Research on Bearing Fault Diagnosis of Submersible Pump Motor Based on LMD and SVDD

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Abstract. The motor is a key component of the submersible pump. The health of the motor would greatly affect the safety and efficiency of the submersible pump. The bearing fault is one of the most common faults in motors. Therefore, detection and diagnosis of bearing faults are essential in the condition monitoring of pumps. In this paper, the local average decomposition (LMD) method is used to analyze the bearing vibration signals of submersible pump motor and extract feature vectors. A fault diagnostic model is established by the support vector data description (SVDD) to determine whether the submersible pump motor is faulty. The developed model exhibits practical significance in condition monitoring of submersible pump motor bearings.

1. Introduction
The bearings of the submersible pump motor are wearing parts, coupled with long-term overload and harsh working environment and other factors. Bearings are more prone to failure. Bearing faults will increase the load current of the submersible pump motor and abnormal working conditions will be induced. If the occurrence, type, and location of fault in submersible pump can be detected and diagnosed in real time, proper maintenance and repair can be carried out in the early stage of the fault, then the service life of the submersible pump can be extended, economic loss can be reduced, and accidents can be avoided.

In general, the reasons for the abnormal vibration of the submersible pump bearings are diversified, such as the misalignment of the rotor, the failure of the impeller, etc. However, these failure patterns can be reflected in the vibration signals. For example, periodic impulses with different frequency occur when the outer race, the inner race, the rolling elements and the cage fail. Therefore, according to the occurrence of the impulses and their frequency, the bearing fault types and locations can be judged. This paper developed a diagnostic model by combing the local average decomposition (LMD) and the support vector data description (SVDD) to detect and diagnose the failure patterns in bearing vibration signals, which aims for the online condition monitoring of submersible pumps.

2. Bearing failure analysis and vibration signal acquisition of submersible pump motor

2.1. Bearing failure
The unbalanced force in the motor, or the harsh operating environment, or the long-term running may induce different bearing failures. There are also various diagnostic methods for bearing faults: torque measurement method, rotational speed measurement method, temperature measurement method, oil analysis method and vibration method. Among them, the vibration method has the best applicability and effectiveness. The
vibration signal processing is simple and intuitive. The fault diagnostic method used in this paper is the vibration method. When a bearing fails, the corresponding characteristic frequency will appear in the vibration spectrum. By observing the waveform, it is easy to judge whether the bearing is faulty, but it is impossible to locate the faulty position. Therefore, the LMD method is used for signal processing and feature extraction, and a diagnostic model is established by the SVDD method. These two methods are combined to locate the faulty position of the bearing.

2.2. Bearing vibration signals acquisition of submersible pump motor
The experimental object of this paper is a BQS30-30-5.5 type mine explosion-proof vertical submersible pump. Its rated working voltage is 660V, power is 5.5KW, and its synchronous speed is 3200 r/min. The bearings are 6305 rolling element bearings. Their inner diameters are 25 mm, the outer diameters are 62 mm and the heights are 17 mm.

![Figure 1. The vibration signal acquisition scheme](image)

The vibration signals in this paper were collected by a NI cRIO-9030 controller. By adding a vibration sensor to the pump bearing, the vibration signals were collected under normal conditions and simulated fault conditions. The NI-9234 Quad C Series Dynamic Signal Acquisition Module in the NI cRIO-9030 controller can simultaneously acquire vibration signals at a frequency of 51.2 kHz per channel.

3. Research on fault diagnosis method based on LMD and SVDD

3.1 Local Mean Decomposition
The local mean decomposition (LMD) method is a new time-frequency analysis method for adaptive non-stationary signals analysis [1]. It has good adaptability and can decompose a complex nonstationary multi-component signal into several instantaneous frequency product functions with physical significance [2]. In terms of feature extraction, the bearing vibration signals were firstly decomposed by LMD, and then the feature vectors were constructed in the form of energy entropy. These feature vectors contain the vibration energy in different frequency bands, which can be used to distinguish various bearing faults [3].

3.2 Support Vector Data Description
Support Vector Data Description (SVDD) is a single-valued classification method. Suppose \{αi, l = 1,2,..., n\} is the training of input space sample set, n is the number of samples, The basic principle is to find a hypersphere defined with a spherical center \(\mu\) and radius R in a high-dimensional feature space, and the hypersphere should contain as much target samples as possible [4]. Considering that, in the absence of faulty samples, only the normal samples are available, and a hypersphere can be trained be able to recognize the normal working condition while detect the abnormal conditions. It is suitable for processing high dimensional and small sample data and has been successfully applied in the field of condition monitoring [5].
In order to allow for outliers in the training sample, a variable $\xi_i$ is introduced to punish the anomaly point away from the hypersphere. Then the SVDD is described by the following equation:

$$\min_{R,\mu,\xi_i} R^2 + C \sum_{i=1}^{n} \xi_i$$

$$\| \phi(x_i) - \mu \|^2 \leq R^2 + \xi_i, \xi_i \geq 0$$  

Which, $C$ is used to achieve the balance between the number of misclassified samples and the volume of the hypersphere. In order to achieve nonlinear mapping, the sample of the input space is mapped to the high-dimensional feature space $\phi(\alpha_i)$.

In order to find the optimal solution for equation (1), a dual form can be used:

$$\max_{\alpha_i} = \sum_{i=1}^{n} \alpha_i K(x_i, x_i) - \sum_{i,k=1}^{n} \alpha_i \alpha_k K(x_i, x_k)$$

$$\sum_{i=1}^{n} \alpha_i = 1, \quad 0 \leq \alpha_i \leq C, \quad l = 1, 2, \ldots, n$$  

Solving equation (2), the sample $\alpha_i$ corresponding to $\alpha_i > 0$ is the support vector. The kernel function $K(x_i, x_i) = \langle \phi(x_i), \phi(x_i) \rangle$ represents the inner product of two vectors in the feature space. A basis Gaussian kernel function in the following form can be used:

$$K(x_i, x_k) = \exp\left( -\frac{\|x_i - x_k\|^2}{2\sigma^2} \right)$$  

where the ' $\sigma$ ' is the width parameter of the radial basis Gaussian kernel function.

The radius $R$ of the hypersphere can be expressed by the distance from the hypersphere sphere $\mu$ to any sample $\alpha_i$ located on the hypersphere:

$$R^2 = K(x_i, x_i) - 2 \sum_{j=1}^{n} \alpha_i K(x_i, x_j) + \sum_{j,k=1}^{n} \alpha_i \alpha_k K(x_i, x_k)$$  

For any sample $z$ to be tested (which may be a known type or a position type), by comparing the distance from the center of the sphere to the $\alpha(z)$ and the radius $R$ in the feature space, it can be determined whether the sample is a normal sample. The decision formula is:

$$f(z) = \| \alpha(z) - \mu \|^2 - R^2$$  

If $f(z) \leq 0$, it means that the sample falls in the hypersphere and is a normal sample, otherwise it is a faulty sample.
3.3 Diagnostic process based on LMD and SVDD

![Flow chart of diagnostic principle]

First, take a set of normal signals (no limit on sample number) for LMD decomposition and feature vector extraction, and then use the SVDD method to train the extracted feature vectors to build the diagnostic model. Then take the same number of fault signal samples, and build the diagnostic model following the same procedures. The developed diagnostic models are to be verified with the acquired vibration signals.

4. Analysis of experimental results

The acquired bearing vibration signals of the submersible pump were from normal and the outer race fault conditions, and a triaxial vibration sensor was used to acquire the bearing vibration in X, Y and Z. The signal sampling frequency is set to 10 KHz. Figures 3 and 4 show the motor bearing vibration signals under the normal and outer race fault condition, respectively.

![Motor bearing vibration signals under normal condition](image1)

![Motor bearing vibration signals under outer race fault condition](image2)

In this paper, the acquired data were analyzed and verified by the developed diagnostic model. Firstly, a single classification model is established with the vibration signals under the normal conditions. The steps for establishing the model are as follows:

- 100 groups (1000 data points for each group) of vibration from the normal condition were selected as the training set, and the other 100 groups (1000 data for each group) of vibration signals under the normal condition were selected as the test set.
- Energy entropy feature vectors were extracted from the training set and test set by the LMD method.
- A minimum hypersphere was obtained for the training set by training with the SVDD method.
- The accuracy of the classification effect of the established diagnostic model was tested.

The LMD method is used to process the data of the training set and the test set respectively. The processing result is shown in Fig. 5 and Fig. 6. The fifth-order PF component of the training set and the test set is used as the feature quantity of the original vibration signal.
The calculated energy of the 5th-order PF component of each vibration signal under normal condition and outer race fault are shown in the Fig.7 and Fig.8.

The kernel function used in this paper was the Gaussian kernel and the penalty factor is 1. A SVDD model of the bearing under normal condition was established. The model was applied on the test set, and the accuracy is 98%.

The 100 groups of outer race fault data were processed with the developed diagnostic model in the same way. The data under normal condition was predicted by the trained model, and the accuracy rate is 0. Then, use the 100 groups of data under outer race fault as the training set, and take the other 100 groups of data under outer race fault as the test set, and the test result is 98%.

Table 1. SVDD based bearing status classification results

| Bearing status          | Kernel function type (t)     | Penalty factor (c) | Accuracy |
|-------------------------|-------------------------------|--------------------|----------|
| normal status           | Gaussian core                 | 1                  | 98%      |
| Outer race fault status | Gaussian core                 | 1                  | 0        |
Finally, 100 groups of bearing data under inner race fault condition were selected as the unknown bearing fault condition. The LMD decomposition and feature extraction were performed in the same way. Then, the accuracy of the test set under the normal condition and the outer race fault condition was predicted.

The predicted results were 0% and 17%, respectively, so it can be concluded that the bearing is neither normal nor outer race fault, a new fault condition was detected.

It can be concluded that if the fault type of the bearing is unknown, after a new training process, the newly detected fault type can also be diagnosed. In this way, the diagnostic ability of the developed model can be evolved during the practical condition monitoring application.

5. Conclusion
In this paper, a diagnostic model is developed by combining the LMD method and the SVDD method for condition monitoring of the submersible pump motor bearings. Vibration signals were acquired from the submersible pump motor bearings, and the vibration signals were processed by the LMD method to obtain the 5th-order PF. The energy entropy of each component was used as the feature vector, and the SVDD method was used to train a hypersphere for fault condition recognition. The results show that the method based on LMD and SVDD can effectively diagnose the known fault condition of submersible pump motor bearing, and can evolve its diagnostic ability in condition monitoring.

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