Blind Source Separation and Dynamic Fuzzy Neural Network for Fault Diagnosis in Machines

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Abstract. Many assessment and detection methods are used to diagnose faults in machines. High accuracy in fault detection and diagnosis can be achieved by using numerical methods with noise-resistant properties. However, to some extent, noise always exists in measured data on real machines, which affects the identification results, especially in the diagnosis of early-stage faults. In view of this situation, a damage assessment method based on blind source separation and dynamic fuzzy neural network (DFNN) is presented to diagnose the early-stage machinery faults in this paper. In the processing of measurement signals, blind source separation is adopted to reduce noise. Then sensitive features of these faults are obtained by extracting low dimensional manifold characteristics from the signals. The model for fault diagnosis is established based on DFNN. Furthermore, on-line computation is accelerated by means of compressed sensing. Numerical vibration signals of ball screw fault modes are processed on the model for mechanical fault diagnosis and the results are in good agreement with the actual condition even at the early stage of fault development. This detection method is very useful in practice and feasible for early-stage fault diagnosis.

1. Introduction

Mechanical equipment plays a very important role in modern industry and its quality, performance and intelligence reflects the level of production capability and development of a country [1, 2]. However, once mechanical faults occur in machines they may cause financial losses and even heavy casualties. It is often reported that machinery faults bring about catastrophic accidents because of damage of key parts. Therefore, the problems of how to ensure mechanical equipment working safely have been the objective of many researchers. Thus, it is very important to study fault diagnosis in machines for machinery reliability.

According to statistics, unrepairable faults of aircraft reduce by 82% due to fault diagnosis technology (FDT) and fault prognostic technology (FPT). Maintenance manpower required reduces by 20%-40%, and logistics incurred reduces by 50%. As a result, aircraft will work more reliably and maintenance and repairing cost is now half of the amount without FDT and FPT. Furthermore, service life of aircraft can be extended to 8000 hours [3]. Above all, research on diagnosis of early faults not
only is beneficial for cost effective maintenance but also increases overall efficiency of operation and life-span of machinery. It can also reduce risk of loss of human lives due to unexpected mechanical equipment failures.

In the case of a ball screw, during its service, there will be wear, cracking, pitting, gaps with other components and so on. Most of these faults evolve over a long operating time and the fault information can be obtained from the mass of fault data so that these mechanical faults can be diagnosed and predicted correctly. However, installation positions of sensors are often limited by the structure of the machine involved, the working environment and the operating conditions and it is often hard to put sensors in the best locations. Usually, important fault data are buried in the large amount of fault data collected and going through them takes much calculation time. On the other hand, even a large amount of data may still miss some important ones because of the poor sensor locations and operating conditions and hence faults developed at their early stages can go unnoticed. Furthermore, it is very difficult to obtain features of an early fault and potential ones in the early fault stage for the feature information of early-stage faults is very weak. Moreover, noise to signal ratio of early fault is very high. All of these make it very difficult to obtain accurate fault diagnosis from the complex signals of measurement [4, 5].

One of the key problems of diagnosis is how to extract useful information and sensitive fault features from weak fault signals subjected to all kinds of interference.

Nowadays, fault detection methods based on measured vibration data have been widely utilised for assessing common machinery faults and many methods on signal processing and feature extraction have been used in the field of machine fault diagnosis including spectrum analysis, correlation analysis, fine spectral analysis, time series analysis, cepstrum analysis, envelopment analysis, holospectrum, wavelet analysis, principal component analysis, Empirical Mode Decomposition (EMD) and so on [6]. Most of the methods mentioned above are shown to be successful in dealing with faults in rotating machinery.

Most of the afore-mentioned signal processing methods cannot separate a mechanical fault as the vibration source from other vibration sources. As for the mixed signal, especially for an early-stage fault, generated by signal sources whose number is unknown, the vibration wave of each signal source is not clear yet. However, the vibration of a machine part itself includes the most important information of the fault, while other vibration sources are interferences that should be excluded. Exacting the vibration wave of the faulty part itself correctly is the key step to predict the performance of the machine part.

Nowadays, there are few studies in which fault features are obtained successfully from weak fault signals. In view of this difficulty, blind source separation is adopted to separate all the vibration sources apart, and then fault information from vibration signals of key machine parts is extracted. In this article, the method combining blind source separation and neural network is used to diagnose the early-stage faults of machines. The results of simulation show blind source separation is suitable for weak fault signals of a ball screw.

2. Signal processing

A ball screw is one of the key parts of a Numerical Control (NC) machine, and its performance is most associated with machining performance of an NC machine because the accurate positioning of the cutter in relation to the workbench is the main factor for machining accuracy. And the accurate position depends on transmission accuracy of the ball screw. If its performance declines or a fault occurs the positioning accuracy of the cutter will get worse rapidly. In order to improve an NC machine’s reliability, it is very important to reveal early fault mechanism of the ball screw and how much any fault affects machining performance, especially the early-stage ones.

2.1. Signal pretreatment

Most real vibration signals contain zero drift, which needs mean value processing to remove it. On the other hand, mechanical fault diagnosis usually needs multi-dimensional data to allow correlation
among them to be assessed. Concerning multidimensional data, a whitening process is an essential step before machine diagnosis and hence will be used here.

2.1.1. Blind Source Separation

Blind source separation (BSS) is a typical method to separate source signals from several different observations provided by sensors. Due to lack of prior knowledge of the source signals, generally, this method assumes that these source signals are independent.

Many examples show that BSS has been successfully used in many fields, such as biomedicine, telecommunications, and so on. However, BSS methods own its special predominance to process mechanical vibration signal for fault diagnosis especially for weak signals [7].

2.1.2. BSS Introduction

Blind source separation is a signal processing method, by which mixed signals, from more than one vibration sources, are separated from the observation of several mixtures without any knowledge of source signals or mixing process. BSS methods include Principal Component Analysis (PCA), Independent Component Analysis (ICA) and Second-Order Blind Identification (SOBI) [8].

Independent Component Analysis (ICA) is adopted in this article to process early-stage fault vibration signals.

2.1.3. Mathematical mode of BSS

The mathematical mode of liner BSS can be expressed as

\[ x(t) = As(t) + n(t) \]  \hspace{1cm} (1)

where \( x(t) \) is a vector of sensor signals, and \( s(t) \) is an independent signal source vector. \( A \) is an unknown mixing matrix, \( n(t) \) is a white noise signal vector, as shown in Figure 1. Equation (1) shows that any signal vector can be expressed by the liner combination of \( s(t) \) with unknown matrix \( A \).

The formula of observation signals and blind separation sources can be expressed in equation (2),

\[ y(t) = Mx(t) \]  \hspace{1cm} (2)

where \( y(t) \) is a vector separated source signals, and \( M \) is the separation matrix.

BSS separation model can be shown in Figure 1.

![Figure 1. Basic theory figure of BSS](image)

2.1.4. Processing and algorithm of BSS

Independent component analysis (ICA) is one of the most common BSS methods, whose advantages include the versatility and the simplicity in practice. By ICA method, it is easy to separate independent signal sources from mixed signals. However, a main drawback of BSS techniques is the need of several sensors. FastICA method is ICA combined with fixed point algorithm, and FastICA method can effectively evaluate source signals when observation signals are independent from each other. Many researchers focus on FastICA method because of fast calculating speed, excellent separated results and so on. Therefore, FastICA is widely used in fields of image processing, telecommunications, speech processing, underwater acoustics. The calculation flow chart is shown in Figure 2.
Process observation signals

Mean value, whiten processing

Optimize separation matrix

Restrain or not?

Source signals

Figure 2. FastICA flow chart

Figure 3. Source signals

Figure 4. Mixed signals

Figure 5. Results of BSS
In order to test the BSS method, a triangular wave, a sine wave and a pulse in different proportions are added together to get different mixed signals, as shown in Figure 4. Then the mixed signals are separated with FastICA method to recover individual signal sources shown in Figure 5.

It can be seen that by comparing Figure 3 with Figure 5, FastICA can extract source signals from mixed ones successfully. Therefore, FastICA method is used to separate early-stage fault signals from mixed signals in this paper.

3. Diagnosis technique

A diagnosis model plays an important role in machine fault detection. The main idea in conventional approaches is to build a mapping function between signals and faults based on mathematical tools. However, these methods have been found to be difficult in coping with ill-defined and uncertain systems, especially for uncertain vibration sources.

Many neural network methods are focused on solving uncertain systems too. Their main idea is to set up a relationship between inputs and outputs, through training neural networks from inputs and outputs.

Dynamic Fuzzy Neural Network (DFNN) is one of neural networks. This kind of neural network fuses fuzzy theory and neural network theory. In many fields, it is widely used for system prediction, realization, on-line control, communications and pattern recognition. Its computational efficiency and dynamic characteristic are better than those of other typical neural networks and DFNN also show excellent adjustment characteristics by uncertain topology structure. A DFNN system starts with no hidden units and neurons can be recruited or deleted dynamically based on their significance in the system so that not only the system parameters can be adjusted, but also the structure can be self-adapted simultaneously. A simple hierarchical learning approach has been proposed for DFNN by pruning technology and significant neurons are selected so that a parsimonious structure with excellent performance can be achieved [9].

The diagnosis model based on DFNN is very suitable to deal with uncertain systems for its dynamic performance. That means changing inputs and DFNN structure, and the network will expand or contract along with inputs. The dynamic performance of DFNN especially meets the process of detecting mechanical faults. In this article, dynamic mechanical fault diagnosis model is built based on DFNN and BSS to predict mechanical faults.

Using DFNN with a Gaussian function to be activation function, each fuzzy rule represents a neural network node that realizes dynamic response to external conditions.

The topological structure of DFNN is shown in Figure 6, where $x_1$, $x_2$, ..., $x_r$ are inputs, and $y$ is output. $MF_{ij}$ represents the $j$th activation function for the $i$th input. $R_j$ is the $j$th fuzzy rule. $N_j$ as the $j$th normalized node, $w_j$ as weight values, $u$ as the total number of rules.

Just as shown in Figure 5, the first layer is input where each node refers to one input. The second layer is activation function layer where each node means one activation function (a Gaussian function). It can be expressed in equation (3).

$$\mu_{ij}(x_i) = \exp \left[ -\frac{(x_i - c_{ij})^2}{\sigma_j^2} \right]$$  \hspace{1cm} (3)

In (3), $\mu_{ij}$ represents the $j$th activation function for $x_i$, $c_{ij}$ is the $j$th Gaussian function center for $x$, and $\sigma_j$ is the $j$th Gaussian function width for $x_i$. 


The third layer of DFNN topology is T-norm, where every node may become a fuzzy rule and the rule number is the node number. The jth rule for $R_j$ can be expressed as

$$
\phi_j = \exp \left[ - \sum_{i=1}^{\frac{C}{2}} \frac{(X_i - c_{ij})^2}{\sigma_j^2} \right] = \exp \left[ - \frac{\|X - C_j\|^2}{\sigma_j^2} \right], \quad j=1, 2, \cdots, u \quad (4)
$$

where $X = (x_1, x_2, \cdots, x_r) \in \mathbb{R}_r$ is input vector, and $C_j = (c_{1j}, c_{2j}, \cdots, c_{rj}) \in \mathbb{R}_r$ is the jth neural network node centre. In a word, each node is one unit of neural network in the third layer.

The forth layer is a normalized layer, where the node number N is equal to number of fuzzy rule nodes. The jth node $N_j$ is expressed as formula (5).

$$
\phi_j = \frac{\phi_j}{\sum_{k=1}^{u} \phi_k}, \quad j=1, 2, \cdots, u \quad (5)
$$

The fifth layer is the output layer and the output vector is expressed by $y(X)$, which can be calculated from (6).

$$
y(X) = \sum_{k=1}^{u} w_k \cdot \phi_k \quad (6)
$$

where $w_k$ is weighting of the kth rule.

The weight model can be expressed as below

$$
w_k = \alpha_{k0} + \alpha_{k1} x_1 + \cdots + \alpha_{kr} x_r, \quad k=1, 2, \cdots, u
$$

This means [10, 11]
\[ y(x) = \sum_{i=1}^{u} \left[ (\alpha_{i0} + \alpha_{i1} x_1 + \ldots + \alpha_{ir} x_r) \exp\left(-\frac{\|x - C_i\|^2}{\sigma_i^2}\right) \right] \]

The algorithm of diagnose model is shown in Figure 7.

4. Example

4.1. 1 Test for a ball screw

The early-stage fault signals of a ball screw are collected in the performance degradation test, which is shown in Figure 8.
Figure 8. Performance degradation test-bed

1-Bed  2-Motor  3-Rolling bearing  4- Ball slide  5- Image acquisition apparatus  
6- Rolling bearing  7- Ball screw  8- Workbench  9- Magnetic powder brake  

On the test-bed, a ball screw driven by motor is supported by two pieces of rolling bearings. The 
nut of the ball screw pair is connected with the workbench, which is supported by two ball slides. The 
load of the ball screw pair is loaded by a magnetic powder brake. Vibration sensors are located on 
both of the rolling bearing seats and the nut seat to collect vibration signals of the ball screw in the X, 
Y, and Z directions, once for every 30 minutes during acceleration test. Acquisition frequency is 5 
kHz, and acquisition time is 10 seconds. The vibration and noise of ball screw increases in the same 
situation. The nut of ball screw vibrate s violently and when adjust pre-tightening force, the ball screw 
can work normally again, which is the early-stage wearing. The information of sensors is shown in 
table 1.

Table 1. Type and accuracy of sensors

| Type of sensor       | Model  | Purpose                  | Installation position       |
|----------------------|--------|--------------------------|-----------------------------|
| Torque sensor        | AKC-215| Load detection            | Magnetic powder brake       |
| Three acceleration sensors | 14530 | Vibration of nut holder   | Nut holder                  |
| Acceleration sensors | 14200 | Vibration of ball screw   | Fixed end of ball screw     |
| Acceleration sensors | 14200 | Vibration of ball screw   | Support end of ball screw   |

Three sensor signals are collected on the nut and both ends of the ball screw. All signals are 
separated by BSS method and the separated results are shown in Figure 9 to Figure 14. Then, early-
stage fault signals and normal signals are processed to test the fault diagnosis method based on BSS 
and DFNN. Compared with normal vibration signal characteristics, most of differences of same kind 
characteristic of early fault signals are getting larger when use BSS method to deal with vibration data, 
which can be seen from Table 2 to Table 4.
Figure 9. Mixed signals of normal signal

Figure 10. BSS of normal signals

Figure 11. Whitened signals of normal signals

Figure 12. Mixed signals of early fault signals

Figure 13. BSS of early fault signals

Figure 14. Whitened signals of early fault signals

As a result, characteristics of signals separated by BSS can be recognized by DFNN more easily than those of early-stage fault vibration signals. 25 groups of normal data and 25 groups of early-stage fault data are used to train the DFNN model, and another 25 groups of normal data and early-stage fault data are used to test diagnosis accuracy. It is found that the early-stage fault of 25 groups data is recognized by the combined method of DFNN and BSS. However, only 23 early fault groups are
recognized without BSS method, which may be affected by other vibration signals that have nothing to do with ball screw faults.

Table 2 Characteristics of fault signal measured on the ball screw nut

| Mean value | Peak value | Peak factor | Kurtosis factor | Pulse factor | Margin coefficient | Centroid frequency | Frequency variance | Mean–square frequency |
|------------|------------|-------------|----------------|--------------|--------------------|--------------------|-------------------|----------------------|
| 0.08       | 0.36       | 4.84        | 3.65           | 6.19         | 7.35               | 0.98               | 0.46              | 1.42                 |
| 0.09       | 0.42       | 4.46        | 3.25           | 5.63         | 6.66               | 1.07               | 0.67              | 1.81                 |
| 0.11       | 0.67       | 6.14        | 4.40           | 7.99         | 9.60               | 1.31               | 0.59              | 2.30                 |
| ……         | ……         | ……          | ……             | ……           | ……                | ……                | ……               | ……                   |

Table 3 Characteristics of normal signal on the ball screw nut

| Mean value | Peak value | Peak factor | Kurtosis factor | Pulse factor | Margin coefficient | Centroid frequency | Frequency variance | Mean–square frequency |
|------------|------------|-------------|----------------|--------------|--------------------|--------------------|-------------------|----------------------|
| 0.15       | 0.39       | 2.58        | 2.86           | 3.19         | 3.71               | 0.38               | 0.35              | 0.50                 |
| 0.20       | 0.51       | 2.54        | 3.02           | 3.16         | 3.69               | 0.32               | 0.29              | 0.39                 |
| 0.25       | 0.57       | 2.30        | 3.04           | 2.84         | 3.29               | 0.21               | 0.15              | 0.20                 |
| ……         | ……         | ……          | ……             | ……           | ……                | ……                | ……               | ……                   |

Table 4 Characteristics of fault signals on the ball screw nut processed by BSS

| Mean value | Peak value | Peak factor | Kurtosis factor | Pulse factor | Margin coefficient | Centroid frequency | Frequency variance | Mean–square frequency |
|------------|------------|-------------|----------------|--------------|--------------------|--------------------|-------------------|----------------------|
| 1.00       | 2.17       | 3.25        | 3.25           | 3.11         | 3.56               | 0.29               | 0.25              | 0.33                 |
| 1.00       | 2.32       | 3.30        | 3.35           | 3.80         | 3.39               | 0.28               | 0.24              | 0.36                 |
| 1.00       | 2.22       | 3.15        | 4.11           | 3.77         | 3.23               | 0.31               | 0.26              | 0.39                 |
| ……         | ……         | ……          | ……             | ……           | ……                | ……                | ……               | ……                   |

5. Conclusion

The fault diagnosis of machines, especially for early-stage faults, is practised to reduce maintenance cost and risk to people. However, it is difficult to diagnose early-stage faults based on vibration signals in practical environment. In this article BSS and DFNN methods are combined to get rid of interference from other sources and provide a more accurate diagnosis for key parts of machines, such as ball screws. Firstly, Fast ICA, one of BSS methods, is tested and found to be suitable to deal with mixed signals from different vibration signals. Then, the diagnosis model is built based on BSS and DFNN. Through an acceleration test, the vibration signals of the ball screw in both normal state and early-stage fault state are collected. The results of numerical simulation by Matlab show that the diagnosis accuracy with BSS method is higher than that without BSS method.

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