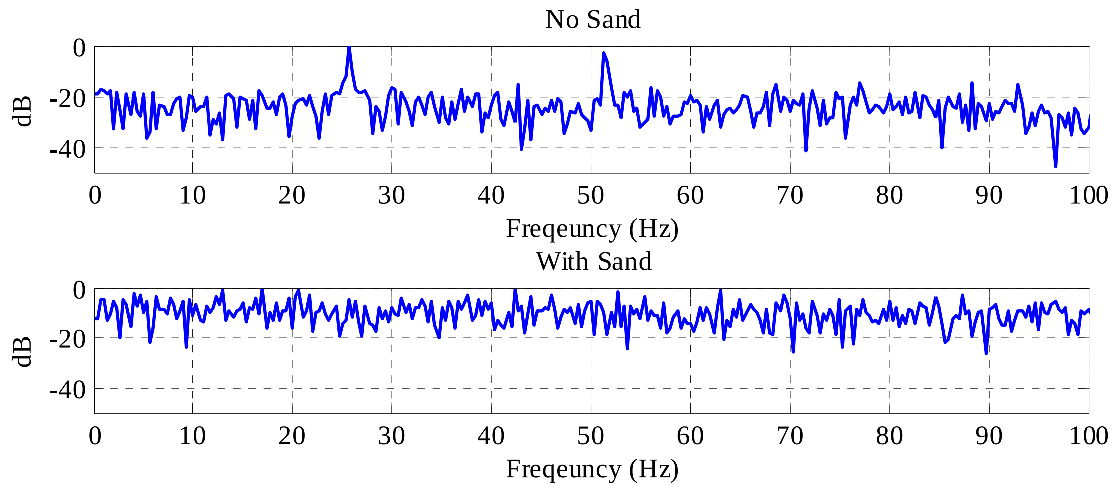

Figure 3 Power Spectra of AE Dynamic RMS

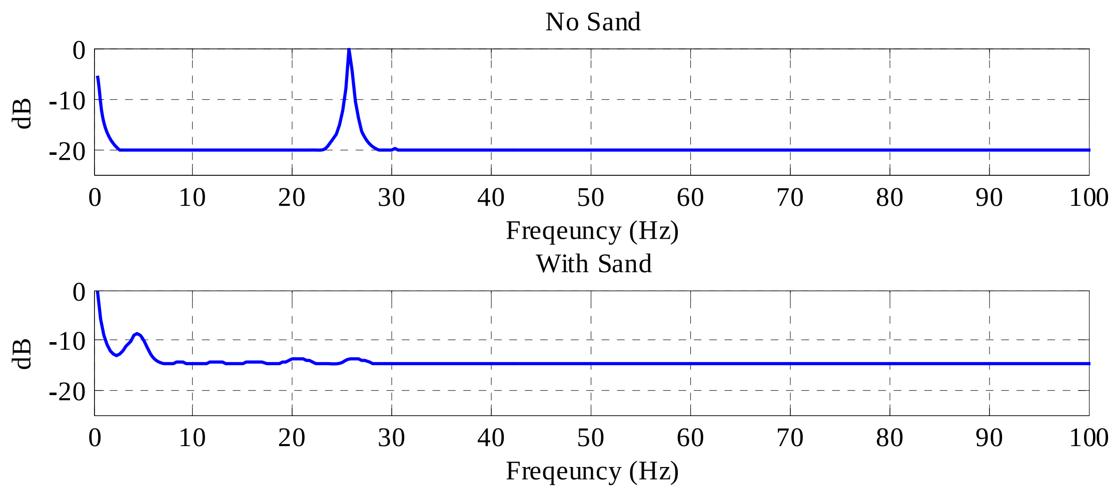

Figure 4 Results of MUSIC based on Autocorrelation

The results of modified MUSIC based on fourth-order cumulant were presented in Fig.5. The AE modulation frequency could clearly be observed from the test without sand. The signal-to-noise ratio was more or less the same as the results of power spectrum and normal MUSIC. In the test with sand, the modified MUSIC algorithm successfully separated the modulation frequency caused by seal face friction. Compared with the results of normal MUSIC, the modified algorithm eliminated the influence of Gaussian background noise observed in Fig.3. It is noted that a 4Hz component was also observed in the test with sand, shown in Fig.5. This frequency is likely to be associated with the abrasive wear at the sealing interface because the inspection of seal faces after test found the wear tracks caused by sand particles.

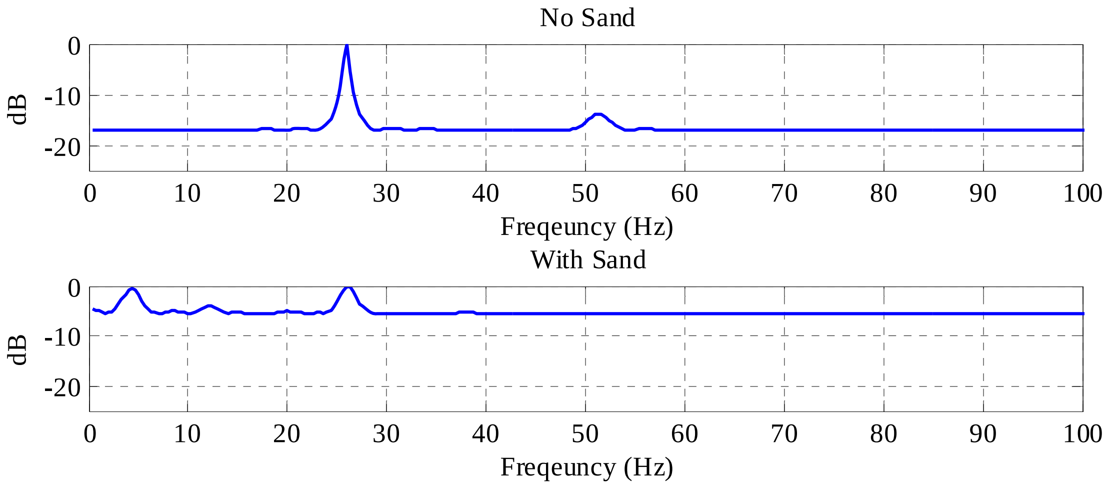

Figure 5 Results of MUSIC based on High Order Statistics

Conclusions

An improved MUSIC algorithm based on higher order statistics was presented and compared with the power spectrum and normal MUSIC method. The ability of the developed method to eliminate strong background noise was demonstrated through the tests conducted in our laboratory. The successful development of this technique will pave the way for the AE condition monitoring of mechanical seals from laboratory research to practical industry applications.

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