Feature extraction of transient signal based on double layer auditory nerve oscillator network

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Abstract. Rolling bearing plays an important role in rotary machines. In rotating machine fault diagnosis, calculating the characteristic frequency of the signal is a useful method. Human auditory nerve system can integrate the binaural information through the mechanism of neurons oscillation and delivery of oscillation. In view of the aspects mentioned above, to simulate the operating mechanism of human binaural auditory system, a double layer auditory nerve oscillator network (DLNON) model whose inputs are two features of the signal, is proposed for features extraction and faults diagnosis. It includes the basement membrane, inner hair cells, feature extraction, oscillation network 1(ON1), oscillation network 2(ON2) and oscillation network 3(ON3). After that, calculating the oscillation period of each oscillating element in the second layer network and according to the size of the oscillation period we can determine whether there is a transient impact component. The performance of DLNON model is evaluated by experiments. The results show that the model can effectively extract fault features, and distinguish fault types.

1. Introduction
Rolling element bearings are widely used in rotating machinery system. Bearing faults may cause complex vibration of the entire machinery system. So, it’s important to diagnose the fault of the rolling bearing. The fault bearing will bring about the impact component which will be caused the difference of the characteristics of frequency. Therefore, for the diagnosis of fault rolling bearing, it is a very effective method to extract the impact component of bearing vibration signal [1].

Neuron is the smallest unit of auditory nerve center, and almost all auditory functions are realized by means of it. The neurons will emerge periodic oscillation, wherein membrane potential of neurons shows a periodic fluctuation, when human auditory nerve center integrates information. Each neuron oscillatory period is directly relevant to frequency and intensity of stimuli and frequency response features of a neuron [2]. The operation mechanism of auditory nerve center has attracted the interests of scholars to propose a number of calculation models on auditory nerve oscillator network. For example, Wang-Brown and others applied two-layer neural network to blind source separation of single-channel mixed speech signal [3]. Hoshino proposed a method of picture recognition based on neural oscillator network [4]. Liu used another double layer neural oscillator network model to segment image [5]. Moreover, Li employed a single layer auditory nerve network model to process vibration signal and realized multi time-frequency features integration in the light of the oscillatory period of neuron [6]. In this paper, according to the operation mechanism of binaural auditory nerve
system, a DLNON model is proposed for feature extraction from vibration signal, and introduced into bearing faults diagnosis.

The DLNON model in this paper that simulates binaural auditory nerve system is essentially a signal processing method, which is different from artificial neural networks such as the BP Neural Network and Deep Neural Network etc [7]. The parameters of network can be set artificially without training samples and data samples are fewer. Those are capable of simplifying the calculation and structure of model.

2. Model overview
Setting the input signal to \( x(t) \). The model established in this paper is shown in figure 1, which is composed of basement membrane, inner hair cells, spectral envelope, ON1, ON2 and ON3. After the signal passes through the ON1 and ON2, different characteristics are extracted. The ON3 integrates the results of the first layer and further highlights the characteristic of the signal.

![Image of the model](image)

**Figure 1.** Double layer neural oscillation network model.

3. Auditory neural oscillation network

3.1. Basement membrane and inner hair cells
In this paper, the filter bank is selected to simulate the frequency decomposition of the basement membrane. Assuming that the signal is band-pass filtered by four filters and the vibration signal is \( x(t) \). The band-pass filtering of the signal is:

\[
y(4,t) = x(t) * h(4,t)
\]

Where, \( y(4,t) \) denotes a base film output, \( * \) denotes a time-domain convolution. The expression of the fourth filter is:

\[
h(4,t) = B^n e^{-\alpha b} \cos(2\pi f_c t)
\]

\( f_c \) is the centre frequency in the fourth filter; Parameter \( B \) determines the filter bandwidth, which can be calculated by the following formula:

\[
B = 1.019 \times B_r (f_c) = 1.019 \times (24.7 + 0.0108 f_c)
\]

Where, \( B_r \) represents the equivalent rectangular bandwidth of the filter.

3.2. Acoustic neural oscillation network model
The structure of the DLNON is shown in figure 2. The first layer uses two single-layer neural networks to deal with the same signal and extract different signal features. The second layer uses a single layer neural network to merge the synchronous oscillation results of the first layer, and further extracts the characteristics of the signal. Each network can be divided into two parts, one part can be seen as a \( I \times J \) plane, where the abscissa is time frames and the ordinate represents frequency. Each time frame contains \( N \) points, called as time-frequency unit \( U_{ij} \), and each node is an oscillation element
$O_y$. The other part is the global inhibitory element, which has the same inhibitory effect on all oscillation elements [8].

![Diagram of oscillator network]

**Figure 2.** The structure of oscillator network.

Oscillatory differential equation of each neuron is shown as following:

$$\begin{align*}
\frac{dx_y}{dt} &= 3x_y - x^2_y + 2 - y_y + M_y + S_y - \lambda \Delta \\
\frac{dy_y}{dt} &= \varepsilon \left( \mu \left[ 1 + \tan \left( \frac{x_y}{\alpha} \right) \right] - y_y \right)
\end{align*}$$

(4)

Where, $x_y$, $y_y$, $S_y$ are function of time, and $i, j \in (I, J)$, $x_y$ denotes incentive variable; $y_y$ represents inhibition variables; $M_y$ is the external input of the oscillator, and $S_y$ denotes coupling term of oscillation that reflects the effect between connected neurons; $\lambda \Delta$ is the effect of non-adjacent neurons on $O_y$, and it's determined by the distance. When calculating the oscillating element, the $\lambda$ values of oscillating elements with distances from 3, 4 and 5 are 0.3, 0.2 and 0.1, respectively. $\varepsilon, \mu, \alpha$ are parameters.

3.3. First layer oscillating network

3.3.1. External input. The two networks in the first layer respectively extract different features of the signal. The connection weights between the neurons and the external excitation have great influence on the characteristics of the signal. Therefore, in the first layer, they need to be different [9].

When the impact signal appears, the amplitude of the vibration signal spectrum will suddenly increase, and the kurtosis will deviate from the normal constant value [10]. So in the actual calculation, we can determine whether the impact will occur by extracting the amplitude of frequency spectrum and kurtosis characteristics. The spectral amplitude of each point in the oscillatory element is calculated and denoted as $Y(i, j)$, and the maximum amplitude in $Y(i, j)$ is recorded as $y_{max}$.

In ON1, the kurtosis in the time frequency unit $U_y$ is obtained, and recorded as $q_d(i, j)$. The $M_y$ is determined by it:

$$M_y = \begin{cases} 
10 & q_d(i, j) > \theta_{M1} \\
1 & \theta_{M2} \leq q_d(i, j) \leq \theta_{M1} \\
0 & q_d(i, j) < \theta_{M2}
\end{cases}$$

(5)

Where, $\theta_{M1}$ and $\theta_{M2}$ are threshold, according to the auditory characteristics of the human ear, in generally $\theta_{M1} = 6$ and $\theta_{M2} = 0.5\theta_{M1}$.

The ON2 determine $M_y$ according to the $Y(i, j)$. 

3
Where, $\theta_{n1}$ and $\theta_{n2}$ are threshold value. The proper values of $\theta_{n1}$ and $\theta_{n2}$ are selected in accordance with the rule that the values of external input uniformly cover all the amplitude range and reflect real distribution of amplitude, so $\theta_{n1} = 0.5y_{max}$, $\theta_{n2} = 0.1y_{max}$.

3.3.2. Coupling term. In a neural oscillation network, interaction between oscillating elements by coupling terms, and the calculation method of the coupling term $S_y$ is:

$$S_y = S_y^n + S_y^w$$

(7)

$S_y^n$ is affected by the upper, lower, left and right four adjacent position oscillation element, so its expression is:

$$S_y^n = \sum_{uv(i,j)} W_{uv}^n H(x_u - \theta_1) - W_H(x - \theta_0)$$

Where, $(u,v) \in \{(i-1,j),(i+1,j),(i,j-1),(i,j+1)\}$, $\theta_1$ and $\theta_0$ are respective thresholds; $H(x)$ is a Heaviside unit step function; $W_{uv}^n$ is the connection weight between adjacent oscillation elements of $O_y$.

In order to extract the impact component of the signal more efficiently, the connection weights of the two networks of the first layer on the time axis are the same, which is the comparison of the maximum amplitude in adjacent time-frequency units.

$$W_{(i,j)}^y = \begin{cases} 1 & Y(i,j) > Y(i,j-1), Y(i,j) > Y(i,j+1) \\ 0 & \text{else} \end{cases}$$

(9)

When an impulse signal presents, the frequency spectrum on the adjacent channel is similar[11], and the position where the maximum value of the frequency spectrum of the oscillating element on the same time axis appears similarly[12]. The similarity of the signal after passing through the filter of adjacent channels is noted as $H_y(i,j)$, and the similarity of the envelope spectrum in the adjacent channels is $H_z(i,j)$. The position of the maximum value of each oscillatory element spectrum is $L_z(i,j)$. The ON1 regards the product of two correlation coefficient as the connection weight; The ON2 regards the difference of the location where the maximum value of the spectrum at the adjacent channel as the connection weight value.

In the direction of the frequency axis, the connection weights of the ON1 are as follows:

$$W_{(i,j)}^y = \begin{cases} 1 & H_y(i,j) \times H_z(i,j) > \varsigma, H_y(i-1,j) \times H_z(i-1,j) > \varsigma \\ 0 & \text{else} \end{cases}$$

(10)

In the direction of the frequency axis, the connection weights of the ON2 are as follows:

$$W_{(i,j)}^y = \begin{cases} 1 & |L_z(i+1,j) - L_z(i,j)| > 5, |L_z(i-1,j) - L_z(i,j)| > 5, Y(i,j) > \theta_{n1} \\ 0 & \text{else} \end{cases}$$

(11)

$W_z$ is the connection weight between the global inhibitor $z$ and each other oscillation element, and the change rule of the global inhibitor $z$ is:

$$\frac{dz}{dt} = \sigma_z - z$$

(12)

If $x_y < \theta_0$, for all the neurons, $\sigma_z = 0$, otherwise $\sigma_z = 1$.

3.4. Second layer oscillation network
Assuming the oscillation periods of each oscillating element in the ON1 and ON2 are $T_z(i,j), T_z(i,j)$. The external excitation of the ON3 is determined by the oscillation periods $T_z(i,j)$. 

$$T_z(i,j)$$


\[
M_y = \begin{cases}
10 & T_i(i, j) > 0, T_j(i, j) > 0, T_z(i, j) = T_z(i, j) \\
1 & T_i(i, j) > 0, T_z(i, j) > 0 \\
0 & \text{else}
\end{cases}
\] 

(13)

In terms of kurtosis, the amplitude of the oscillating element expresses the impact component of the signal more directly, so comparing the amplitude of two adjacent oscillating elements is still used in the direction of the time axis, which is same as formula (9).

As the same reason, in the direction of the frequency axis, we choose the difference in the location of the maximum value of the adjacent channel as the connection weight, like formula (10).

In addition, whether the signalling constellation in the time-frequency unit \(U_{ij}\) which is indicated by \(v_{ij}S\) is a power frequency component or a higher harmonic of the power frequency; For a complex frequency structure signal, it is characterized that whether signal component in \(U_{ij}\) is the main component of the signal [13]. The signal components of the first and second layer oscillating networks are the same, so the \(s'_v\) of the network is same.

\[
s'_v = \begin{cases}
4 & Y(i, j) > 0.9y_{\max} \\
0 & \text{else}
\end{cases}
\] 

(14)

4. Experimental test

Calculating the oscillation period of each oscillating element in the second layer network. The reciprocal of the oscillation period is frequency [14]. So, calculating the period of the oscillation can determine whether there is a transient impulse response signal. After the signal passes through the filter, the result of each oscillation element is multiplied by its corresponding frequency, then, the result of the frequency channel is summed up, and the final feature extraction is obtained [15].

Experimental data provided by Case Western Reserve University is used to examine the performance of the DLNON model. An acceleration sensor is respectively arranged above the bearing seat at the fan end and the drive end (SKF deep-groove ball bearings: 6203-2RS JEM and 6205-2RS JEM, respectively) of the motor to collect vibration acceleration signals of the fault bearing, and the sampling frequency is 12kHz. Selecting the signals of the drive end. Failure of the two sets of signals occurs in the inner and outer ring of the bearing at speeds of 1797r/min. The bearing fault signal is processed by the model of DLNON. The time for the human auditory nerve system to process signals is 20ms, so the length of the fault signal is 20000. The number of channels in \(\text{Gammatone}\) filter is 100. The impact signal of the bearing takes a very short time, in order to extract the impact signal better, within each channel, the time frame length is 500 and the frame overlap 200 points, so \(I \times J = 66 \times 100\).

\(\varepsilon, \mu, \alpha\) respectively as 0.04, 9, 0.1; \(\theta, \theta\) respectively as 0 and 0.5. \(\varsigma\) is the threshold, \(\varsigma = 0.8\). In the following figures, figure (a) and (b) respectively show the inner and the outer ring of the bearing.

Figures 3 and 4 respectively show the original waveform and traditional Hilbert envelope spectrum of the signal. In the figures 3, the impact of the fault signal is not obvious and there is lots of noise. In the figures 4, it’s difficult for us to find the characteristic frequency.
After the signal passes through the filter, signal feature extraction and oscillation network, the projection of the signals period is shown in figures 5. The signals are mainly concentrated in the high frequency part, and the red points in the pictures represent the periods of the impulse response signal. Thus, we initially know where the impact component appears.

The final feature extractions are shown in figures 6, it’s clear that the signal has an impact component and the impact component is more strengthened than the original waveforms which are shown in the figures 3. Therefore it can be judged that this rolling bearing has failed. The spectrum diagrams of extracted signal are shown in figures 7. Comparing figures 4 and figures 7, we can find...
that the interference in the frequency spectrum increases, but it doesn't have much impact on the result. Apparently, the characteristic frequency of the transient signal is more obvious than figures 4.

![Figure 6. Final feature extraction.](image)

![Figure 7. Spectrum diagram of extracted signal.](image)

5. Conclusions
Simulating human auditory nerve system, a model based on double-layer neural synchronous oscillating network is proposed. This model extracts features from the time frequency analysis results of neural oscillations, which provides a method for the fusion expression of multiple signal features.

Different fault types have their own fault characteristics. According to the different oscillation periods, the different eigenfrequencies can distinguish the different faults. A DLNON model put forward in this paper is a new method for extracting signal feature frequencies and introduced into bearing fault diagnosis. Meanwhile, the intelligent recognition of faults is realized by numerical calculation, and the method is stable and anti noise.

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