A Hydraulic Fault Diagnosis Method Based on IMF Entropy Feature Fusion

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Abstract: A feature extraction and fault diagnosis method based on IMF entropy feature fusion was proposed for external vibration signals in five common fault states of hydraulic equipment: normal, leakage, blockage, air cavity and impact. Firstly, all kinds of signals were decomposed by improved EMD based on frequency cutoff, and effective IMF components were screened, then the fusion features of multiple information entropy were extracted, and then the deep learning method of DBN was adopted for feature learning and status recognition. The experimental results show that this method has high recognition accuracy and can effectively realize multi-fault recognition of hydraulic system.

1. Introduction
The working environment of hydraulic equipment is relatively harsh, and it is often exposed to unstable working state such as high load and strong impact. Therefore, the hydraulic system is most prone to faults in the mechanical equipment. In addition, the hydraulic oil used in the hydraulic system is easy to be polluted by environment and impurities inside the equipment. As a result of the oil pollution, the hydraulic system is prone to blockage, air pockets, leakage and other failures, resulting in damage to the operation of mechanical equipment. The oil leakage will also cause serious pollution and damage to the environment. Therefore, the study of the state monitoring and fault diagnosis technology of the hydraulic system is of great significance to extend the service life of equipment, ensuring product quality, preventing major economic losses, avoiding serious safety accidents and environmental pollution. The core of fault diagnosis of hydraulic system is elimination of disturbance, extraction of effective features and fusion recognition.

2. EMD decomposition and IMF component acquisition
Four typical hydraulic faults, including leakage, blockage, air cavity and impact, are set up through the hydraulic test bench. Empirical Mode Decomposition (EMD)[1,2] is an adaptive processing method based on the characteristic scale of signals, which can decompose a complex non-stationary signal into Intrinsic Mode Function (IMF) [3]and a residual trend Function according to its Intrinsic characteristics. The IMF component contains the intrinsic frequency of the signal, reflecting the inherent volatility within the signal. In theory, IMF components should meet the following conditions: 1) the difference between all extreme points and the number of zeros is not greater than 1; 2) the upper
and lower envelope is locally symmetric about the horizontal axis.

Screening flow chart and specific steps are as follows:

1. Determine all local extremum points of the analysis signal, and use cubic spline interpolation method to fit all maximum points to get upper envelope lines, and similarly fit all minimum points to get lower envelope lines.

2. Calculate the mean value of upper and lower envelope lines. The average envelope curve \( m_i(t) \), \( h_i(t) = x(t) - m_i(t) \)

3. Judge whether \( h_i(t) \) meets the two IMF conditions. If yes, then \( h_i(t) \) is the first IMF component. \( c_1(t) = h_1(t) \); If not, Repeat steps (1)–(2) in place of \( x(t) \) with \( h_i(t) \), Until the new \( h_i(t) \) is an IMF, let's call it \( c_1(t) \).

4. Subtract IMF component \( c_1(t) \) from \( x(t) \) and get residual \( r_1(t) \), Replace the analysis signal \( x(t) \) with \( r_1(t) \) and repeat steps (1)–(3) until \( c_1(t) \) is a monotonic function.

5. Finally, signal \( x(t) \) is decomposed into \( n \) IMF components and a residual value. The IMF component \( c_i(t), c_2(t), \cdots, c_n(t) \) represents the components of different frequency bands from high to low, and the residual function \( r_n(t) \) reflects the average trend of signals.

\[
(x(t) = \sum_{i=1}^{n} c_i(t) + r_n(t) \quad (3)
\]

It is proved that some problems are easy to occur when using EMD directly to process signals. For example, mode mixing[4], endpoint effect problem[5]. The problem of false components and overshoot and undershoot makes IMF components doped with many false components, which is not conducive to feature extraction and accurate identification of faults.

3. Improvement of EMD method based on frequency cutoff

This method takes the minimum characteristic frequency of the signal itself as the decomposed cutoff frequency of the EMD method. When the main frequency component of the decomposed IMF component is less than the cutoff frequency, the decomposition ends. The detailed decomposition steps are as follows:

1. carry out spectral analysis on decomposed signal \( s(t) \) to obtain the effective characteristic frequency of the signal, and select the minimum characteristic frequency as the cutoff frequency of decomposition termination condition, denoted as \( f_{sd} \).

2. EMD screen \( s(t) \). For each decomposition, one IMF component \( c_i \) is obtained, and power spectrum analysis is carried out to find the frequency with the maximum amplitude in the frequency component of \( c_i \), which is denoted as \( f_{\text{max}} \).

3. Compare the sizes of \( f_{\text{max}} \) and \( f_{sd} \). If \( f_{\text{max}} \) is greater than \( f_{sd} \), go back to step (2) and continue the decomposition; If \( f_{\text{max}} \) is less than or equal to \( f_{sd} \), the decomposition stops.

4. Finally, a set of IMF components \( c_1, c_2, \cdots, c_n \) and a residual function \( r_n \) are obtained, and there are

\[
s(t) = \sum_{i=1}^{n} c_i + r_n \quad (4)
\]
4. Feature extraction based on IMF entropy feature fusion

Taking a typical cavitation fault signal in the experimental sample as an example, the extraction process of the fusion IMF entropy feature vector is described. Figure 1(a) is the spectrum diagram of typical normal state signals as a reference, Figure 1(b) is the spectrum diagram of cavitation fault signal, and Figure 2 is the decomposition result.

After EMD decomposition, the cavitation fault signal was decomposed to obtain the IMF component of 11th order and the residual of 1st order, among which, the frequency components of IMF2, IMF3, IMF7 and IMF8 components were the most obvious, and some of the components without obvious frequency components were interference components or false components.

For the effective IMF component group \( \{ c_i(t), i = 1, 2, \ldots, 6 \} \) of the selected air-hole fault signal, energy entropy \( E_{W_i} \), singular value entropy \( E_{S_i} \), power spectrum entropy \( E_{S_{P_i}} \), Hilbert spectrum entropy \( E_{H_{i}} \), Hilbert envelope spectrum entropy \( E_{S_{H_i}} \), fuzzy entropy \( E_{F_z} \).

The fusion entropy feature vector \( F = [E_{W_1}, E_{S_1}, E_{S_{P_1}}, E_{H_1}, E_{S_{H_1}}, E_{S_{H_1}}, E_{F_z}] \) of the signal is composed of the \( 8 \times 6 \)-dimensional entropy vectors, and obviously the dimension of \( F \) is 48. The fusion entropy feature vectors of all experimental samples were extracted by similar methods.

5. Classification identification of DBN

The DBN network of 2 hidden layers is selected as the recognition classifier, and the number of hidden layers is 100, so the DBN network structure is \( 48 \times 100 \times 100 \times 5 \). According to the feature vectors of the 500 groups of experimental samples extracted from table 1, a total of 350 groups of 70 feature vectors in each state were selected to form the training set, and the remaining 30 groups of feature vectors in each state were 150 groups to form the test set. After normalization processing, as the input of DBN, the classification recognition result of DBN is obtained through training test, as shown in Figure 3.
Figure 3. DBN classification recognition result of multiple faults in hydraulic system

From the recognition results, 147 of 150 test samples were accurately identified, and the recognition rate reached 98%, which was quite ideal. The air cavity and impact state with independent features are accurately identified. In general, the IMF entropy feature fusion method combined with DBN can effectively realize the intelligent multi-fault identification of hydraulic system.

6. Conclusion

In this paper, vibration signals of the hydraulic system of five states, including normal, leakage, blockage, air cavity and impact, are taken as the research objects. An intelligent hydraulic multi-fault identification method based on the combination of IMF entropy feature fusion and DBN is proposed. Entropy features of IMF components are extracted by using multi-types of information entropy. Through experimental verification, it can accurately realize intelligent multi-fault identification of the hydraulic system and effectively meet the condition monitoring and fault diagnosis requirements of the hydraulic system.

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