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Aero-engine Fault Diagnosis Based on Multilayer Perceptron BP Neural Network

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Abstract

The performance of the aero-engine is an important safeguard to flying security. We can diagnose and predict the fault type through obtaining and analyzing the vibration signals based on the fault characters of the aero-engine. But, because of the complexity of the aero-engine's structure, the vibration signals acquired from multiple groups of the piezoelectric sensors are often composed of several signal aliasing and other noise jamming, etc. Thus, the vibration signals are in the nonlinear or weak nonlinear state, the traditional blind source separation (BSS) algorithms usually adopt linear hypothesis to approximate equivalent to the nonlinear problems, which leading to the separation results not ideal even wrong. This paper applied a kind of multilayer perceptron BP neural network algorithm to realize the aero-engine vibration signal separation with high precision through the simulation and experiment, which proved this algorithm has a certain practical value to the aero-engine fault diagnosis and prediction.

Keywords*: Aero-engine vibration signal, fault diagnosis, multilayer perceptron, BP neural network*

1. Introduction

Aero turbofan engine is a kind of complex dynamic rotating machinery equipment with high temperature and high load. According to statistics, about 80% of aero-engine fault coming from the rotor parts composed of the main rotor, crankshaft, plate, vane, bearing and gear. Due to its complex structure, high speed, heavy load, easily lead to serious flight accidents, which is pay much more attention. [1, 2] Analyzing the vibration signal and carrying out the fault diagnosis is an important task to the aircraft condition monitoring and fault diagnosis. Due to the complexity of aero-engine structure, the vibration signals are blind mixed by a number of signals and also contain some noise. The fault signals are un-stationary signal usually with noises and other aliasing, *etc.* The purpose of fault diagnosis is to extract the signal characters, and based on the fault signal characteristics, to understand the fault types. For this kind of the nonlinear phenomenon, only using power spectrum, Fourier transform, linear blind source separation and other traditional signal processing method are difficult to fundamentally solve this.[3] In this paper, we used a kind of multilayer perceptron BP neural network algorithm to complete the aero-engine vibration source signals' separation. From the results of simulation experimental, using the multilayer perceptron BP neural network algorithm effectively extract the high/low pressure rotor vibration signal and other noise signal, which proved the accuracy of the multilayer perceptron BP neural network algorithm.

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2. Aero-Engine Fault Feature

Aero-engine vibration problem is very complex, and the causes of vibration may be varied, but it has a trace to be found. In the research of the aero-engine vibration, in order to query the vibration source and troubleshooting the fault, we often classify the fault position as the vibration sources, such as rotor, blade, bearing, gear, *etc.* And among them, the rotor fault is more serious. For the double turbofan aero-engine rotor as example, it includes high pressure rotor, low pressure rotor, their rotation frequency respectively is the fundamental frequency, and when some fault appear, aero-engine will produce vibration signals with all kinds of frequencies, but they are produced as reference point of fundamental frequency, can use the concept of "harmonic" to analyze. Common faults and spectrum characteristics are as follows: [4]

2.1. Rotor Imbalance

Because of the mass eccentricity, rotor imbalance is kind of normal fault. This kind of fault producing may be manufacturing errors, assembly errors or uneven material, so, the initial state of equilibrium is not meet. In addition, because the rotor is running for a long time, dirt corrosion wear can shape the gradually imbalances, all these can lead to the occurrence of rotor imbalance. This kind of phenomenon producing vibrations has mainly the characteristics: (1) the time domain waveform similar to sine wave of vibration, vibration energy concentrates on the fundamental frequency; (2) vibration character is more sensitive to the changes of rotate speed.

2.2. Rotor Axis Center Line Deviation

Rotor often occur misalignment in the process of assembling deviation. For double rotor aero-engine, the concentric coordinates of high pressure rotor and low pressure rotor are supported by the intermediate bearing. Due to the disalignment of the adjacent bearing, axis center line occur deflection. Aero-engine rotor misalignment on the spectrum diagram can be observed double frequency and other higher order frequency phenomena.

2.3. Rotor rubbing fault

During the aero-engine running process, in order to reduce reveal of the air, fuel gas and lubricating oil, many positions of aero-engine are fixed several oil throwers. Because of the elements of imbalance and misalignment, the radial direction rubbing will produce the vibration fault between the rotor and static component. In the early process, the rubbing phenomenon only occurs in the part of the circumference, the dynamic stiffness periodically alternating-changing contact out again with impact character. This unstable contact pressure makes friction has obvious nonlinear. And in the spectrogram, it expresses high order harmonic component nf (n=1, 2, 3, …) frequency composition nf (n=1/2, 1/3, 1/4, …). When the rubbing becomes serious and expands to the entire circumference, it will spare additional supporting rotor, thus, high frequency vibration will reduce gradually, the rubbing conditions of fundamental frequency will be prominent, and trigger multiple frequency division.

2.4. Blade Vibration Fault

Under the effect of aerodynamic force, the high frequency vibration from the fan, compressor, turbine blades transmits to the power brake through the brake disc. The main reason of the blade vibration is of the air is hindered by the next level of guide vane's leading edge and lose the uniformity, which leading to the aerodynamic load of the blade on the front level. The spectrum is shown as: if the rotor speed is n, the numbers of some level blade is $\mathbf{z}$, the vibration frequency $f = z/60$. Usually this kind of vibration occurs at

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the long blade on the front of blade or the first, secondary compressor impeller. For the turbofan engine, the blade vibrations' another important reason is for the chatter phenomenon because of the air flow.

2.5. Bearing Vibration Fault

About 30% of aero-engine fault is produced from bearings, which is severity. Especially the aero-engine bearing usually works under the overload, high speed and complex work environment, which prone to wear and fatigue spalling, ablation, agglutination, corrosion and other failure. Because when the roller generated periodic impact through the point of fault, on the spectrum diagram is shown as the gradual loss of infinite harmonic series, and expands into discrete spectrum.

2.6. Gear Drive Fault

Aero-engine main rotor drives the fuel pump, hydraulic pump, starter generator work through gear in the accessory casing. When gear in working, only one or two teeth alternating-meshing, the tooth root generating pulse cyclic stress, coupled with the dividing error of the gear, the tooth profile error, and the influence of technological parameters, as well as the working tooth surface wear, corrosion fatigue spalling, agglutination in the effect of factors, etc, all these will cause the vibration of the gear. Although the gear fault is varied, most of the fault is related to the meshing frequency. The meshing stiffness change once when one tooth meshes from present position to another. So, the gear rotates around once, the change rule accurately repeat once. In the spectrum diagram, because of the relationship of the teeth number of z, the meshing frequency usually appears in a high frequency band. When the gear in fault, the spectrum peak of vibration signal will appear in the near of some evenly spaced side band. The interval of edge band reflects the information of the fault source, and the changing of amplitude reflects the extent of the fault.

3. Multilayer Perceptron BP Neural Network algorithm

3.1. Nonlinear BSS Model

The BSS algorithms normally are assumed to be linear aliasing, however, in practice, the aliasing model is more nonlinear or weak nonlinear, linear hypothesis is only a kind of nonlinear approximation, and this kind of situation will lead to separation results not ideal and even failure. Especially for aero-engine vibration signal blind source separation, due to the vibration signal is produced by the rotor and bearing, etc, and outward radiation through the brake, the nonlinear characteristics is outstanding, with the help of traditional linear BSS algorithm can't achieve the accuracy of the vibration signal separation, especially in the case of noises, the noise suppression effect is poorer, therefore, we need to effectively seek a kind of nonlinear separation algorithm.

At present, the BSS algorithm to nonlinear system mainly includes nonlinear maximum entropy [5] and nonlinear minimum mutual information [6]. But, they are only suitable to this kind of weak nonlinear (post-nonlinear).To the aero-engine vibration signal in strong nonlinear, traditional algorithm all have the characteristics of poor robustness, therefore, the signal separation effect is poorer. The nonlinear aliasing BSS can be summed up in the following models:

$$\mathbf{x}(t) = f(\mathbf{s}(t)) \tag{1}$$

Among formula (1), $s(t)=[s_1(t), s_2(t), ..., s_m(t)]^T$, which is m groups of independent source, Assuming that each source signal is zero mean, any order of matrix exist, and the source signals only have one Gaussian signal [5]. $f(\cdot)$ is unknown and reversible

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nonlinear function, which can be a very complex nonlinear function and can't even given analytical form, $x(t)=[x_1(t), x_2(t), ..., x_n(t)\ ]^T$ is n groups of observation signals, it is a output vector of the nonlinear aliasing model. Here, the goal of the nonlinear blind separation problem is to identify nonlinear function $f(\cdot)$ through the observation signal $\boldsymbol{x}(t)$, namely by seeking an appropriate nonlinear function to restore the source signal $\boldsymbol{s}(t)$, that is:

$$\mathbf{s}(t) \approx \mathbf{y}(t) = g(\mathbf{x}(t)) \tag{2}$$

Among the formula (2), $\boldsymbol{y}(t)$ is called the estimated vector of $\boldsymbol{s}(t)$. The nonlinear BSS model is shown as Figure 1.

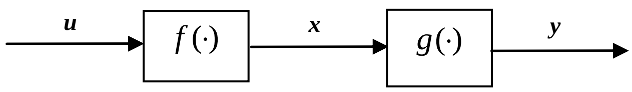

Figure 1. The Nonlinear BSS Model

3.2 BP Neural Network

3.2.1. Backward Propagation Neural Network Based on the Multilayer Perceptron

We estimate the input each component probability density, and make the amount of mutual information as the objective function, to design the BP neural network blind source separation algorithm. We adopt **F** module and $\boldsymbol{\psi}$ module to make up of a specific structure to the nonlinear network, and complete the source signal separation and estimation. Algorithm design model is shown as Figure 2.

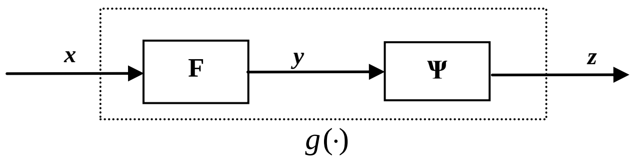

Figure 2. Algorithm Model

In Figure 2, $\boldsymbol{x}$ is n numbers of observation vector signal, usually, assuming that $m=n$, A is nonlinear blind mixed system model. F is separation model, which is a nonlinear function in the nonlinear mixed separation, $\boldsymbol{y}$ is a separation vector, $\boldsymbol{\Psi}$ is cumulative probability density function for each separate vector and z is the corresponding cumulative probability function.

$\boldsymbol{F}$ module realizes the separation signal as independent as possible, which can realize the signal separation by the means of minimum mutual information $I(y)$. By the information maximization (Infomax) algorithm, the maximize network output entropy $H(\boldsymbol{z})$ will result in the minimum mutual information $\boldsymbol{I}(y)$ of the separation vector y has minimum. Need to prove that $H(\boldsymbol{z})$ will also result in each module $\boldsymbol{\psi}$ approximate with the cumulative probability function of the y_i as soon as possible. Due to the minimum mutual information can be converted to the output entropy of the maximize network, maximum output entropy will tend to make each $\boldsymbol{z_i}$ as the uniform distribution on the interval [0, 1]. By using the output entropy criterion of the maximize network, the output nonlinear characteristics are similar to the desired cumulative probability function, there are the maximum entropy uniformly distribute on the finite interval, and the expression formula of the entropy can be written as formula (6).

$$H(\mathbf{z}) = \sum_i H(\mathbf{z}_i) - \mathbf{I}(\mathbf{z}) = \sum_i H(\mathbf{z}_i) - \mathbf{I}(\mathbf{y}) \tag{6}$$

Assume that the distribution of $\boldsymbol{y}_i$ remains the same, because each of the component

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among $\boldsymbol{z}$ depends on a series of separation parameters in front module, then, $H(\boldsymbol{z})$ will make every edge entropy $H(\mathbf{z}_i)$ maximization. Assume that ψ_i is an increasing function in the interval [0, 1], due to there are the maximum entropy among uniform distributing on the finite interval. Maximizing $H(\mathbf{z}_i)$ will allow $\mathbf{z}_i$ close to the uniform distribution on the interval [0, 1], which will also make the ψ_i close to $\boldsymbol{y}_i$ expected cumulative probability function. In this way, we only need $H(\mathbf{z})$ to solve the optimization problem of the F module and M of module.

In this paper, we design ψ function with the aid of multilayer perceptron. First important problem is that how to constraint the multilayer perceptron function to make it as much as possible close to $\boldsymbol{y}_i$ expected cumulative probability function; Second, how to training the whole system by $H(\mathbf{z})$.[7]

3.2.2. Multilayer Perceptron Function Ψ Constraints

Implementation of multilayer perceptron ψ function must be constrained, so that in the interval [0,1] an increasing function can be got. First of all, each unit of the multi-layer perceptron must be the monotonically increasing nonlinear function. Second, all of the weight value must be nonnegative. As a result, this algorithm adopts increased Sigmoid function of hidden layer units with values in the interval [0,1] to achieve this constraint, and uses linear output unit. Through standardizing the weight vector of the Euclidean norm, each unit of output can be changed into $1/h$, h refers to the hidden layer unit number that connected to the output. If using the nonnegative weights throughout the entire network, a reduction function in the interval [0,1] will be got. But, in the actual network training, if the algorithm appears a nonnegative weight, after a few iterations, the value often return to positive.

In practical training, the hidden layer unit used Sigmoid function in the interval [-1,1], so, the resulting value of ψ function will lie in the interval [-1,1]. The estimation of the cumulative probability function will be measured in this interval, which can still complete the minimum mutual information. In this model, the Sigmoid function has the advantages of speed up the training.

3.2.3. Training of the Maximum Entropy

We adopt the optimization algorithm based on gradient by using the same standard of Infomax method and carrying out the training with the aid of maximum entropy. The output entropy can be written as the following formula (7):

$$H(\mathbf{z}) = H(\mathbf{o}) + < log\,|\,det\mathbf{J}\,| > \tag{7}$$

Among the formula (7), $\mathbf{J} = \partial\mathbf{z} / \partial\mathbf{o}$, $\mathbf{J}$ is Jacobi determinant of network transformation, Angle brackets express mathematical expectation, $H(\mathbf{o})$ expresses the entropy of the observation vector, $H(\mathbf{o})$ do not rely on separation network parameters, so, in the process of optimization, it don't be considered and only the second item of the formula (7) need to be considered. The objective function can be represented as formula (8).

$$< log\,|\,det\mathbf{J}\,| > \approx \frac{1}{K}\sum_{k=1}^{K} log\,|\det\mathbf{J}^k\,| \tag{8}$$

Among the formula (8), $\boldsymbol{J}^k$ expresses the J value of K^{th} times training. K is the number of training patterns. $<log|det\mathbf{J}|>$is a function of Jacobi determinant $\boldsymbol{J}^k$. Due to directly computer the gradient of corresponding parameter is very difficult, this paper is based on the theory of neural network backward propagation method, using the spread method to calculate the output function corresponds to the weight of the gradient is relatively simple and efficient [8]. In order to effectively calculate the gradient of the output function corresponding to the weight, first, we design a network to calculate the $\boldsymbol{J}^k$, the network structure ***F*** modules include the hidden layer ***S*** function units, multiple linear output units, and the input and output unit is not directly connected. The same as $\boldsymbol{\psi}$ modules with similar structure, which including hidden layer ***S*** function unit, a single linear output unit, input/output also is not directly connected between units. After then, we adopt back-propagating method to traverse the entire network. The detailed network structure is shown as Figure 3.

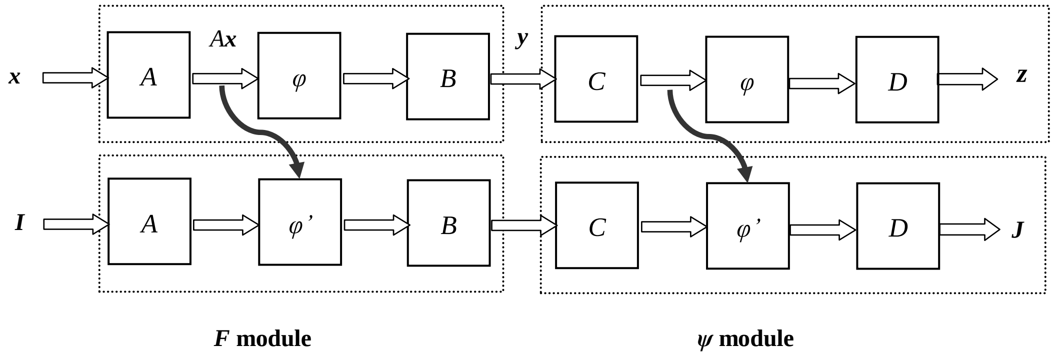

Figure 3. Multilayer Perceptron Network Structure

In Figure 3, *A* expresses the weight matrix of the ***F*** module hidden layer, the input signal output vector *Ax* after *A*. φ expresses the hidden layer ***S*** function applied to each element of $A\boldsymbol{x}$, its output is hidden layer units incentives of ***F*** module, and *B* expresses weight matrix of ***F*** module output unit, the output is $\boldsymbol{y}$. $\boldsymbol{\psi}$ module and ***F*** module have the similar structure. By C, φ and D, we put together various $\boldsymbol{\psi}_i$ units to form multilayer perceptron networks including the single hidden layer and the linear output units.

When carrying out Jacobi determinant computation for the multi-layer perceptron network structure, the input signal is an $n\times n$ unit matrix $\boldsymbol{I}$, where n is equal to the number of elements of x. φ' of the ***F*** module produces a diagonal matrix φ'_l. Matrix elements are derivative corresponding unit *S* function of φ module. A, B, C and D modules respectively is the weighting matrix. φ' of the $\boldsymbol{\psi}$ module also produces a diagonal matrix φ'_r, matrix element is the signal's derivative of S function going through the φ module in the network. To compute the derivative of S function, φ' of the $\boldsymbol{\psi}$ modules need to use the corresponding input of hidden layer units as incentives received from the network, as shown in Figure 5 the arrow drawn by the bold solid lines. After the deduction, the Jacobi determinant of the output expression formula is: [9][10]

$$J = D\phi'_r CB\phi'_l A \tag{8}$$

4. Algorithm Simulation

Some aero-engine vibration signals were acquired through the sensors planted on the brake, and the vibration signal mixed by the high pressure rotor, low pressure rotor and noise signal aliasing, *etc.* Assuming that the rotating speed of the high pressure and low pressure we can know, so, the rotor rotational frequency of high and low pressure can be computed, which are the fundamental frequency. We simulate a group of fault signal which is caused by the imbalance of the high pressure and low pressure. From the signals' characters we can find the fundamental frequency of the vibration signal is outstanding, accompanied by the multiple frequency signal, multiple signal peak value is less than the base frequency peak, blind mixed signal and noise signal interference signal, according to the characteristics of the aircraft engine fault assumption aircraft engine high pressure and low pressure rotor are caused by unbalanced vibration machine brake surface, the fault characteristics, its vibration characteristics for the fundamental frequency is outstanding, accompanied by the multiple frequency signal, and the peak

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value of the multiple frequency signal is less than the peak value of the fundamental frequency signal. Through the Matlab simulation tools, we simulate two groups of aero-engine vibration signal and one group of noise signal respectively is: (1) the fundamental frequency of the high pressure rotor and double frequency harmonic signal, (2) the low double frequency of the pressure rotor and other multiple frequency harmonic signals, (3) the noise aliasing signal, *etc*. The source signals by take 1000 numbers of sampling point are shown as Figure 4.

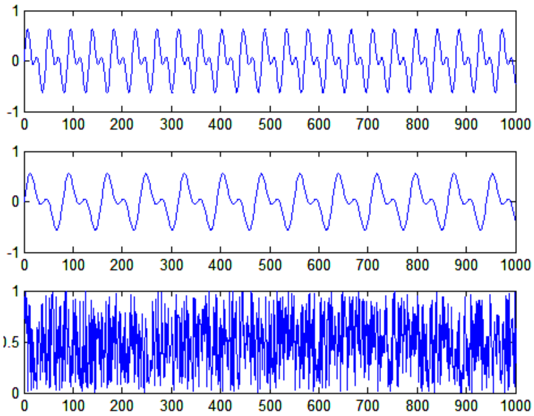

Figure 4. The Waveform Diagram of the Source Signal

Mixing the three kinds of signal blind mixed at the characteristics of the actual aero-engine vibration signal simulation, we set a random mixing matrix $\boldsymbol{A}$:

$$A = \begin{bmatrix} 0.3447 & 0.3213 & 0.9564 \\ 0.3465 & 0.9154 & 0.2382 \\ 0.1465 & 0.2154 & 0.9382 \end{bmatrix}$$

The blind mixing vibration signal by cutting out 1000 sampling points, the time domain waveform is shown as Figure 5.

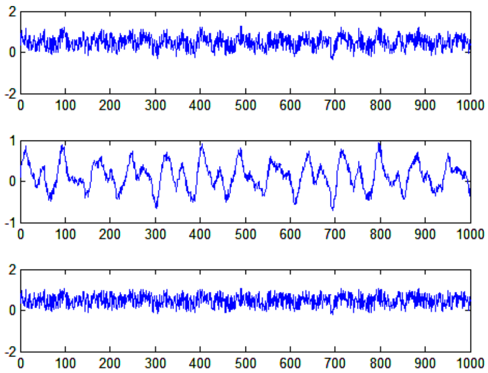

Figure 5. Waveform Diagram of Blind Mixing Vibration Signal

From the blind mixing waveform Figure 5 we can see the spectrum diagram can't distinguish the high pressure rotor, low pressure rotor fundamental frequency and their multiple frequency signals. The separation result used by the multilayer perception BP neural network algorithm is shown as Figure 6.

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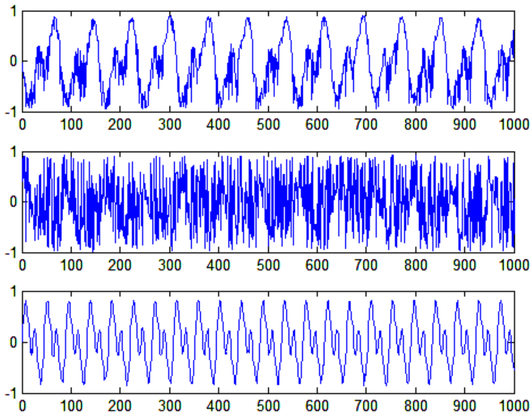

Figure 6. The Separation Signal Waveform Diagram

From the Figure 6 we can't see the signal characters from the separation signal time domain waveform. So, we carry out the waveform spectral analysis to the separation signal. The spectral analysis result is shown as Figure 7.

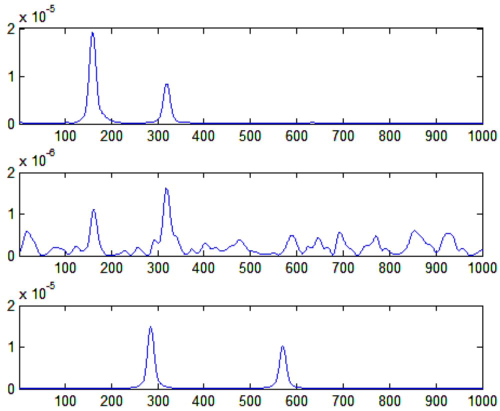

Figure 7. Spectrogram of the Separation Signal

From Figure 7, after using the neural network algorithm we can see, Figure 7 (a) is the low pressure rotor and double frequency signal, Figure 7 (c) is the fundamental frequency signal and double frequency signal of the high pressure rotor, Figure 7 (b) is the noise aliasing signal, *etc*. From Figure 7 we can accurately separate the high pressure rotor, low pressure rotor and noise signal, *etc*. The fundamental frequency value and double frequency of the low pressure rotor respectively is 159.6Hz and 319.5Hz. The fundamental frequency signal and double frequency signal of the high pressure rotor respectively is 285Hz and 570.1Hz. Thus, we can extract the useful signal from the blind mixed signals with noise signal based on the multilayer perceprotn BP neural network algorithm.

5. Aero-Engine Fault Diagnosis Experiment

In order to further verify the role of the algorithm in the aero-engine fault diagnosis, we carry out the blind separation practice through acquiring the vibration source signal of five groups of experimental sensors and take 4096 sampling points. The five groups of observation signal is shown as Figure 8.

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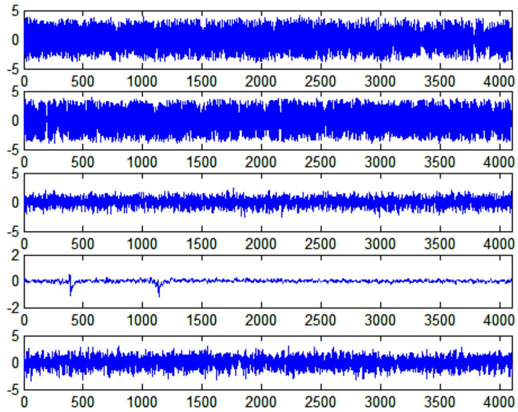

Figure 8. Waveform Diagram of Actual Aero-Engine Vibration Signal

We carry out the separation to the actual waveform by the multilayer perceptron BP neural network algorithm, and divide the mixed signal into three groups of signal, which respectively is high press rotor, low press rotor, and other noise signal, *etc*. And the separation result is shown as Figure 9.

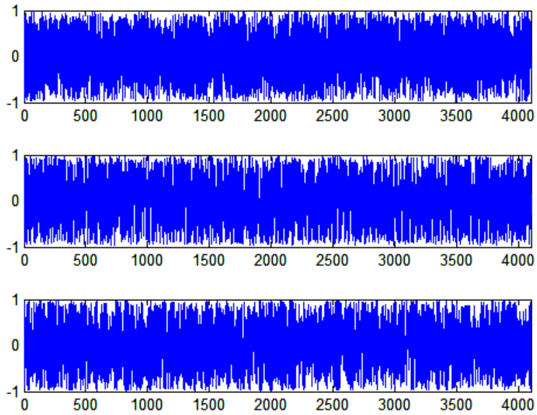

Figure 9. Waveform Diagram of the Separation Signal

We carry out the spectral analysis to the separation signal, and the spectrogram is shown as Figure 10.

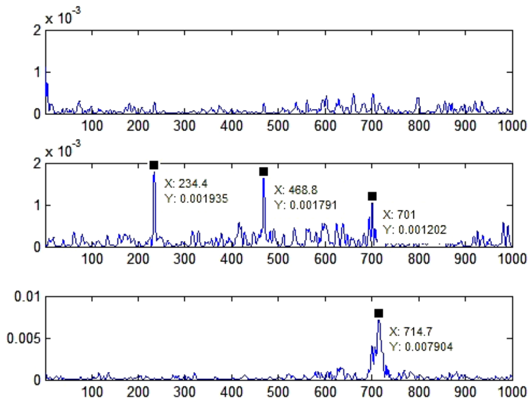

Figure 10. Spectrogram of the Aero-Engine Separation Signal

From the Spectrogram of the aero-engine separation signal we can see, the signal mainly includes the fundamental frequency (714.7Hz) of the high pressure rotor of

Figure 10 (a). Figure 10 (b) includes the fundamental frequency (234.4Hz), double frequency (468.8Hz) and four times frequency signal (701Hz) of the low-pressure rotor. From the Figure 10 (b) we can judge the vibration is caused by the rubbing between the low-pressure rotor and the stator. But the separation signal of the high pressure rotor did not appear the multiple frequency components. We can know that the high pressure rotor is at the early stage of rubbing fault state. So, this algorithm can better separate the blind mixed vibration signals, and the spectrum analysis can be used to judge the fault characteristics of the aero-engine fault.

6. Conclusion

In this paper, we introduced a kind of multilayer perceptron BP neural network algorithm to realize the blind source separation of the aero-engine vibration signal with noise by the Matlab simulation tool. Based on the multilayer percettron BP neural network algorithm, the aero-engine fault vibration signal with noise can be accurately separate into the high pressure rotor, low pressure rotor fundamental frequency and double frequency signal, and other noise interference signal. But, during the process of the actual aero-engine vibration signal blind source separation practices, how to accurately obtain the number of the aero-engine vibration source and when the signal that sensors acquired is underdetermined. In addition, how to effectively obtain the entire source signal is the key and difficult point for future research.

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