Research Article

The Contact State Monitoring for Seal End Faces Based on Acoustic Emission Detection

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Monitoring the contact state of seal end faces would help the early warning of the seal failure. In the acoustic emission (AE) detection for mechanical seal, the main difficulty is to reduce the background noise and to classify the dispersed features. To solve these problems and achieve higher detection rates, a new approach based on genetic particle filter with autoregression (AR-GPF) and hypersphere support vector machine (HSSVM) is presented. First, AR model is used to build the dynamic state space (DSS) of the AE signal, and GPF is used for signal filtering. Then, multiple features are extracted, and a classification model based on HSSVM is constructed for state recognition. In this approach, AR-GPF is an excellent time-domain method for noise reduction, and HSSVM has advantage on those dispersed features. Finally experimental data shows that the proposed method can effectively detect the contact state of the seal end faces and has higher accuracy rates than some other existing methods.

1. Introduction

As a kind of noncontact seal, hydrodynamic seal works by a thin fluid film between the pair of end faces for sealing and lubricating [1]. But when the seal is just started up, the film cannot be formed immediately, and the two end faces still keep contact with each other. This contact will cause continuous scratching and wearing and produce strong force and heat to reduce the working life of the seal. From the above, monitoring the contact state of seal end faces would help the early warning of the seal failure.

For monitoring the face contact, the fluid film has been measured via approaches of capacitance and resistance [2, 3], and eddy current method has also proved to be useful [4]. However, since the seal pair should be modified for sensors installation, these methods can only be taken in laboratory.

Ultrasonic detection is another classical method for mechanical seal, and the film thickness can be estimated based on the ultrasonic attenuation [5, 6]. However, considering the sensors' cost, this method is also unsuited for wide application.

Considering nondestruction and low cost, acoustic emission (AE) detection has a better application prospect, and this

method has been well applied on many machines [7–9]. But for seal, there are very few successful cases. The most major problem of this method is difficult to isolate the seal signal from background noise [10, 11], and this makes the existing methods cannot work well in practice [12–14].

The purpose of this paper is to develop a reliable approach to monitor the seal face contact by AE detection. For the problem of the difficulties in signal denoising and features classification, a new approach based on genetic particle filter with autoregression (AR-GPF) and hypersphere support vector machine (HSSVM) is presented. In this processing, AR model is used to build the dynamic state space (DSS) of the AE signal, and GPF is used for signal filtering. Then following feature extraction, a classification model based on HSSVM is constructed. Data shows that the proposed approach can effectively detect the contact state of the seal end faces and has higher accuracy rates than some other existing methods.

2. Related Work

For mechanical seal, the AE occurs when the equipment is distorted, being rubbed or under collision. In order to extract

FIGURE 1: Sensors installation.

useful information, some new studies and methods have been attempted in recent years.

Fan et al. have processed the AE signal by multiple signal classification with higher order statistics (HOS-MUSIC) [12] and extracted the information about seal end faces under noisy condition. But in his case, the noise circumstance is artificial, and the paper's focus is not on the state monitoring of the seal end faces. Gao et al. have studied the AE characteristics of dry gas seal during the seal startup and used RMS of the signal to describe the friction strength of the seal end faces [15]. However, no denoising method has been presented in their paper, and the unique feature is not reliable enough to detect the seal face contact. Zhang et al. have described the seal face contact in the view of tribology and used Laplace wavelet and its coherent coefficient [13] for state monitoring. Then for improving the detection rates, another method based on wavelet packet and radial basis function (RBF) artificial neural network (ANN) [14] has been presented. But because of the unstable spectrum structure of the seal signals and the dispersed distribution of the AE features, both the methods will be ineffective when random contact occurs. Particle filter is a time-domain method for signal denoising, and this method has been applied to measure the film thickness [16]. However, since the particle diversity reduces during the resampling procedure, this method cannot reach the best performance.

Compared with the above methods, AR-GPF is a time-domain method with higher denoising performance, and the model based on HSSVM has more advantage in dealing with the features under dispersed distribution.

3. Experiment and Signal Observation

3.1. Experiment. We take hydrodynamic mechanical seal as research object and water as sealing medium. The sensors installation is given by Figure 1.

In Figure 1, an eddy current sensor is used to measure the film thickness. In order not to damage the seal end faces, a metal ring with a through hole is inlaid in the static ring for sensor installation. The type of the eddy current sensor is KD2360, and its resolution is $0.1 \mu\text{m}$.

FIGURE 2: The monitoring system.

An AE sensor of 8152B12SP type is mounted on the shell of the seal cavity. Its effective frequency ranges from 50 KHz to 500 KHz. To achieve high sampling rate, the data generated by AE sensor is acquired by a high-frequency DAQ board, and the sampling frequency is set to 1 MHz.

Finally, based on PCI data bus, the two-channel signals can be transmitted into the industrial personal computer (IPC).

The monitoring system of this experiment is given by Figure 2.

For comparing end faces signal with background noise, we operate the experiment as follows.

Step 1. Start the seal under 0.5 MPa, then raise the spindle speed up to 1500 rpm linearly, and save the measured data into IPC.

Step 2. Repeat Step 1 several more times, so that enough data samples are collected.

Step 3. Start the seal without seal rings, then raise the spindle speed up to 1500 rpm linearly, and save the measured data into IPC.

3.2. Signal Observation. According to the experimental data, the eddy current curve and its corresponding AE signal during the seal startup are given by Figure 3.

In Figure 3, there are three contact states that can be observed.

- (1) Face-contact: since the fluid film is not formed, contact friction occurs between the end faces and it makes the AE energy powerful.
- (2) Face-opening: the film is not yet fully formed, so random contact occurs between the end faces and causes the AE energy sharply fluctuating.
- (3) Face-separate: the film has been well formed, and fluid friction between the end faces weakens the energy and makes it stable.

FIGURE 3: The signals during the seal startup.

FIGURE 4: The AE signals in different contact states.

Based on the above classification, Figure 4 shows the AE signals in the different contact states.

Due to noise interference, there are some strong random fluctuations that can be observed in Figure 4. They make the signal energy unstable and bring difficulties to feature analysis and state recognition.

To further observe the effect of the noise on the signals, Figure 5 gives the AE RMS at different spindle speed.

Noise energy can be estimated by the signal collected without seal rings. Figure 5 suggests that the spindle is the main noise source, and the signal noise ratio (SNR) decreases with the increase of the spindle speed. When the seal is exceeding 1200 rpm, the observed signal is almost spindle noise.

4. Signal Denoising

Based on noise study, AR-GPF is presented for signal denoising. In this algorithm, AR model is used to build the DSS of the AE signal, and GPF is used for signal filtering.

4.1. Theory of AR-GPF. PF is a filtering algorithm based on Bayesian estimation and Monte Carlo method. Its core idea is to extract a series of random samples from DSS to simulate the probability density function (PDF) of system state. In this algorithm, integral is replaced by sample expectation, and the samples extracted from the DSS are called “particles” [17].

FIGURE 5: Variations of AE energy.

The DSS of a system can be expressed as

$$\begin{aligned} x_t &= f(x_{t-1}, w_t), \\ z_t &= h(x_t, v_t), \end{aligned} \quad (1)$$

where $f(\cdot)$ is a state function with process noise w_t and $h(\cdot)$ is an observation function with observation noise v_t . They describe the system at time t by its true state x_t and observed value z_t .

GPF is an improved algorithm. It replaces the resampling by genetic algorithm to solve the problem of particle diversity reduction through three steps of selection, crossover, and mutation [18, 19]. For those selected particles, the improvement based on genetic algorithm can be described as follows.

(1) *Crossover.* For any two particles $(x_t^{(i)}, x_t^{(j)})$ from the particle set, whose weights are $(\omega_t^{(i)}, \omega_t^{(j)})$, the crossover equations can be given by

$$\begin{aligned} \tilde{x}_t^{(i)} &= \alpha x_t^{(i)} + (1 - \alpha) x_t^{(j)}, \\ \tilde{x}_t^{(j)} &= \beta x_t^{(j)} + (1 - \beta) x_t^{(i)}, \end{aligned} \quad (2)$$

where α, β are crossing coefficients, $\alpha = \omega_t^{(i)} / (\omega_t^{(i)} + \omega_t^{(j)})$, $\beta = \omega_t^{(j)} / (\omega_t^{(i)} + \omega_t^{(j)})$. If $p(z_t | \tilde{x}_t^{(i)}) > \max\{p(z_t | x_t^{(i)}), p(z_t | x_t^{(j)})\}$, $x_t^{(i)}$ is replaced by $\tilde{x}_t^{(i)}$, or $\tilde{x}_t^{(i)}$ is accepted with probability p_c :

$$p_c = \frac{c_1 (\omega_{\max} - \omega_c)}{(\omega_{\max} - \omega_{\text{avg}})}, \quad (3)$$

where c_1 is a constant no greater than 1, $\omega_{\max}$ is the maximum weight of the particle set, ω_{avg} is the average weight of the particle set, and ω_c is the larger weight of the two selected particles.

Then the same operation can be executed on $x_t^{(j)}$.

(2) *Mutation.* For any one particle $x_t^{(i)}$ in the particle set, its mutation equation can be given by

$$\tilde{x}_t^{(i)} = x_t^{(i)} + \eta, \quad \eta \sim N(0, \omega_{\text{avg}}). \quad (4)$$

If $p(z_t | \tilde{x}_t^{(i)}) > p(z_t | x_t^{(i)})$, $x_t^{(i)}$ is replaced by $\tilde{x}_t^{(i)}$, or $\tilde{x}_t^{(i)}$ is accepted with probability p_m :

$$p_m = \frac{c_2 (\omega_{\max} - \omega_t^{(i)})}{\omega_{\max}}, \quad (5)$$

where c_2 is a constant no greater than 0.5.

To use GPF, the DSS of the system should be constructed first. We use AR model to analyze the implied time-series relation of the observed signal, so the signal sequence can be written as:

$$Y = XA + E, \quad (6)$$

where $Y = [x_{n+1}, x_{n+2}, \dots, x_m]^T$ is the recursive sequence of the signal, $A = [\alpha_1, \alpha_2, \dots, \alpha_n]^T$ is an autoregressive coefficient vector, $E = [\varepsilon_{n+1}, \varepsilon_{n+2}, \dots, \varepsilon_m]^T$ is an random error vector, and X is a matrix that can be given by

$$X = \begin{bmatrix} x_1 & x_2 & \cdots & x_n \\ x_2 & x_3 & \cdots & x_{n+1} \\ \vdots & \vdots & & \vdots \\ x_{m-n} & x_{m-n+1} & \cdots & x_{m-1} \end{bmatrix}. \quad (7)$$

The least square estimation of A can be given by

$$A = (X^T X)^{-1} X^T Y. \quad (8)$$

The optimal order n of the AR model can be determined by the rule of FPE or AIC [20], so the DSS of the end faces signal can be expressed as

$$\begin{aligned} x_t &= (x_{t-n}, x_{t-n+1}, \dots, x_{t-1}) A + w_t, \\ z_t &= x_t + w_t. \end{aligned} \quad (9)$$

Since the AE signal is observed without transformation, we assume that the observation noise is equivalent to w_t . The procedure of GPF is given as follows.

Step 1. For particle initialization, a particle set $\{x_{1:n}^{(i)}\}$ is produced according to the distribution of the measured data, in which each particle is weighted as $1/N$. The N here is the number of the sampled particles and i is gotten by $i = 1 \sim N$. Thus the initialized state of the signal can be estimated as

$$\hat{x}_{1:n} = \frac{1}{N} \sum_{i=1}^N x_{1:n}^{(i)}. \quad (10)$$

Step 2. Based on (9), the state particles $x_t^{(i)}$ and their observation values $z_t^{(i)}$ can be obtained through importance sampling. Then the corresponding weights $\omega_t^{(i)}$ can be calculated by

$$\omega_t^{(i)} = \omega_{t-1}^{(i)} p(z_t^{(i)} - y_t), \quad (11)$$

$$\omega_t^{(i)} = \frac{\omega_t^{(i)}}{\sum_{k=1}^N \omega_t^{(k)}}, \quad (12)$$

where y_t is the collected data at time t and $p(\cdot)$ is the PDF of the sampling space.

FIGURE 6: The statistical distribution of the signal noise.

Step 3. For genetic selection, N_{eff} is defined as the number of effective particles, which can be gotten by

$$N_{\text{eff}} = \frac{1}{\sum_{i=1}^N (\omega_t^{(i)})^2}. \quad (13)$$

If N_{eff} is less than the given threshold N_{th} , a new set $\{\tilde{x}_t^{(i)}\}$ is obtained by updating those low weighted particles through genetic variation until $N_{\text{eff}} \geq N_{\text{th}}$, or $\{\tilde{x}_t^{(i)}\}$ is replaced by $\{x_t^{(i)}\}$ directly.

Step 4. With the particles and the weights, the signal point at time t can be evaluate by

$$\hat{x}_t = \sum_{i=1}^N \tilde{x}_t^{(i)} \omega_t^{(i)}. \quad (14)$$

Then go back to Step 2 to update particles at time $t + 1$.

What needs to be explained is that, by using AR analysis, the weight recursion will be much more complex than (11). But for convenience, we still assume that ω_t is only related to x_t and ω_{t-1} in this paper.

4.2. AE Denoising. We extract 36 AE data segments from every contact state, and each segment contains 20,000 data points.

For sampling particles, the noise space should be studied first. Figure 6 gives the statistic distribution of the signals collected without seal rings.

According to Figure 6, the noise obeys Gaussian distribution, and its distribution parameters at different spindle speed are estimated in Table 1.

By letting $p(\cdot) = N(\mu, \sigma^2)$ in (11), we sample the state particles based on the fitted normal distributions. Since the sampling function is an approximation of the real noise space, AR-GPF can effectively reduce the signal noise in time domain.

The processed signals are given by Figure 7.

From Figure 7, the noise is effectively restrained by AR-GPF, which makes the signal energy more stable than before.

TABLE 1: Noise distribution.

Spindle speed (rpm)	(0,300)	(300, 600)	(600, 900)	(900, 1200)	(1200, 1500)
$N(\mu, \sigma^2)$	$\mu = 0$ $\sigma = 0.210$	$\mu = 0$ $\sigma = 0.225$	$\mu = 0$ $\sigma = 0.235$	$\mu = 0$ $\sigma = 0.245$	$\mu = 0$ $\sigma = 0.250$

FIGURE 7: The filtered signals in different contact states.

5. Contact State Recognition

Seven features are extracted to describe the characteristics of the different states, and a model based on HSSVM is constructed for state monitoring.

5.1. Theory of HSSVM. SVM is a general machine learning method based on statistical learning theory. Its core idea is to construct an optimal separating hyper plane (OSH) in a higher dimensional sample space to solve the problem of nonlinear classification. Since the principle of structural risk minimization is applied, SVM usually has advantage on small-sample recognition [21, 22].

HSSVM is a variation of SVM. It replaces the OSH by a minimum hypersphere to wrap the samples belonging to the same class [23]. The classification sketch of HSSVM is given by Figure 8.

For an n -dimensional sample space $\{x_i, y_i\}$, in which $i = 1 \sim m$, $y_i \in \{1, -1\}$, and y_i is the classifying label of x_i . The classification model can be given as

$$\begin{aligned} \min_{R, a} \quad & R^2 + c \sum_{i=1}^l \xi_i, \quad \xi_i \geq 0 \\ \text{s.t.} \quad & \|\phi(x_i) - a\|^2 \leq R^2 + \xi_i, \quad y_i = 1, \end{aligned} \quad (15)$$

where a is the sphere center, R is the radius of the sphere, l is the sample size, $\phi(\cdot)$ is a high-dimensional projection function, c is a penalty factor, and ξ_i is a slack variable. By using Lagrange theorem, we construct the Lagrangian as

$$\begin{aligned} L(R, a, \xi_i, \alpha_i, \beta_i) = & R^2 + c \sum_{i=1}^l \xi_i - \sum_{i=1}^l \beta_i \xi_i \\ & - \sum_{i=1}^l \alpha_i (R^2 + \xi_i - \|\phi(x_i) - a\|^2), \end{aligned} \quad (16)$$

FIGURE 8: Sketch of HSSVM.

where $\alpha_i \geq 0$ and $\beta_i \geq 0$ are Lagrange multipliers. Then the optimization problem can be turned into

$$\begin{aligned} \min_{\alpha_i} \quad & \sum_{i=1, j=1}^l \alpha_i \alpha_j \langle \phi(x_i) \cdot \phi(x_j) \rangle - \sum_{i=1}^l \alpha_i \langle \phi(x_i) \cdot \phi(x_i) \rangle \\ \text{s.t.} \quad & \sum_{i=1}^l \alpha_i = 1, \quad 0 \leq \alpha_i \leq c. \end{aligned} \quad (17)$$

So the distance of a random sample x to the sphere center can be calculated by

$$\begin{aligned} D_x^2 = & K(x, x) - 2 \sum_{i=1}^l \alpha_i K(x, x_i) \\ & + \sum_{i=1, j=1}^l \alpha_i \alpha_j K(x_i, x_j), \end{aligned} \quad (18)$$

where $K(\cdot)$ is a kernel function which is used to replace the sample inner product in (17).

According to (18), when x is located on the sphere, D_x is the radius. Thus a sample can be classified according to whether the condition $D_x^2 - R^2 \leq 0$ is satisfied.

5.2. State Recognition. According to the characteristics of the different states, we extract the following features from each data segment.

In Table 2, $\hat{x}$ is the filtered signal, $E(\cdot)$ is the expectation, and $\hat{p}_i$ is the signal amplitude at frequency f_i . Table 3 gives the normalized features, where number 1~number 36 belong to

TABLE 2: Features extraction.

Code name	Feature	Equation
$\hat{x}_{\text{RMS}}$	Root Mean Square (RMS)	$\hat{x}_{\text{RMS}} = \sqrt{\frac{1}{n} \sum_{i=1}^n \hat{x}_i^2}$
$\hat{x}_{\text{EV}}$	Energy Variance (EV)	$\hat{x}_{\text{EV}} = E(\hat{x}_{\text{RMS}}^2) - E^2(\hat{x}_{\text{RMS}})$
$\hat{x}_{\text{PAR}}$	Peak to Average Ratio (PAR)	$\hat{x}_{\text{PAR}} = \frac{ \hat{x} _{\text{peak}}}{\hat{x}_{\text{RMS}}}$
$\hat{x}_{\text{PV}}$	Peak Variance (PV)	$\hat{x}_{\text{PV}} = E(\hat{x}_{\text{Peak}}^2) - E^2(\hat{x}_{\text{Peak}})$
$\hat{x}_{\text{AS}}$	Absolute Skewness (AS)	$\hat{x}_{\text{AS}} = \frac{(1/n) \sum_{i=1}^n (\hat{x}_i - \hat{x}_{\text{mean}})^3}{\hat{x}_{\text{RMS}}^3}$
$\hat{x}_{\text{CF}}$	Center Frequency (CF)	$\hat{x}_{\text{CF}} = \frac{\sum_{i=1}^n f_i \hat{p}_i}{\sum_{i=1}^n \hat{p}_i}$
$\hat{x}_{\text{FV}}$	Frequency Variance (FV)	$\hat{x}_{\text{FV}} = \frac{\sum_{i=1}^n (f_i - \hat{x}_{\text{CF}})^2 \hat{p}_i}{\sum_{i=1}^n \hat{p}_i}$

TABLE 3: Normalized features.

Sample number	RMS	EV	PAR	PV	AS	CF	FV
Number 1	0.842	0.012	0.293	0.134	0.232	0.043	0.771
Number 2	0.873	0.021	0.349	0.157	0.918	0.091	0.642
⋮				⋮			
Number 36	0.484	0.025	0.886	0.096	0.325	0.208	0.513
Number 37	0.512	0.801	0.492	0.841	0.116	0.813	0.670
⋮				⋮			
Number 72	0.525	0.921	0.413	0.652	0.301	0.461	0.135
Number 73	0.021	0.829	0.127	0.013	0.072	0.492	0.041
⋮				⋮			
Number 107	0.076	0.027	0.104	0.127	0.100	0.573	0.062
Number 108	0.048	0.035	0.175	0.101	0.040	0.521	0.122

face-contact, number 37~number 72 belong to face-opening, and number 73~number 108 belong to face-separate. Taking the mean of the features from every 12 samples as statistical data, a histogram is given by Figure 9.

According to Figure 9, the features belonging to face-contact can be easily divided from those belonging to face-separate. However, because of the dispersed distribution of the features, the state of face-opening is hard to be detected.

In this paper, we construct two sphere structures to wrap the features belonging to face-contact and face-separate and consider the rest features belonging to face-opening. 12 feature samples under each state are selected for model training, and the remaining are used for testing. By taking RBF as kernel function, the final results are given by Table 4.

In order to further validate the paper's method, we deal the same data by some other methods for comparison. From Table 4, the detections for face-contact and face-separate have gotten satisfied results, but the accuracy rates on face-opening are quite different. Among them, the method based on Laplace wavelet got the lowest detection rates, and only limited improvements can be obtained by wavelet packet and RBF ANN. Cascade ANN has advantages on dealing nonstationary data, but the final detection rate on face-opening is still below 85%. Compared with the above, the all

FIGURE 9: Histogram of sample features.

states are well detected by paper's method, and the average accuracy rate reaches 95%.

In addition, the deficiency of this method is its lower operation speed. But at the cost of time, the method can work best in practice. In conclusion, we can get that the paper's method is very effective in contact state monitoring for seal end faces.

6. Conclusion

The paper studied the contact state monitoring for seal end faces by AE detection and presented a new approach based on AR-GPF and HSSVM to improve the detection rates.

TABLE 4: The detection rates.

Method	Detection rate			
	Face-contact	Face-opening	Face-separate	Average
Paper's method	100%	91.7%	95.8%	95.8%
Laplace wavelet with coherent coefficient	87.5%	29.2%	91.7%	69.4%
Wavelet packet and RBF ANN	91.7%	54.2%	91.7%	79.2%
PF and cascade ANN [24]	95.8%	83.3%	95.8%	91.7%

Following signal processing, some conclusions can be gotten as follows.

- (1) In the AE monitoring for the seal end faces, spindle is the main noise source, and the SNR decreases with the increase of the spindle speed. When the seal exceeds 1200 rpm, the observed signal is almost noise.
- (2) Based on the noise space estimation, an improved method based on AR-GPF is presented for AE denoising. For the seal end faces, AR-GPF is an excellent time-domain method for noise reduction. Data shows that it can effectively restrain the background noise of the seal and makes the signal energy more stable than before.
- (3) Due to random contact, the features belonging to face-opening are distributed dispersedly. HSSVM has advantage on such features. Data shows that the final model can effectively detect the contact state of the seal end faces, and it has higher accuracy rates than some other existing methods.

Conflict of Interests

The authors declare that there is no conflict of interests regarding the publication of this paper.

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