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# Application of Improved Particle Swarm Optimization in Gear Fault Diagnosis of Automobile Transmission

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**Abstract**

The current fault diagnosis method has the problems of long time and low recognition rate of fault diagnosis for the gear fault diagnosis of automobile transmission. For these problems, a fault diagnosis method for gear of automobile transmission based on improved particle swarm optimization algorithm is proposed in this paper. The speed information of gear fault vibration signal is extracted. The extracted speed information is used for uniform angular resampling of gear fault vibration signal and converted to angular domain signal. The cyclostationary demodulation analysis is carried out to the angular domain signal, and the slice demodulation is performed at each order of the fault feature of the cyclic autocorrelation function. Compound fault diagnosis of gearbox is achieved based on slice demodulation spectrum of each slice signal. In order to improve the accuracy of fault diagnosis and reduce the time of fault diagnosis, the CGA algorithm is introduced. The CGA acceleration operator is introduced in every step of iterations of particle swarm optimization, so that the local search ability of particle swarm optimization can be improved. The local convergence speed and convergence accuracy of PSO can be greatly improved. Simulation results show that the proposed method can effectively shorten the time of fault diagnosis and improve the efficiency of fault diagnosis and recognition.



*Keywords:* Improved particle swarm optimization; automobile transmission; gear fault diagnosis;

## 1. Introduction

Gear is an essential part of mechanical equipment to transmit power and change speed and direction. It has strong bearing capacity, accurate and reliable transmission, and large transmission power and speed of gear [1, 2]. Once a failure occurs, it will cause the mechanical equipment to fail. If it is diagnosed in advance, it can effectively avoid accidents, eliminate continued damage, and save a lot of maintenance costs [3]. The automobile gearbox is the main driving part of the car. Accurately monitoring the running status of the transmission, and forecasting the possible faults in advance are important for product improvement, testing equipment, and personnel safety [4]. How to efficiently diagnose the gear fault of transmission has become the primary problem of current research.

In recent years, some new algorithms for fault diagnosis have been proposed by scholars. In the literature [5], a new gear fault diagnosis method which reflects the complexity or nonlinearity of the signal, which is called partial mean multiscale fuzzy entropy (PMMFE), is proposed. PMMFE is proposed based on multiscale fuzzy entropy. Although multiscale fuzzy entropy contains temporal pattern information at different scales, the representation of signals with similar feature is not ideal at most scales. PMMFE synthetically considers fuzzy entropy of multiple scales. By using the skewed distribution characteristics of fuzzy entropy at different scales, the complexity or nonlinearity of signals can be quantitatively characterized, and the characteristics of signal can be reflected more accurately. However, the gear fault vibration signal in gearbox is multi-source vibration signal, so the feature extraction must be carried out after the original signal of gear vibration is separated. The adaptive and sparsest time-frequency analysis (ASTFA) method can effectively separate the original signal of gear fault vibration according to the initial phase function determined by the gear meshing frequency. The combination of ASTFA and PMMFE is applied in gear fault diagnosis. The fault vibration signal of gear in the gearbox is separated by ASTFA, and the multiscale fuzzy entropy of the signal is calculated. The fault diagnosis of the gear is accomplished by calculating the PMMFE based on the multiscale fuzzy entropy. This method is not ideal for most of the similar feature signals, resulting in low recognition rate. In the literature [6], a gear fault diagnosis method based on two classes of features of kurtosis and intrinsic mode component energy and least squares support vector machine is proposed. Based on ensemble empirical mode decomposition, the effective IMF components of the measured gear vibration signal are extracted to calculate energy characteristics and kurtosis values. Two classes of feature vectors in time and frequency domain are built. Secondly, the two class feature vectors in time-frequency domain of the 3 kinds of states of the normal gear, the tooth root crack and the broken tooth are taken as the input to build the gear fault diagnosis model for the gear fault identification. However, this method cannot accurately identify the type of fault. In the literature [7], a dual-tree complex wavelet denoising fault diagnosis method based on morphological component analysis is proposed. The wavelet transform coefficients of different layers are

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obtained by dual-tree complex wavelet transformation of the fault signal with strong background noise. The wavelet coefficients with the obvious periodicity are selected for MCA denoising. After the single parameter reconstruction of the denoised coefficients, the fault feature signal can be obtained. The envelope analysis of the denoised signal can determine the fault feature frequency of the signal. However, this method can effectively remove strong background noise in signals. In the literature [8], a gear fault diagnosis method based on adaptive stochastic resonance and sparse coding shrinkage algorithm is proposed. Correlation kurtosis is used as a measure function of stochastic resonance to detect periodic impact components. The periodic impact features in the signal is adaptively extracted by using genetic algorithm. On this basis, the sparse coding contraction algorithm is used to further denoise the random resonance detection results, thus highlighting the impact feature and completing the fault identification of the gear. However, this method has a long fault diagnosis time.

For these above problems, a gear fault diagnosis method for automobile transmission based on improved particle swarm optimization algorithm is proposed in this paper. The main research is described as follows.

(1) The rotational speed information of gear fault vibration signal is extracted.

(2) The extracted speed information is used for uniform angular resampling of gear fault vibration signal and converted to angular domain signal. The cyclostationary demodulation analysis is carried out to the angular domain signal, and the slice demodulation is performed at each order of the fault feature of the cyclic autocorrelation function. Compound fault diagnosis of gearbox is achieved based on slice demodulation spectrum of each slice signal.

(3) To improve the accuracy of fault diagnosis and reduce the time of fault diagnosis, the CGA algorithm is introduced. The CGA acceleration operator is introduced in the iterations of particle swarm optimization. Then the local search ability of particle swarm optimization can be improved and the local convergence speed and accuracy of PSO can be greatly improved.

## 2. Fault Diagnosis Method

### *2.1. Gear Feature Parameter Extraction Method Based on VMD Algorithm*

In the fault diagnosis of gearbox, because the original vibration signal of the gear is not easy to distinguish the gear fault mode, it is particularly necessary to extract the feature parameters of the gear vibration signal. Therefore, a gear feature parameter extraction method based on VMD is proposed.

In order to reduce the influence of other idle gears on the vibration response of gearbox, the single-stage fixed shaft gearbox is selected as the simulation object. The schematic diagram of single-stage fixed shaft gearbox is shown in Figure 1, where the red path represents the transmission path of meshing vibration of fixed shaft gearbox: meshing point gear bearing box sensor.

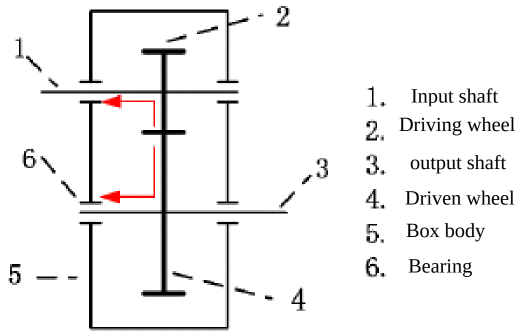


**Figure1.** Schematic diagram of gear box

The gear can be regarded as a vibration system with the gear tooth as the spring and the gear body as the mass. The exciting force of the self-excited vibration of the system is caused by the periodic change of gear stiffness, gear assembly error and torque change. Once generated, the gear will generate the torsional vibration in the circumferential direction and the bending vibration of the gear shaft, resulting in the gear noise corresponding to the meshing frequency.

In the VMD algorithm, the concept of intrinsic mode function (IMF) in EMD algorithm is applied and redefined. The IMF in the VMD algorithm is made as amplitude modulated and frequency modulated signal, which is expressed as

$$u_i(t) = A_i(t)\cos\phi_i(t) \tag{1}$$

where $A_i(t)$ is a non-negative envelope function, that is, $A_i(t) \geq 0$, $\phi_i(t)$ is a non-decreasing function, that is, $\phi_i(t) \geq 0$.

The instantaneous frequency $w_i(t) = \phi_i'(t)$ and $A_i(t)$ is far less than the phase $\phi_i'(t)$, that is , $u_i(t)$ can be considered as a harmonic signal with the amplitude $A_i(t)$ and the frequency $w_i(t)$ in the $[t-\delta, t+\delta]\left(\delta = 2\pi / \phi_i'(t)\right)$ region.

In order to construct the variational model, the following steps are needed.

(1) The Hilbert transform is used to transform all the modal functions $u_i(t)$ into the corresponding analytic signals, so as to obtain the unilateral spectrum of the signal.

(2) All modal functions are demodulated to the corresponding baseband according to the estimated center frequency and the exponential correction method.

(3) In order to obtain the constrained variational model given by Eq. (2) and Eq. (3), the bandwidth of each band must be used. The bandwidth can be obtained based on Gaussian smoothing demodulation signal, that is, the square root operation of the $L_2$ norm gradient.

$$\min_{\{u_i\}\{w_i\}} \left\{ \sum_i \| \partial_t \left[ \left( \partial(t) + \frac{j}{\pi t} \right) \times u_i(t) \right] e^{-jwt} \|_2^2 \right. \tag{2}$$

$$\sum_i u_i = f \tag{3}$$

In order to solve the optimal solution of the constrained variational model given by Eq. (2) and Eq. (3), the augmented Lagrange function is constructed by penalty factor $a$, which is given by

$$L(\{u_i\},\{w_i\},\lambda)=\alpha\sum_i \partial_t\left[\delta(t)+\frac{j}{\pi t}\times u_i(t)\right] + f(t)-\sum_i u_i(t) \tag{4}$$

where $\lambda$ is the Lagrange multiplier, $a$ is the penalty factor.

In order to obtain the extremal solution of Lagrange function, it is necessary to transform it from time domain to frequency domain. The modal component and frequency domain is calculated by using as follow:

$$u_i^{n+1}(w)=\frac{f-\sum_{i\neq k}u_i(w)+\frac{\lambda(w)}{2}}{1+2\alpha(w-w_i)} \tag{5}$$

$$w_i^{n+1}=\frac{\int_0^\infty w\,|u_i(w)|^2\,dw}{\int_0^\infty |u_i(w)|^2\,dw} \tag{6}$$

(4) The alternating direction multiplier algorithm is used to obtain the optimal solution of the constrained variational model. The original analytical signal is decomposed into $k$ modal components. The steps of solving the optimal solution are as follows;

1) Initialize $\{u_i^1\}$, $\{w_i^1\}$, $\lambda^1$, $n$, and $\lambda^1=n=0$.

2) Iteratively update $u_i$ and $w_i$ by using Eq. (5) and Eq. (6).

3) Iteratively update $\lambda^{n+1}$ by using Eq. (7).

$$\lambda^{n+1}(w)\leftarrow\lambda^n(w)+\tau\left[f(w)-\sum_i u_i^{n+1}(w)\right] \tag{7}$$

4) When $\sum_i \| u_i^{n+1}-u_i^n\|_2^2/\|u_i^n\|_2^2<\varepsilon$ is satisfied, the iteration stops, otherwise it returns to step 2) to continue the iteration, and finally to output $k$ modal components.

VMD is compared with EMD and LMD. The decomposition of EMD and LMD signals is recursive filtering mode, while VMD is a non-recursive and variational mode decomposition method, which can make the decomposed modal component no longer cause modal aliasing [9]. Therefore, VMD has excellent robustness in noise signal processing. Through properly controlling the convergence condition of VMD, the sampling effect is much lower than that of EMD and LMD. In addition, VMD can effectively separate the signals with similar frequencies.

The vibration signal of gear is decomposed by VDM, and several modal components of different components are successfully separated. The singular features are extracted by using modal component. But there is a problem in the VMD algorithm. The parameters $k$ and $a$ in the algorithm need to be set in advance depending on personal experience [10]. If the number of modal decomposition $k$ is not set reasonably, the modal separation after decomposition will be different from the actual situation. According to a priori knowledge, the decomposition of EMD algorithm can adaptively adjust the number of the decomposed modal components. By using the EMD decomposed signal, the decomposition parameter $k$ of VMD can be obtained according to the EMD decomposition result.

The feature extraction of gear includes two steps:

1) With Optimal parameter combination, the collected vibration signal of the gear is decomposed by VDM, and the $k$ modal components are obtained.

2) The gear speed information is extracted by using the VMD-based gear feature parameter extraction method, which is given by

$$\begin{cases} A=USV^T=U\left[\sum_X 0\right]V^T \\ U\times U=I_K V\times V^T=I_n \end{cases} \tag{8}$$

where $\sum_X = diag(\delta_1,\delta_2,\cdots,\delta_k)$ and the feature vector of gear fault $D=(\delta_1,\delta_2,\cdots,\delta_k)$.

### 2.2. Gear Fault Diagnosis Method Based on CPP Algorithm

The CPP algorithm, order tracking and cyclostationary demodulation method are combined to diagnose the gear fault. The gearbox fault is composed of partial fault of gear and partial fault of bearing in wheel box [11]. The process of the fault diagnosis is described as follows.

If the statistical characteristics of non-stationary random signal $x(t)$ change periodically or periodically with time, $x(t)$ is called cyclostationary signal. Autocorrelation function of asymmetrical form of the signal $x(t)$ is given by

$$R(t,\pi)=E\{x(t)x^*(t+\tau)\} \tag{9}$$

where $\tau$ is the time delay, $E\{*\}$ is the mean operation, and $*$ denotes conjugate.

Assume the signal satisfies time ergodicity, the signal is sampled with the sampling period, and then it can be expressed as an average of time:

$$R(t,\tau)=E\{x(t)x^*(t,\tau)\}=\lim_{N\to\infty}\frac{1}{(2N+1)}x^*(t+nT_0) \tag{10}$$

where $T_0$ is the sampling period, $N$ is the sampling length.

In the case of the fixed $\tau$, the correlation function $R(t,\tau)$ is a function of time, with a period of $T_0$. Therefore, the Fourier series expansion of $R(t,\tau)$ is given by

$$R(t,\tau)=\sum_\alpha R_\alpha(\tau)\exp(i2\pi\alpha t) \tag{11}$$

where $\alpha$ is the cycle frequency, which includes zero cycle frequency and non-zero cycle frequency. The zero cycle frequency represents the stationary part of the signal, and the non-zero cyclic frequency represents cyclostationarity of the signal.

Fourier coefficient in Eq. (11) is given by

$$R_\alpha(\tau)=\lim_{T\to\infty}\frac{1}{T}\int_{T12}^{T12}x(t)x^*(t+\tau)\exp(i2\pi\alpha t)dt \quad (12)$$

where $T$ is the sampling interval, $T=(2N+1)T_0$, $R_\alpha(\tau)$ is the cyclic autocorrelation function, which is the joint function of cycle frequency $\alpha$ and time delay $\tau$. The AM signal expression is as follows:

$$AM(t)=Q\left[1+B\cos(2\pi f_n t)\right]\cos(2\pi f_z t) \quad (13)$$

where, $f_n$ is the modulation frequency of AM signal, $f_z$ is the carrier frequency of AM signal, $Q$ is the amplitude of carrier signal, $B$ is the spectrum of AM modulation signal

Eq. (13) is substituted into Eq. (12), cyclostationary demodulation analysis of angular domain signal is expressed as

$$\lim_{T\to\infty}\frac{1}{T}\int_{T12}^{T12}\exp(iw_1 t)\exp(iw_2 t)dt=0(w_1\neq w_2) \quad (14)$$

Compound fault diagnosis of gearbox is obtained according to slice demodulation spectrum of each slice signal, which is expressed as

$$R_\alpha(\tau)=\begin{cases}\dfrac{A^2}{2}\cos(2\pi f_z\tau) & \alpha=0\\ \dfrac{A^2B}{2}\cos(2\pi f_n\tau) & \alpha=\pm f_n\\ \dfrac{A^2B^2}{8}\cos(2\pi f_n\tau) & \alpha=\pm 2f_n\end{cases} \quad (15)$$

From Eq. (15), the non-zero value of the cyclic autocorrelation function $R_\alpha(\tau)$ is only located at the cycle frequency $\alpha=0$, $\alpha=\pm f_n$, $\alpha=\pm 2f_n$, etc. At other cycle frequencies, the value of cyclic autocorrelation function $R_\alpha(\tau)$ is zero.

When the gear in gearbox has partial fault, the rotational frequency modulation phenomenon will occur in its vibration signal. When local fault occurs in rolling bearing, the feature frequency modulation of bearing fault will occur in its vibration signal [12]. Therefore, when the gear box and bearing local fault occur simultaneously in the gearbox, the diagnosis of the composite fault of the gear box containing the local fault of the gear and the local fault of the bearing can be diagnosed according to the difference of the modulation frequency of the two defaults.

The cyclostationary demodulation analysis method can extract modulation information of amplitude modulated signal according to the modulating frequency of each amplitude modulated signal. However, for the non-stationary signals with varying speed, the second-order statistics change with time and do not satisfy the second-order cyclostationary assumption. Then the cyclostationary demodulation method is no longer applicable, and the signal needs to be stabilized in advance. The computed order tracking method can effectively realize signal stabilization by resampling the signal. But the computed order tracking method needs to predict the speed information of the signal.

Therefore, combining the CPP algorithm, order tracking and cyclostationary demodulation method, a gear fault diagnosis method based on CPP and cyclostationary demodulation is proposed for analysis of local fault of gear and local fault of rolling bearing. Assume the measured fault vibration signal of gear is $x(t)$, the number of gear teeth is $T$, then the steps of gear fault diagnosis based on CPP and cyclostationary demodulation are described as follows.

(1) The meshing frequency $f_z(t)$ of gear box is extracted from the vibration signal $x(t)$ of gear fault by CPP method. The rotational frequency curve $f_r(t)$ of the shaft can be obtained by dividing the meshing frequency $f_z(t)$ with the number of the gear teeth $T$.

(2) According to the estimated frequency curve $f_r(t)$, the order analysis of the vibration signal $x(t)$ is carried out to obtain the angular domain signal $x(\theta)$.

(3) The cyclostationary demodulation of the angular domain signal $x(\theta)$ is carried out to obtain the cyclic autocorrelation function $R_\alpha(\tau)$.

(4) The cyclic autocorrelation function $R_\alpha(\tau)$ is sliced separately at the order of gear fault cycle and the order of bearing failure cycle. The slice signal is demodulated and analyzed, and its slice demodulation spectrum is obtained.

(5) If there is a significant peak in the rotational frequency order or its frequency doubling order in the slice demodulation spectrum of the gear fault cycle order, it is determined that a local fault occurs in the gear. If in the slice demodulation spectrum of the rolling bearing fault cycle order, the fault order of the rolling bearing appears obvious peak, it is determined that there is a local fault in the gear bearing.

### *2.3. Introducing CGA Algorithm to Improve the Local Convergence Speed and Convergence Accuracy of Particle Swarm Optimization Algorithm*

Particle swarm optimization algorithm is based on the simulation of migration and gregarious foraging process. The mathematical expression is described as follows. Assume target search space is $d$-dimensional and the population consists of $m$ particle groups. The velocity of the $i$ th particle is $V=(v_{i1},v_{i2},\cdots v_{id})$ and the position vector is $X=(x_{i1},x_{i2},\cdots x_{id})$, the searched optimal location of the population is $P_g=(p_{g1},p_{g2},\cdots,p_{gd})$, the current searched optimal position of the $i$ th particle is $P_i=(p_{i1},p_{i2},\cdots,p_{id})$. The particle expression is as follows:

$$v_{id}(t+1)=v_{id}(t)+c_1r_1(p_{id}-x_{id}(t))+c_2r_2(p_{id}-x_{id}(t)) \quad (16)$$

$$x_{id}(t+1)=x_{id}(t)+v_{id}(t+1) \quad (17)$$

where the range of the value of $i$ is $[1,m]$, the range of the value of $d$ is $[1,D]$, $r_1$ and $r_2$ are random numbers with uniform distribution in $[0,1]$, $c_1$ and $c_2$ are acceleration factors, which is non-negative number, $p_{id}$ is the current searched optimal position of the $i$ th particle, $v_{id}$ is the current velocity of the $i$ th particle, $x_{id}(t)$ is the current position of the $i$ th particle.

Although particle swarm optimization is an excellent global optimization algorithm, it is not good to process the discrete optimization problem, and easy to fall into local optimum [13]. It will lead to long time and low recognition rate of fault diagnosis. The CGA acceleration operator is introduced in iterations of particle swarm optimization, so that the local search ability of particle swarm optimization can be improved. The specific implementation process is as follows.

$$v_{id}(k+1)=\chi\Big[w(k)\cdot v_{id}(k)+c_1r_1\big(p_{id}-x_{id}(k)\big)+c_2r_2\big(p_{ag}-x_{id}(k)\big)\Big] \quad (18)$$

$$x_i(k+1)=x_i(k)+\varphi_1(k)\times v_i(k+1)+\varphi_2(k)\times\mu\times d_i(k) \quad (19)$$

where $\mu$ is influence scale factor of CGA, which is a fixed value in $(0,1]$, $\chi$ is the constraint factor, which is a constant in $(0,1]$, $d_i(k)$ is the direction of the conjugate gradient or the steepest descent direction, $\varphi_1$ and $\varphi_2$ are the scale factors of the relative influence of CPP algorithm. The selection of $\varphi_1$ and $\varphi_2$ influences the overall performance of the algorithm. The selection of $\varphi_1$ and $\varphi_2$ are given by

$$\varphi_1(k)=\frac{k_{\max}-k}{k_{\max}} \quad (20)$$

$$\varphi_2(k)=\frac{k}{k_{\max}} \quad (21)$$

where $k$ is the number of current evolutionary generation, $k_{\max}$ is the maximum number of current evolutionary generation. $\varphi_1(k)+\varphi_2(k)=1$. $\varphi_1(k)$ and $\varphi_2(k)$ are variables and change with $k$. The purpose is to dynamically adjust the update of each particle and determine the influence of the basic CPP algorithm and CGA.

The specific steps of the improved particle swarm algorithm are as follows.

(1) Initialize all particles. Randomly determine the initial position and velocity of each particle. Particle swarm optimization is designed to optimize the target value of the desired error for a given optimization problem [14, 15].

(2) Design the fitness function of population.

(3) Calculate the initial fitness value of each particle and determine the optimal position of the initial individual of each particle. Initialize global optimal position and calculate $\varphi_1(k)$, $\varphi_2(k)$, and initial gradient and initial search direction of each particle.

(4) The current generation is the $k$ th generation, $k=k_1,\cdots,k_{\max}$. If $k=1$, the initial fitness value of the current generation of each particle is the initial fitness value. The individual optimal position of each particle is the initial individual optimal position, and the global optimal position is the initial global optimal position. If $k\neq 1$, the fitness value of the current generation of each particle is calculated by fitness function. Then the optimal location $p_{id}(k)$ and global location $p_{gd}(k)$ of each particle are updated with the next steps.

(5) Update the individual optimal position $p_{id}(k)$.

(6) Update the global optimal position $p_{gd}(k)$.

(7) Calculate the conjugate gradient $d_i(k)$ of the current generation of each particle. Then calculate $\varphi_1(k)$ and $\varphi_2(k)$ by using Eq. (20) and Eq. (21).

(8) Update the velocity and position of each particle by using Eq. (18) and Eq. (19).

(9) Calculate new gradient $g_i(k)$ and search direction $d_i(k)$.

(10) The number of evolutionary iterations plus 1.

(11) Check whether the condition is satisfied. If it is satisfied, the optimization ends. Otherwise, go to step (4) for loop executing, until the optimal number of evolution $k_{\max}$ is reached or the optimization error corresponding to the global optimal particle is less than the given error.

## 3. Experimental Results and Analysis

In order to prove the validity of the proposed algorithm, a simulation experiment is carried out. The test platform of gear box fault detection system is built by using PCI1712 data acquisition module.

In the gearbox, about 60% of the faults are caused by gear faults. The three faults of the gear are identified, which are no fault, tooth root crack, and broken tooth. The 2, 4, and 6 gear position were selected in the frequency domain feature signal extraction. The amplitudes at the side band $f_s+nf_z$ of the 1, 2, and 3 bearing are $A_{ij1}$, $A_{ij2}$, and $A_{ij3}$, where $f_z(t)$ is the meshing frequency of the gear, $f_z$ is the rotational frequency of the bearing, $n=1,2,3$, $i=2,4,6$ is the gear position, $j=1,2,3$ is the number of the bearing. Because there are two pairs of gears on the 2 bearing and 3 bearing, 1 and 2 represent two meshing frequencies respectively. So, the input of the network is a 15-dimensional vector. The schematic of the transmission is shown in Figure2. the sensor accelerometer is shown in figure 3. The transmission vibration data is shown in Table 1.


**Figure 2.** Schematic of the transmission Figure 3 Sensor Accelerator

In CATIA, a 3D model of gearbox components is established, which is endowed with specific material attributes, and local coordinate system is added to the 3D model according to the relative position relationship; the 3D model of the components is imported into LMS virtual lab software, and the geodetic coordinate system is added to the motion module to simulate the gearbox workbench; the coordinates on the components are one-to-one corresponding, which is based on the actual situation For the inter contact relationship, four fixed pairs are added between the earth and the gearbox box, and rotating pairs are added between the driving wheel and the driven wheel and the earth respectively; bushing force is added at the bearing to simulate the rolling bearing, and joint position driver is added on the rotating pair between the driving wheel and the earth to simulate the gear drive.

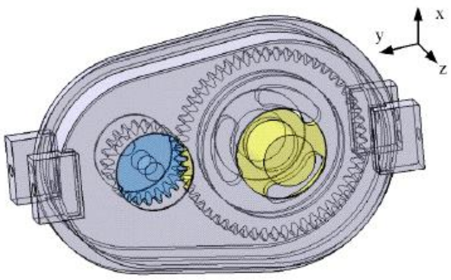


**Figure 4.** Dynamic model of gear box multi-rigid body

Set the gear breaking or eccentric fault on the driving wheel and driven wheel respectively, and record the gear breaking of driving wheel as condition 1, the gear breaking of driven wheel as condition 2, and the common fault as condition 3.

**Table 1**. transmission vibration data

| Vibration parameters | Working condition 1 | Working condition 2 | Working condition 3 |
|---|---|---|---|
| Swing around X-axis at front box bearing | 334.02 | 351.65 | - |
| Box swinging around X-axis | 413.45 | 410.34 | 211.93 |
| Tilt vibration of xoy surface of front box diaphragm | 446.25 | 447.53 | - |
| Inclined vibration of box on xoy surface | 528.93 | 526.12 | 273.65 |
| Reciprocating vibration of front box rib in Y-axis direction | 647.78 | 643.38 | 384.65 |

Because these data have different units and orders, the input variables are normalized. Experimental data are collected with MATLAB R2007, and 12 sets of data are collected, of which 9 sets used as training samples and 3 sets as test samples. During the training process, the CPP package of MATLAB is called. The CPP network design function selects newbre, and the feature samples in the training samples are used as input variables of the CPP network, and the gear state is used as the output of the network. The following form is used: No fault (1, 0, 0), gear crack (0, 1, 0), and broken tooth (0, 0, 1). The training set finally determines that when the expansion constant is 0.0838, the training effect is the best, and the network output is consistent with the actual output.

In order to verify the effectiveness of the experiment, the data shown in Table 2 is used as the test sample set, and the gear state is used as the output of the network to verify the built CPP network model. The results are shown in Table 3. In Table 1, S represents the number of the data, S1, S2, and S3 are the number 1, 2, and 3 of the data, T represents feature sample, C represents gear fault, Nf represents no fault, Gc represents gear crack, Bt represents broken tooth. In Table 3, Ao represents actual output, No represents network output, result represents diagnosis results.

**Table 2.** Test sample

| S | T | C |
|---|---|---|
| | 0.2102 0.096 | Nf |
| | 0.1358 0.2602 | |
| S1 | 0.1002 0.7534 | |
| | 0.090 0.0388 | |
| | 0.1452 0.0129 | |
| | 0.160 0.2453 | |
| | 0.511 0.1320 | |
| | 0.2594 0.19 0.712 | Gc |
| | 0.2802 0.1500 | |
| S2 | 0.1297 0.1002 | |
| | 0.1892 0.2531 | |
| | 0.0876 0.0059 | |
| | 0.1802 | |
| | 0.0993 0.0803 | |
| | 0.1003 | |
| | 0.2600 0.2236 | Bt |
| S3 | 0.1202 0.1172 | |
| | 0.1103 0.0684 | |
| | 0.0623 0.2598 | |
| | 0.2603 0.1169 | |
| | 0.0050 0.1003 | |
| | 0.1521 0.2283 | |
| | 0.3206 | |

**Table 3.** Diagnosis results

| S | Ao | No | result |
|---|---|---|---|
| S1 | 1 0 0 | 0.9815 0 0 | Nf |
| S2 | 0 1 0 | 0 0.9736 0 | Gc |
| S3 | 0 0 1 | 0.0286 0.0268 1 | Bt |

From Table 3, it can be seen that, the first set of data errors are 0.0185, 0, and 0, respectively, the second sets of data errors are 0, 0.0264, and 0, respectively, and the second sets of data errors are -0.0286, -0.0268, and 1, respectively. It shows that the error between the actual output and the network output is relatively small, and the diagnosis result is consistent with the gear fault, indicating that the diagnosis result is correct.

The fault diagnosis time of the proposed method is compared with that of the literature [5] method and the literature [6] method. The comparison results are shown in Fig. 5, Fig. 6, and Fig. 7.

From Fig. 5, Fig. 6, and Fig. 7, it can be seen that, when the number of samples is 9, the fault diagnosis time of the proposed method is 3s, the literature [5] method is 10s, and the literature [6] method is 8s. The fault diagnosis time of the proposed method is the least, which shows that the proposed method can effectively shorten the fault diagnosis time.

In order to further verify the fault diagnosis performance of the proposed method, the fault recognition rate of the proposed method, the literature [5] method, the literature [6] method, and the literature [7] method is compared. In the case of different faults, the comparison results of fault recognition rate of different methods are shown in Table 4.

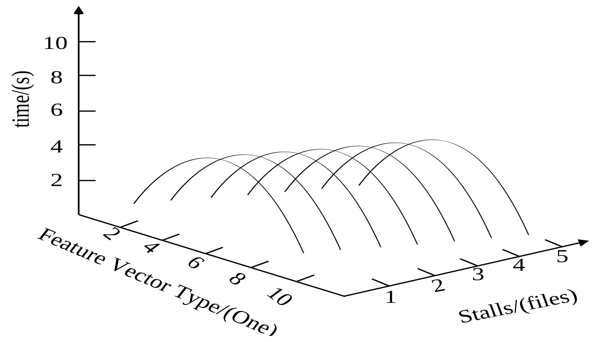


**Figure 5.** The fault diagnosis time of the proposed method

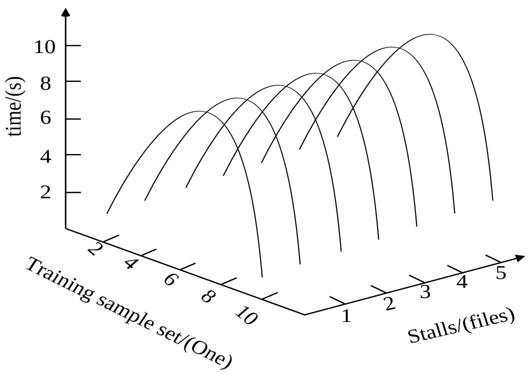


**Figure 6.** The fault diagnosis time of the literature [5] method

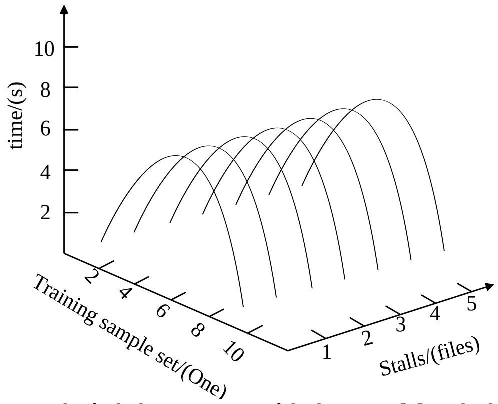


**Figure 7.** The fault diagnosis time of the literature [6] method

**Table 4.** Fault diagnosis accuracy rate of different methods

| Method | Accuracy rate of fault diagnosis (%) | | | | | |
|---|---|---|---|---|---|---|
| | Normal state | Tooth root crack of intermediate shaft | Ulnar wear of intermediate shaft | Root wear of output shaft | Ulnar wear of output shaft | Accuracy rate of diagnosis (%) |
| The proposed method | 100 | 98.0 | 95.0 | 90.0 | 95 | 95.6 |
| The literature [5] method | 98.0 | 90.0 | 90.0 | 80.0 | 75.0 | 86.6 |
| The literature [6] method | 99.0 | 85.0 | 81.0 | 79.0 | 65.0 | 81.8 |
| The literature [7] method | 99.0 | 80.0 | 75.0 | 70.0 | 68.0 | 78.4 |

 

From Table 4, it can be seen that, when the different faults of transmission gear of occur, the fault recognition rates of different methods are different. When the tooth root crack of intermediate shaft of the transmission is cracked, the fault diagnosis accuracy of the proposed method is 98%, the literature [5] method is 90%, the literature [6] method is 85%, and the fault literature [7] method is 80%. The fault recognition rate of literature [7] method is the lowest. The diagnostic accuracy of the proposed method is 95.6%, the literature [5] method is 86.6%, the literature [6] method is 81.8%, and the literature [7] method is 78.4%. The diagnosis accuracy of the proposed method is obviously better than other methods. The improved particle swarm algorithm significantly improves the fault diagnosis performance of the proposed method.

## 4. Conclusions

In the process of driving, the gears, shafts and bearings in the gearbox often fail because of the frequent shifting. According to the relevant statistics, among all the automobile faults, about 60% of the automobile transmission faults are caused by gear failure. At present, the fault diagnosis method of automobile transmission gear has the problems of long diagnosis time and low recognition rate. In order to solve these problems, a fault diagnosis method based on improved particle swarm optimization algorithm is proposed. The speed information of gear fault vibration signal is extracted, which is used for uniform angle resampling of gear fault vibration signal and converted into angle domain signal. The cyclic stationary demodulation of the diagonal domain signal is analyzed, and the fault characteristics of the cyclic autocorrelation function are demodulated by slice. Based on the slice demodulation spectrum of each slice signal, the composite fault diagnosis of gearbox is realized. In every iteration of particle swarm optimization algorithm, CGA acceleration operator is introduced to optimize the fault diagnosis results and realize the fault diagnosis of automobile transmission gears. The simulation results show that compared with the traditional method, this method has higher fault diagnosis efficiency and shorter fault diagnosis time. This method provides a new idea for the further development of fault diagnosis technology of automobile transmission gears, improves the accuracy of fault identification, reduces the time of fault diagnosis, and ensures the driving safety.

The fault detection and diagnosis technology of automobile transmission gear usually completes the diagnosis under a single condition, which has good effect. However, in practice, due to the relatively cumbersome mechanical mechanism and the interference of other elements, many diagnosis technologies are difficult to fully use. In the future work, for the fault diagnosis of different specifications of gears, we should continue to try to improve the accuracy of fault diagnosis of automobile transmission gears.

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