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Gear fault detection and diagnosis under speed-up condition based on order cepstrum and radial basis function neural network †

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Abstract

Varying speed machinery condition detection and fault diagnosis are more difficult due to non-stationary machine dynamics and vibration. Therefore, most conventional signal processing methods based on time invariant carried out in constant time interval are frequently unable to provide meaningful results. In this paper, a study is presented to apply order cepstrum and radial basis function (RBF) artificial neural network (ANN) for gear fault detection during speed-up process. This method combines computed order tracking, cepstrum analysis with ANN. First, the vibration signal during speed-up process of the gearbox is sampled at constant time increments and then is re-sampled at constant angle increments. Second, the re-sampled signals are processed by cepstrum analysis. The order cepstrum with normal, wear and crack fault are processed for feature extracting. In the end, the extracted features are used as inputs to RBF for recognition. The RBF is trained with a subset of the experimental data for known machine conditions. The ANN is tested by using the remaining set of data. The procedure is illustrated with the experimental vibration data of a gearbox. The results show the effectiveness of order cepstrum and RBF in detection and diagnosis of the gear condition.

***Keywords*:** Order cepstrum; Radial basis function; Neural network; Gearbox; Fault diagnosis; Signal processing

1. Introduction

Rotating machine fault diagnosis is typically based on vibration. The spectral contents of emitted vibration signals are analyzed to ascertain the current condition of the monitored process. At present, for the fault diagnosis of rotating machinery, many research outcomes have been obtained in the stationary process. However, little research has been done for the run-up or run-down process. The reason why we stress the run-up or run-down process is that non-stationary vibrations signals from varying speed machinery may include more abundant information about its condition. Some phenomena, which are usually not obvious at constant speed operation, may become more apparent under varying speed conditions. Therefore, the behavior characteristics of the run-up or run-down process have a distinct diagnostic value, and the fault diagnosis of run-up or run-down process has owed its distinct standing in the fault diagnosis of rotating machinery. In the last decade vibration analysis and condition monitoring techniques for varying speed machinery have attracted the attention of scientists and engineers. Lopatinskaia et al. [1, 2] presented the application of recursive filtering and angle domain analysis to non-stationary vibration analysis. The approach is implemented and validated through computer simulation and experiments. Meltzer [3, 4] dealt with the recognition of faults in gear tooth during non-stationary start-up and run-down of planetary gear drives using the time-frequency approach and the time-quefrency approach. Wu et al. [5] presented the application of adaptive order tracking fault diagnosis technique based on

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recursive Kalman filtering algorithm to gear-set defect diagnosis and engine turbocharger wheel blades damaged under various conditions. Li et al. [6] presented the hidden Markov model-based fault diagnosis method in speed-up and speed-down process for rotating machinery.

However, the vibration signal of the run-up or run-down process is more complex than that of the stationary process. Conventional signal processing methods, which were developed for constant speed machinery monitoring, are based on digital sampling carried out in equal time intervals. If the machine operates under varying speed or load, its dynamic and vibrations become non-stationary. The vibration signal sampled from the rotating machinery is a non-stationary signal, whose amplitudes and frequencies both vary with time. Fixed time sampling cannot cope with the varying rotational frequency of the machine, resulting in increasing leakage error and spectral smearing [1, 2]. Therefore, most of the conventional methods for signal processing become inappropriate when monitoring the vibrations of varying speed machinery [1, 2]. Some progress has been made in the theoretical analysis [7, 8], the signal processing methodology [9, 10], measurements and practical applications of varying speed machinery monitoring [11-13].

At present, two techniques are mainly used to process the non-stationary signal: time frequency analysis (such as the short time Fourier transform (STFT), wavelet transform (WT) [14], Wigner-Ville distribution (WVD) [15-17] and Hilbert-Huang transform [18-20]) and order tracking technique [11-13]. The time frequency analysis involves three-dimensional functions that allow for visualizing the frequency and amplitude variations of the spectral components [14]. However, when the analyzed vibration signal is composed of many spectral components and with large changes of the machine speed during measurement, they become very difficult to analyze. Recently, order tracking has been become one of the important methods for fault diagnosis in rotating machinery [11-13]. Vibration signals produced from rotating machinery are speed dependent and hence orders as opposed to absolute frequencies are preferred as the frequency base. Orders represent the number of cycles per revolution and are thus ideal for representing speed-dependent vibrations. Therefore, order tracking technique normally exploits a vibration or a noise signal supplemented with the information of shaft speed for fault diagnosis of rotating machinery. The order spectrum gives the amplitude of the signal as a function of harmonic order and shaft speed in rotating machinery [11].

Artificial neural networks (ANN) have potential applications in automated detection and diagnosis of machine conditions [21, 22]. Multi-layer perceptions (MLPs) and radial basis functions (RBFs) are the most commonly used ANNs [23, 24], though interest in probabilistic neural networks (PNNs) is also increasing recently. The main difference among these methods lies in the ways of partitioning the data into different classes. The applications of ANNs are mainly in the areas of machine learning, computer vision, and pattern recognition because of their high accuracy and good generalization capability [24].

In this work, the computed order tracking approach and order cepstrum analysis are introduced and applied specifically to gearbox fault diagnosis during run-up. This method is based on the re-sampling technique and the cepstrum estimation of the re-sampling signal, which is a function of the angle of the input shaft of the gearbox. This re-sampling signal can be obtained by re-sampling of the vibration signal that has been previous sampled in the time domain. The order cepstrum techniques are based on the signal processing of the angle domain signal, where the resample signal is in accordance with the shaft angle of the gearbox. The order cepstrum is then evaluated for the vibration signal re-sampled constantly in angle at equidistant phases of the input shaft of the gearbox. The usefulness of this approach will be shown by experimental example in Section 5.

To address the issues discussed above, this paper is organized as follows. Section 2 presents the principle and procedure of computed order tracking. Section 3 briefly describes the cepstrum. Section 4 looks at the radial basis function neural network. Section 5 gives the applications of the method based on computed order tracking, order cepstrum and radial basis function neural networks to faults diagnosis of gear. Finally, our conclusions are provided in section 6.

2. The principle and procedure of computed order tracking

There are two popular techniques for producing synchronously sampled data: the traditional approach that uses special hardware to dynamically adapt the sample rate and a technique where the vibration signals and a tachometer signal are synchronously sampled, that is, they are sampled conventionally at equal time increments. From the synchronously sampled tachometer signal re-sample times required to produce synchronous sampled data are calculated. This process is referred to as computed order tracking and is particularly attractive, as it requires no special hardware. Also, this approach is more flexible than the traditional method, as for example different sample rates may be synthesized. The computed order tracking is considerably more flexible than the traditional approach. It may be organized to produce equally accurate or more accurate results than the traditional method. An added benefit is that computed order tracking requires no specialized hardware, which is an important factor in many condition monitoring applications. Therefore, computed order tracking techniques are introduced and applied in this paper.

The objective of computed order tracking (COT) [9] is a calculation of the vibration signal sampled constant in angle from sampled constant in time. From the mathematical point of view, this task could be solved by interpolation theory.

The computed order tracking (COT) method first records the data at constant Δt increments, using conventional hardware, and then re-samples this signal to provide the desired constant $\Delta\theta$ data, based on a keyphasor signal.

To determine the resample times, it will be assumed that the shaft is undergoing constant angular acceleration. With this basis, the shaft angle $\theta(t)$ can be described by a quadratic equation of the following form [9]:

$$\theta(t) = b_0 + b_1 t + b_2 t^2 \tag{1}$$

The unknown coefficients b_0 , b_1 and b_2 are found by fitting three successive keyphasor arrival times (t_1 , t_2 and t_3), which occur at known shaft angle increments $\Delta\phi$. This can be obtained by the following conditions:

$$\begin{cases} \theta(t_1) = 0 \\ \theta(t_2) = \Delta\phi \\ \theta(t_3) = 2\Delta\phi \end{cases} \tag{2}$$

The arrival times t_1 , t_2 and t_3 are known from the sampling of the keyphasor pulse signal.

Substituting these conditions into Eq. (1) and arranging in a matrix format gives,

$$\begin{pmatrix} 0 \\ \Delta\phi \\ 2\Delta\phi \end{pmatrix} = \begin{bmatrix} 1 & t_1 & t_1^2 \\ 1 & t_2 & t_2^2 \\ 1 & t_3 & t_3^2 \end{bmatrix} \begin{Bmatrix} b_0 \\ b_1 \\ b_2 \end{Bmatrix} \tag{3}$$

This set of equations is then solved for the unknown $\{b_i\}$ components. Once these values are known, Eq. (1) may be solved for t , yielding

$$t = \frac{1}{2b_2}\left[\sqrt{4b_2(k\Delta\theta - b_0) + b_1^2} - b_1\right] \tag{4}$$

where k is the interpolation coefficient that can be obtained as follow:

$$\theta = k\Delta\theta \tag{5}$$

where θ is the shaft angle and $\Delta\theta$ is the desired angular spacing between resamples.

Once the resample times are calculated, the corresponding amplitudes of the signal are calculated by interpolating between the sampled data. After the amplitudes are determined, the resample data are transformed from the angle domain to the order domain by means of an FFT.

The order spectrum and order cepstrum techniques are based on the signal processing of the angle domain signal, where the resample signal is in accordance with the shaft angle of the gearbox. The order spectrum and order cepstrum are then evaluated for the resample signal. The usefulness of this approach will be shown with an experimental example in Section 5.

3. Brief introduction of cepstrum

As mentioned in the literature [25], gear vibration spectra commonly show sidebands of the meshing frequency and its harmonics. Such sidebands typically arise from the modulation of the tooth meshing waveform by the gear rotational frequency. For gearboxes in good condition the sideband level generally remains constant with time. Changes in the number and amplitude of the sidebands normally indicate a deterioration condition. In the particular case of a local fault in one of the teeth, a localized modulation effect takes place once per revolution of the faulted gear. Several modulation phenomena may be present, each producing a different family of sidebands characterized by the same spacing in the spectrum, equal to the corresponding modulating frequency. As a consequence, the sideband spacing contains diagnostic information, since it is related to the modulation source [25]. However, it can be difficult to distinguish and evaluate the sideband spacing by means of spectral analysis, due to the contemporary presence of several families of sidebands and other components.

To overcome this problem, cepstrum analysis can be employed. Various forms of cepstrum exist, but all of them can be considered as a spectrum of a logarithmic spectrum [25]. For applications to machine diagnostics, the power cepstrum, $c_x(\tau)$, is well suited and generally applied; as shown in the literature, it is defined as the inverse Fourier transform of the logarithmic power spectrum:

$$C_x(\tau) = F^{-1}[\log S_x(f)] \tag{6}$$

where $F^{-1}[]$ is the inverse Fourier transform, $S_x(f)$ is the power spectrum; it is usually represented in dB scale, as the corresponding logarithmic power spectrum. The independent variable, τ, known as quefrency, has the dimension of time.

The cepstrum analysis can be useful in interpreting the spectrum, as a tool for detection of periodic structures. Each family of sidebands, emphasized by the logarithmic scale, produces a peak in the cepstrum at a quefrency corresponding to the reciprocal of the spacing of the spectrum components, as well as other peaks at multiple quefrencies, called rahmonics. Thus, the quefrency of the fundamental cepstrum component represents the average sideband level over the whole spectrum. The higher-order rahmonics contain information about the shape of the spectrum, which depends not only on the type of modulation phenomenon but also on the dynamic properties of the mechanical system and transmission path between vibration sources and transducer location. As a consequence, rahmonics are generally less meaningful for detection and diagnosis than the fundamental cepstrum component. This fact gives the obvious advantage that the averaged information concerning a whole sideband family is basically represented with high accuracy by one cepstrum peak. Thus, cepstrum makes it possible to separate mixtures of sidebands, even in the case of periodicities not immediately apparent in the spectrum.

After the power spectrum is defined, the cepstrum impulse index can be given as follows:

$$f_{pulse} = \frac{C_m}{\overline{C}} \tag{7}$$

where C_m is the peak of the power cepstrum, $\overline{C}$ is defined as the mean of power cepstrum as follows:

$$\overline{C} = \frac{1}{N_c}\sum_{i=1}^{N_c}|C_i| \tag{8}$$

where C_i is the amplitude of ith quefrency, N_c is the number of sampling points.

4. Radial basis function neural network (RBFNN)

It is conceivable that a neural net can be used as a monitoring device to detect major changes in the operation of the system. Specifically, one approach may be that the artificial neural network is trained on a well-behaved system, and then operated with no more training in parallel to the actual system. The artificial neural network output will then be compared to that of the physical system, and any anomalies in the output of our system will be detected.

As shown in Fig.1, RBFNN can be expressed as a two-layer network. The activations of the hidden units are radial basis functions (RBF) of the inputs, centered at different locations. For example, when the RBF is chosen to be Gaussian,

$$g_j(\mathbf{x}) = \exp\left[-\frac{(\mathbf{x}-\mu_j)^2}{2\sigma^2}\right] \tag{9}$$

where μ_j is the RBF center of the j th hidden unit, and σ the RBF width. The final output of RBFNN is a weighted summation of all RBFs:

$$y(\mathbf{x}) = \sum_{j=1}^{M} w_j g_j(\mathbf{x}) \tag{10}$$

The universal approximation ability of RBFNN with adequate RBFs is also guaranteed. The adjustable parameters in the case of Gaussian RBFs include the centers and widths, and the network weights in the second layer. The efficiency of RBFNN comes from splitting the training process into two simple steps. The first step is an un-

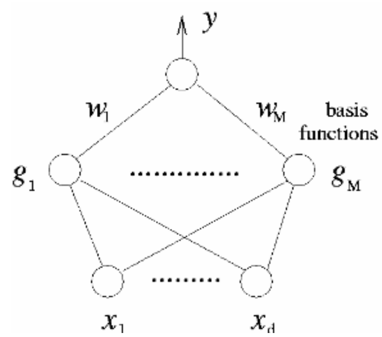

Fig. 1. The radial basis function neural network.

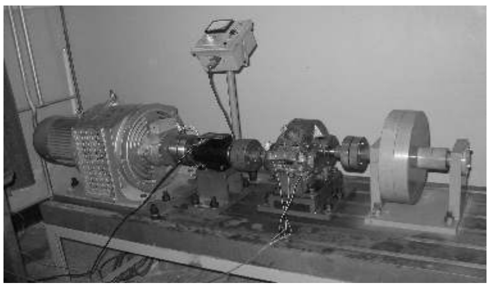

Fig. 2. Experimental set-up.

supervised procedure aimed at finding the centers and widths, which is often done through modeling the density distribution of input data by using methods such as K-means clustering or EM algorithm. The second step is to optimize the network weights by using supervised learning analogous. Note that in the second step of training,the cost function is linear in weights, whose minimum can be easily obtained.

5. Gear faults diagnosis based on order cepstrum and RBFNN

In this section, the order cepstrum and radial basis function neural network will be applied to vibration signal measured from a gearbox during speed-up process.

5.1 Experimental set-up

A crack, wear or broken gear tooth failure may cause fatal accidents, so the recognition of gear tooth fault is very important for the safety of a gearbox. The gear test apparatus used in this study is shown in Fig.2. The vibration signals of the gear fault are sampled on a single-state gearbox during running-up. A pair of spur gears, with the module of 2.5mm, is tested. The driving gear has 30 teeth and the driven gear has 50 teeth. Therefore, the transmission ratio is 50/30, which means that a decrease in rotation speed is achieved. The motion is produced by an AC motor. The tested gear was used to study only one kind of failure: crack in the root or wear on the tooth. Therefore, we prepared three gears, named as health gear, cracked gear and weared gear. Localized crack defect was seed in the root of the driving gear of the input shaft by an electric-discharge machine to keep their size and depth under control, to simulate serious gear crack. The artificial defect was 1mm in depth and the width of the groove was 0.5mm. Localized wear defect of the driving gear had a chipped tooth, from zero thickness at pitch point to 25% thickness at the tooth top, to simulate serious wear. The monitoring and diagnostic system was composed of three accelerometers, amplifiers, a rotating speed and torque transducer, B&K 3560 spectrum analyzer and a computer. The vibration signals and a tachometer signal were synchronously sampled. The sampling span was 3.2 kHz, the sampling frequency was 8192 Hz and the sampling time was 2 second. The data sampling point was 16384.This time included one speed up of the gearbox from idle speed up to steady. After sampling, the measured vibration signals were loaded into MATLAB from data-files. Then, the vibration signals were resampled. For their resampling, the algorithm described in the previous section was used. As a result of experiment, the vibration signals generated by the tested gearbox were obtained sampled constant in time as well as sampled constant in angle.

The characteristic parameters of the gearbox are given as follows:

The gear mesh frequency:

$$f_m = 30 f_{r1} \tag{11}$$

The characteristic frequency of gear crack:

$$f_{crack} = f_{r1} \tag{12}$$

The gear mesh order:

$$x_m = 30 \tag{13}$$

The characteristic order of gear crack:

$$x_{crack} = 1 \tag{14}$$

The quefrency of the gear mesh frequency:

$$\hat{f}_m = \frac{1}{f_m} \tag{15}$$

The quefrency of the gear crack or wear fault:

$$\hat{f}_{crack} = \frac{1}{f_{r1}} \tag{16}$$

The order cepstrum of gear mesh frequency:

$$\hat{x}_m = 12° \tag{17}$$

The order cepstrum of gear crack or wear fault:

$$\hat{x}_{crack} = 360° \tag{18}$$

where f_{r1} is the rotating frequency of the input shaft.

5.2 Features selection of gear fault pattern

The rotating speed signal of the input shaft for the tested gearbox is displayed in Fig. 3. Fig. 3(a) represents the sampling pluses of the input shaft from the optical encoder (60 pulses per rotational period). The encoder signals consist of 16384 points and have a total duration of 2 seconds. To obtain approximate values of rotational speed for every data point, polynomial curve fitting was used. It was found that linear approximate was sufficient for this research. Polynomial coefficients were determined for each data and analytical descriptions of the rotational speed were obtained. Fig. 3(b) is the calculated instantaneous rotating speed using interpolating method. Fig. 3(b) clearly shows that the rotating speed of the input shaft runs up from idle to steady speed about 700 rpm.

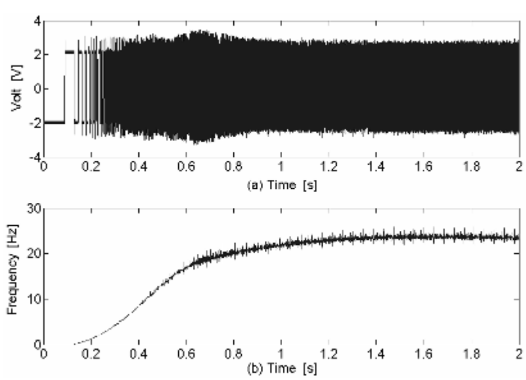

Fig. 3. Rotating speed of the input shaft.

The original vibration signal with gear crack fault is displayed in Fig. 4(a). Fig. 4(a) shows that the vibration signals are non-stationary, which the amplitude of the vibration is increasing during the input shaft speed up. The result of applying conventional spectral analysis method (FFT) to the specified non-stationary signal is given in Fig. 4(b). Fig. 4(b) displays the FFT of the vibration signals with gear crack fault. It is clear that the resulting spectrum is significantly obscured by spectral smearing. Besides, traditional spectral averaging cannot be applied to the non-stationary signal during the input shaft run-up. Fig.4 (b) clearly shows that spectral smearing substantially affects the result of conventional analysis based on time sampling. Therefore, classical Fourier analysis has some limitation such as being unable to process non-stationary signals.

The angular resampling technique is applied to the original vibration signal in Fig. 4(a). Fig. 5 displays

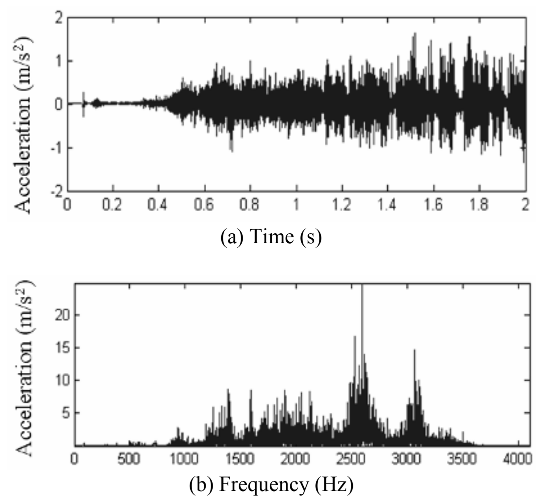

Fig. 4. Time-domain vibration signal with crack fault and FFT.

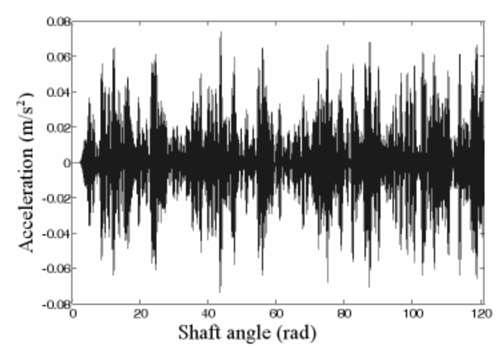

Fig. 5. Angular resample signal with gear crack fault.

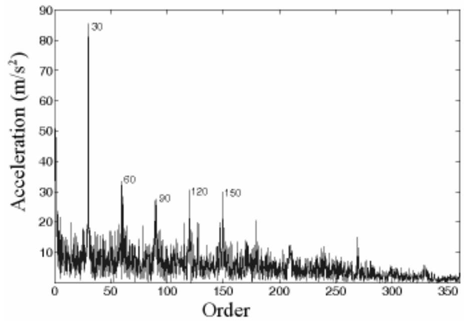

Fig. 6. Order spectrum with gear crack fault.

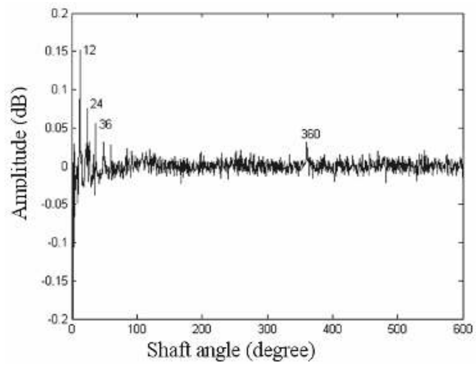

Fig. 7. Order cepstrum with crack fault.

the angular resample data. Fig. 6 shows the order spectrum. The order spectrum is dominated by the repetition order of the gear mesh order and its harmonics. The conventional order spectrum was not capable of revealing the characteristic order of gear crack fault that was corrupted by the modulation and noise.

The order cepstrum was evaluated according to Eq. (6). The order cepstrum is depicted in Fig. 7. In case of the order cepstrum, it can be identified that the characteristic order (x_{crack}) of gear crack fault, gear mesh orders (x_m) and its harmonics are represented in the order cepstrum. The simplicity of the order quantity representation can be put down to the ability of the order signal processing method to eliminate undesirable spectral smearing and modulation effects. Fig. 7 demonstrates the advantage of the order cepstrum for the analysis vibration signals generated by gearbox during speed-up process.

Fig. 8 and Fig. 9 are the order cepstrum of gear wear fault and normal condition, respectively. From Figs. 7-9, one can draw a conclusion that the order cepstrum can identify the characteristic order. Therefore, it can be used to detect the fault type of the

Table 1. Cepstrum impulse index.

Gear condition	Cepstrum impulse index
Normal	3.5697
Crack fault	5.6191
Wear fault	13.2091

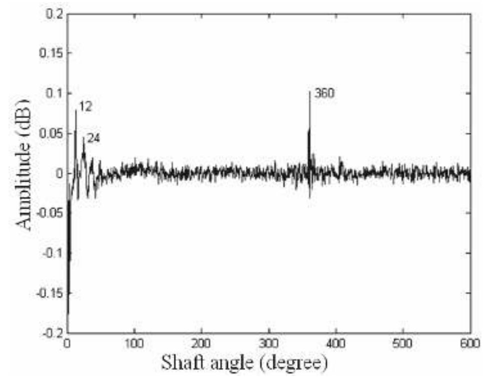

Fig. 8. Order cepstrum with wear fault.

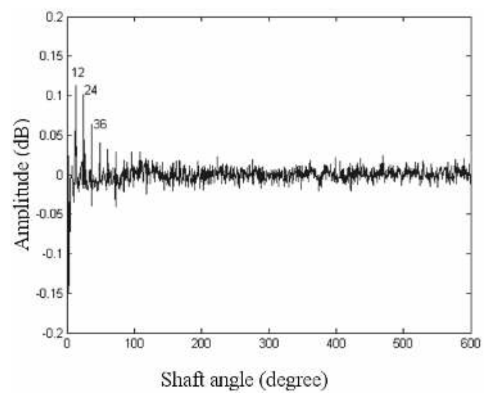

Fig. 9. Order cepstrum with normal condition.

gear. Table 1 shows the cepstrum impulse index, which is calculated according to Eq. (7), of gear for normal condition, crack fault and wear fault, respectively. Therefore, the cepstrum impulse index can be applied to the parameters of the input layer for radial basis function neural network.

5.3 Gear fault detection based on RBFNN

The fault diagnosis involves collecting various symptom signals, analyzing whether the indexes exceed the predefined thresholds, and distinguishing the kinds of faults and the ranking problem.We may construct a N dimension vector composed of the symptom features. The typical symptoms and their numbers are determined according to the different diagnosis examples.

We take the measured fault symptoms of cepstrum impulse index as the input of the network, the machine's status signals as the output of the network. Then the characteristic of the network is able to embody this certain mapping relationship between the fault symptoms and causes. It is due to the hidden neurons that allow the network to extract high-order correlations from the information, transformed the input pattern to the appropriate output pattern.

The number of the input symptoms is selected to be 1. For simplicity, we only consider three states of the gear: normal, crack fault and wear fault. Then the number of the output unit is 3, so (1,0,0) denotes the normal condition, (0,1,0) denotes the crack fault, and (0,0,1) denotes the wear fault. For each type of the gear fault, we have tested and collected 15 data of the gear vibrantion signals. When we collect the fault signals, we should aim at the different fault situation and the different fault level as far as possible, so as to ensure the completeness of the training patterns.

The test experiment was executed fifteen times for three gears of different faults, respectively. We collected 10 data to train the RBFNN and the others to test the system. Therefore, there were totally 45 real-time testing data sets to train and test the accuracy of the trained neural network to diagnose different gear faults.The features of cepstrum impulse index extracted from the order cepstrum were used as inputs to the RBFNN and the results obtained are shown in Table 2. Table 2 shows the performance of the neural network for gear fault diagnosis scheme. The success rate for each condition is 100%. The features are effective in RBFNN-based diagnosis of gear failures using order cepstrum of the resample signal. The result demonstrates that with proper processing of the measured data and possible training procedure, the neural network for gear fault diagnosis schema can diagnose gear faults with desired accuracy. The results show the effectiveness of the RBFNN in diagnosis of the gear condition.

Table 2. Test condition and its output.

Test condition	Output 1	Output 2	Output 3
	0.9997	0.0001	0.0001
	0.9995	0.0001	0.0002
Normal condition	1.0001	-0.0001	-0.0001
	1.0002	-0.0001	-0.0001
	0.99989	0.00002	0.0000
	0.0002	0.9999	-0.0001
	-0.0003	1.0002	-0.00015
Crack fault	-0.0001	1.0003	0.0000
	0.0002	0.9876	-0.0001
	-0.0011	1.00021	-0.0003
	0.0014	-0.0001	0.9998
	0.0013	0.0004	0.9785
Wear fault	0.0002	-0.0001	0.9997
	0.0003	0.0000	0.9998
	-0.0001	-0.0002	1.0002

6. Conclusions

A method for fault diagnosis of gear faults during speed-up process was presented based on a newly developed signal processing technique termed computed order tracking and order cepstrum. The radial basis function neural network has been used in this paper to perform gear fault diagnosis based on the extracted information features. Using computed order tracking technique, the non-stationary vibration signals of gear faults in time domain can be converted into stationary ones in the angle domain. The definition of the order cepstrum for analysis of vibration signals generated by rotating machinery was introduced. This method is based on the cepstrum estimation from the vibration signal sampled constant in angle with respect to the shaft speed of the gearbox. The order cepstrum method assists in the elimination of spectral smearing and modulation effects caused by the variation in shaft speed. The results show that the radial basis function neural network can be effectively used in the diagnosis of various gear faults through appropriate measurement and interpretation of gear vibration signals.

Acknowledgments

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