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Research on Quality Detection Methods for Automotive Transmission

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Abstract: Given the problems in intelligent diagnosis methods for automotive transmission, it is difficult to obtain the fault signal features and a large enough sample size to study. To solve these problems, a method integrating order tracking, cepstrum, support vector machine (SVM) and extremal curve is proposed in this paper. Order tracking and cepstrum are combined for processing the non-stationary vibration signal emitted by automotive transmission. As conventional intelligent methods cannot produce true results for insufficient samples, a method that combines SVM and extremal curve is presented. Input the vector acquired from the feature signals into the SVM model for the first detection, and then do the second detection by means of extremal curve which in turn can enrich the training samples in SVM model thus making the SVM model be more perfect. Analytical description and experimental studies are presented for the methods of signal processing and quality detection. The experimental results demonstrate the effectiveness and practicability of the proposed method. *Copyright © 2014 IFSA Publishing, S. L.*

Keywords: Transmission, Order cepstrum, Support vector machine, Extremal curve, Quality detection.

1. Introduction

Since the transmission has significant impacts on the overall performance of automobile, its quality detection methods have received a deep attention. For the reasons that the vibration signal contains various fault information, vibration signal is commonly utilized for rotating machinery fault diagnosis [1]. Numerous methods for signal processing such as power spectrum estimation, fast Fourier transform, cepstrum analysis and envelope spectrum analysis have been developed. Many faults may not be found when the shaft speed is near constant, however are likely to occur during the process of run-ups, run-downs and shifting in automotive transmission [2-4]. Therefore, signals acquired from the aforementioned non-stationary process are more meaningful for its fault diagnosis. However, conventional methods are prone to produce aliasing, when applied to the non-stationary signal processing. Hence these methods relying on stationary signal are not suited to this case. To solve this problem, a method known as order tracking which can convert the non-stationary signal to the stationary signal is employed. Periodicities in spectrum obtained by using order tracking sometimes are contaminated with noise. To find the periodicities and inhibited noise, cepstrum is employed to do the second processing in this paper. The method for signal processing using order tracking and cepstrum called order cepstrum is presented. The acquired feature signal will be used for quality detection. Artificial intelligent (AI) methods are based on sufficient samples which is not always true in practice where sufficient samples are not available. The support vector machine (SVM) [5] is introduced into machines fault diagnoses due to its high accuracy and good generalization for a smaller number of samples. After the first detection by SVM, it is recommended to do the second detection to ensure more faults can be recognized. The extremal curve is employed for this task. Moreover, the extremal curve can improve the accuracy and efficiency of SVM through enriching the training samples in SVM model during the process of quality detection. From the above discussion, order tracking, cepstrum, SVM and extremal curve are joined together as a whole method for automotive transmission quality detection. A testing platform supported by both hardware and software has been built according to the proposed method.

This paper is organized as follows. Section 2 describes a signal processing method known as the order cepstrum. In Section 3, we propose SVM and the extremal curve as a combined technique for quality detection. In what follows, an experiment is given to test the effectiveness of the proposed method in Section 4. Finally, some conclusions are drawn.

2. Signal Processing

2.1. Order Tracking

Classical vibration analysis methods work very well in the time or frequency domain when the shaft speed is near constant, however, are prone to produce aliasing when applied to the situation where the shaft speed changes during run-ups and run-downs or the shifting process. To overcome the shortcoming above, one method of vibration analysis, called the order tracking [6], is employed in this paper. This is a frequency analysis method that uses orders (cycles per revolution), instead of absolute frequency (*Hz*), as the frequency base. In this way, the time-domain non-stationary signal is converted to angle-domain stationary signal thus making speed-related vibrations, such as shaft defects and bearing wear, easier to defect.

Accurate order analysis requires vibration signals to be sampled at constant angular increments and hence at a rate proportional to the shaft speed [7]. The accuracy and reliability of the monitoring system largely depends on the quality of the synchronous samples.

The synchronously sampling is accomplished by two popular techniques: the traditional approach known as the hardware order tracking which uses hardware to dynamically adapt the sample rate and the computed order tracking (OCT) [8, 9] where the vibration signals and a tachometer signal are asynchronously sampled.

The traditional approach tends to produce error since the equipment is known to have problems following rapidly changing shaft speed. In addition, the associated cost and complexity of the equipment restrict its use. The computed order tracking method first records the data at constant Δt increments, using conventional hardware, and then resamples this signal to provide the desired constant $\Delta\theta$ data, based on a keyphasor signal [10]. The computed order tracking approach is preferred as it requires no specialized hardware. Moreover, this approach is considerably more flexible and can produce more accurate and reliable results than the traditional approach. The latter is chosen in this paper. The implementation steps are as follows:

1) Synchronously sample the vibration signal and the tachometer signal.

2) Process the vibration signal by low-pass filtering.

3) Interpolate the tachometer signal to obtain the time sequence at constant angular increment.

4) Use the time sequence to extract signal amplitude at constant angular increment, and then resample the filtered vibration signal.

5) Transform the resampled data from the angle domain to the order domain by means of an FFT.

2.2. Cepstrum

Cepstrum is an analysis function with many applications in signal processing. Power cepstrum, the most common cepstrum function used in noise and vibration analysis, which is defined as the inverse Fourier transform of the logarithm of an autopower spectrum [11, 12], is proposed. It finds periodicities via the inverse Fourier transform and the logarithm which amplifies low levels, and compresses high levels further enhance the ability of the cepstrum to find periodicities also where the harmonics are low. The added benefit is that if the analyzed signal is a composition of an input going through a linear system, then the cepstrum can sometimes separate the input cepstrum from the linear system frequency response. In addition, if the linear system and the spectrum have different main frequency ranges, then it is possible to filter out the effect of the linear system. Note that, power cepstrum function is not suited to the spectrum generated by means of the FFT when shaft speed changes, for it will produce aliasing in spectrum.

2.3. Order Cepstrum

The power cepstrum as mentioned above cannot produce a satisfactory result when the condition that the shaft speed is near constant is not met. Since order tacking as discussed is an ideal method to generate cepstrum when shaft speed changes, it is reasonable to come up with a new method, known as the order cepstrum, for vibration analysis which may generate the cepstrum first via order tracking and then produce the ultimate result using this cepstrum by means of the power cepstrum. As the resampling is affected by the modulation and noise, it is not likely to obtain nice analysis results only by using order tracking. The angle-domain signal should be processed by cepstrum so that the periodic component can be simplified to a single spectral line. Then the noise will be inhibited. The order cepstrum, denoted $C_x(q)$ [13], is calculated as:

$$C_x(q) = F^{-1}[LogS_x(f)], \tag{1}$$

where $F^{-1}[\ ]$ is the inverse Fourier transform; $S_x(f)$ and q denote the power spectral density and the angle variable, respectively.

3. Quality Detection

Most artificial intelligence methods for fault diagnosis are based on empirical risk minimization (ERM) principle and the result is not always true in practice where it cannot provide sufficient samples. Support Vector Machine (SVM) based on the structural risk minimization (SRM) principle gives better generalization ability for a small number of samples. SVM has a very good performance in classification in linear classification tasks [14]. It can also be used in non-linear classification task which is the substance of fault diagnosis. The process of non-linear classification using SVM is as follows: First, the data to be classified is mapped to a high – dimensional feature space where the linear classification is possible by using a non-linear vector function ϕ. Then partition the training sample set by finding the optimal hyperplane which creates the maximum distance between the plane and the nearest data, i.e. the maximum margin.

SVM working in the high-dimensional feature space also generates the computational problem due to over-fitting. It can be solved by using the kernel function which returns a dot product of the feature space mappings of the original data points, defined as: $K(x_i, y_i) = f(x_i) \cdot f(y_i)$. By projecting the original sample space onto a high-dimensional feature space with a kernel function [15-18] $K(x, x_i)$, the non-linear classification problem is converted to linear classification problem in the high-dimensional feature space, in this way, the over-fitting problem is solved.

Any function satisfies the Mercer's theorem can be used as a kernel function. There are different functions used in SVM, such as linear, polynomial and Gaussian. It is proved that different selection of the kernel function has little influence on the performance of SVM. In this paper, the polynomial kernel function which provides the algorithm with less complexity is selected for the sake of improving the classification speed. The polynomial kernel function is given by:

$$K(x, y) = (x \cdot y + 1)^d ; d = 1,2,3... \tag{2}$$

The objective function of optimization for quadratic programming problem can be written as:

$$Q(\partial) = \sum_{i=1}^{n} \partial_i - \frac{1}{2} \sum_{i,j=1}^{n} \partial_i \partial_j y_i y_j K(x_i, y_j) \tag{3}$$

The general formula [19-21] for data classification in the support vector machine is:

$$f(x) = \operatorname{sgn}\left[\sum_{i,j=1}^{n} \partial_i y_j K(x_i, y_j) + b \right], \tag{4}$$

where ∂_i is the optimized coefficient, $K(x, x_i)$ is the kernel function.

In order to ensure that more faults can be recognized, it is better to detect again by using a different method. A method based on extremal curve is proposed here. The extremal curve is a curve acquired from the stored data which underwent a series of treatment by means of mathematics statistics, i.e. following $3\delta + \Delta$ principle, calculate the standard deviation δ for each data in the spectrum and adjust the offset of the spectral line relative to the zero curve and so on. The procedure of using the extremal curve is as follows: compare the current order spectrum with the extremal curve. If the current order spectrum exceeds the extremal curve, find out the corresponding order of the excess part to query the database so that the type of defect will be found. Otherwise, update the extremal curve. The extremal curve can in turn enrich the training samples in SVM by finding the faults which have not been recognized by means of SVM.

It is seen that the method of quality defection using extremal curve can remedy the shortage of data samples in the manner that the database can update frequently during the process of quality detection.

The whole procedure followed for quality detection using SVM as well as extremal curve is presented as shown in Fig. 1. Original signal is required to be processed firstly through the process of low-pass filtering, time domain averaging, order analysis and cepstrum to obtain the order spectrum from which the vector acquired from the feature signals will be extracted. Then detect the quality of the transmission for the first time after the feature signal has been input into the support vector machine model. If no defects occur after detection, then do the further detection by means of the extremal curve. Update the extremal curve if the current order spectrum does not exceed the extremal curve after comparison, otherwise, find out the corresponding order of the excess part, and then obtains the type and location of the defect by querying the database. Moreover, the test samples can be utilized to update the training sample library so that more training samples will be contained in the support vector machine model.

4. Experimental Verification

Following the aforementioned discussion, a complete hardware and software quality detection system for automotive transmission has been built. The online detection task for transmission is accomplished through steps from signal processing to quality detection. In what follows, an experiment is done to verify the feasibility of the method.

The scene of experiment is shown in Fig. 2. The left picture is the pre-delivery test rig on which an automotive transmission being detected is installed. The right picture shows the software testing platform.

The internal structure diagram of transmission is shown in the Fig. 3. The gear parameters and the bearing parameters are shown in Table 1 and Table 2 respectively. The speed change is achieved through changing the transmission ratio.

The results of transmission analysis vary at different revolution speed, hence each shaft of different gears corresponds an extremal curve.

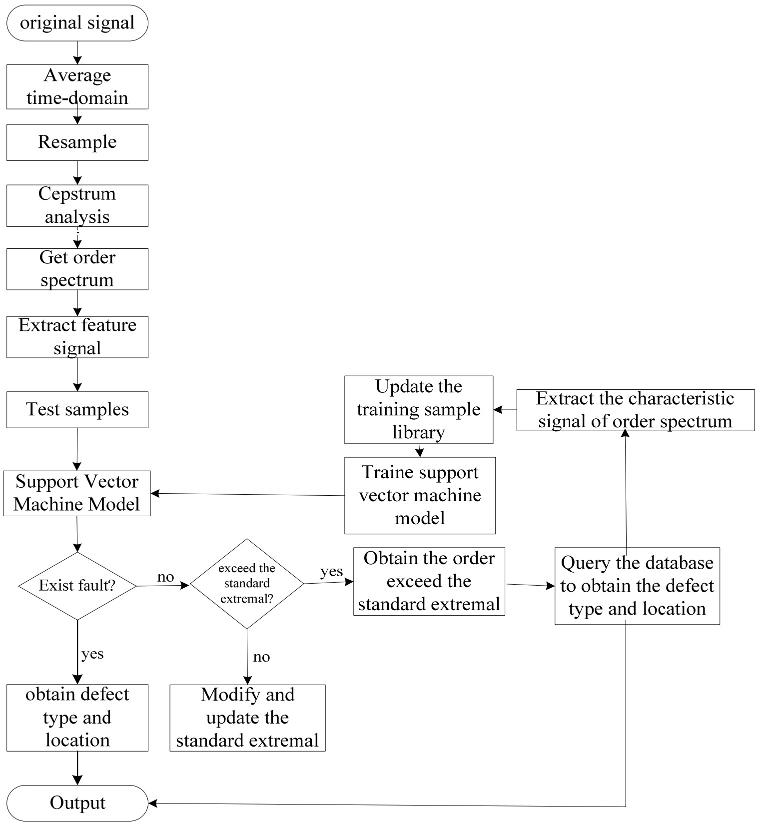
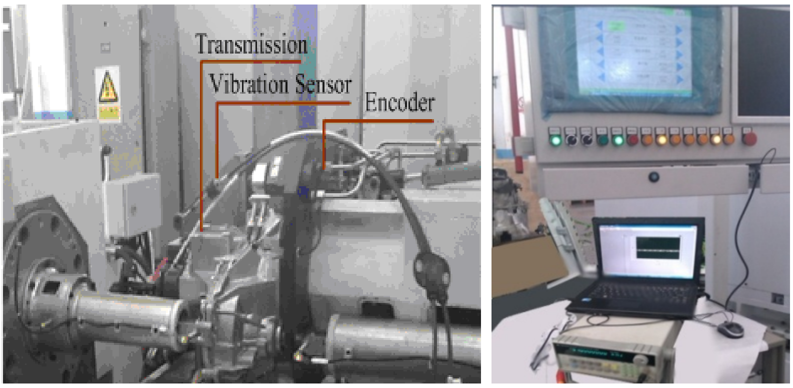


Fig. 1. The flow chart of quality detection.



a) b)

Fig. 2. The scene of experiment.

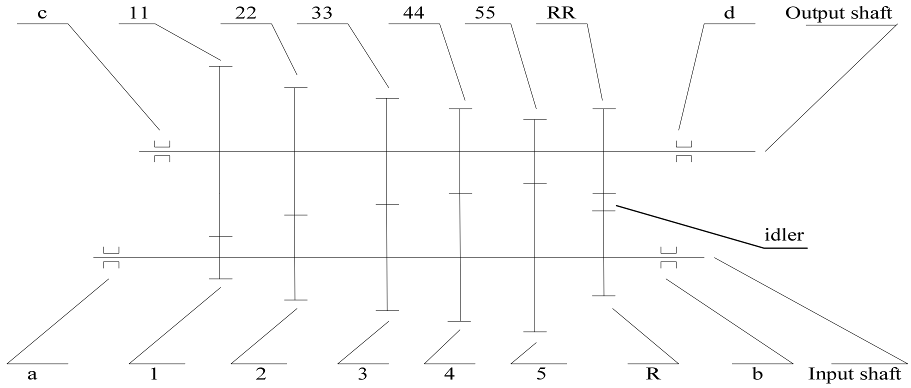


Fig. 3. The internal structure diagram of the transmission.

Table 1. Gear parameters.

Code	Number of teeth	Code	Number of teeth
1	11	11	40
2	22	22	45
3	29	33	41
4	39	44	41
5	41	55	35

Table 2. Bearing parameters.

Code	Bearing diameter	Roller diameter	Contact angle	Number of rolls
a	24.25	2.55	1	21
b	21.24	13.8	1	7
c	39.38	5.136	1	21
d	26.16	4.16	1	14

The sampling frequency of vibration signal is 5000 Hz in the experiment, and the encoder is 2000 lines/rev. The analysis object is the input shaft in raising speed condition, the number of analysis revolutions is 4, the number of time-domain average is 3, and the analysis order is 256. The number of pulses needed to intercept the input shaft is $M \geq 2000 \times 3 \times 4$. Upload these data to the signal processing module. The number of the analysis points is 1024. The interpolation angle is 1.4. The number of data interception points is 24000. According to Table 1, Table 2 and the characteristic order formula of gear and bearing, the characteristic parameters are shown in Table 3.

The output vector i.e. the result of SVM classification is $Y = \{1 \quad 2 \quad 3\}$. "1" represents the normal condition of the transmission; "2" represents gear misalignment on the input shaft; "3" represents surface machining error of gear on the input shaft. In what follows, the three types of defect will be discussed in detail.

Table 3. Characteristic parameters.

Characteristic parameters	value
Order of shaft(f_r)	f_r
Order of Gear meshing (f_m)	11 f_r
The outer ring order of "a" bearing(f_{1w})	9.3 f_r
The inter ring order of "a" bearing (f_{1n})	11.6 f_r
Rolling body rotation order of "a" bearing (f_{1z})	8.4 f_r
The outer ring order of "b" bearing (f_{2w})	1.2 f_r
The inter ring order of "b" bearing (f_{2n})	5.8 f_r
Rolling body rotation order of "b" bearing (f_{2z})	0.4 f_r

4.1. The Normal Condition of the Automotive Transmission

In Fig. 4, the order cepstrum of normal condition is shown. It follows from the characteristic order calculated above that peak should appear at the shaft order, second harmonic of shaft order, gear mesh order and the outer ring order of "*a*" bearing in the normal condition. The effect of noise has been effectively inhibited in the power spectrum due to the use of cepstrum. Moreover, the periodic component has been simplified to a single spectral line thus making signal observation and feature extraction much easier to achieve.

The time-domain characteristic values consist of RMS (X_1), Peak (X_2), and Crest (X_3). The frequency-domain characteristic values consist of the shaft order (X_4), the second harmonic of shaft order (X_5), the outer ring order of "*a*" bearing (X_6), the inter ring order of "*a*" bearing (X_7), the rolling body rotation order of "*a*" bearing (X_8), the outer ring order of "*b*" bearing (X_9), the inter ring order of "*b*" bearing (X_{10}), the rolling body rotation order of "*b*" bearing (X_{11}), gear mesh order (X_{12}), the second harmonic of gear mesh order (X_{13}). Table 4 and Table 5 show the extracted time-domain characteristic values and frequency-domain characteristic values respectively.

In this test, the output of SVM model is "1", which indicates that the transmission has no defect.

If no defects occur after detection by means of SVM, it needs to be detected again by using the extremal curve. The detection result is shown in Fig. 5. The continuous thin line represents the extremal curve. The dot dash line represents the order cepstrum of the transmission. It can be seen that the order cepstrum does not exceed the extremal curve, which indicates the transmission has no defect and the results produced by the two detection methods are the same.

Table 4. The time domain characteristic values.

Code	X_1	X_2	X_3
Value	0.8600	0.3641	2.3620

Table 5. The frequency domain characteristic values.

Code	X_4	X_5	X_6	X_7
Value	0.1139	0.4493	0.8600	0.7702
Code	X_8	X_9	X_{10}	X_{11}
Value	0.0012	0.0081	0.1511	0.7083
Code	X_{12}	X_{13}	--	--
Value	0.3463	0.0315	--	--

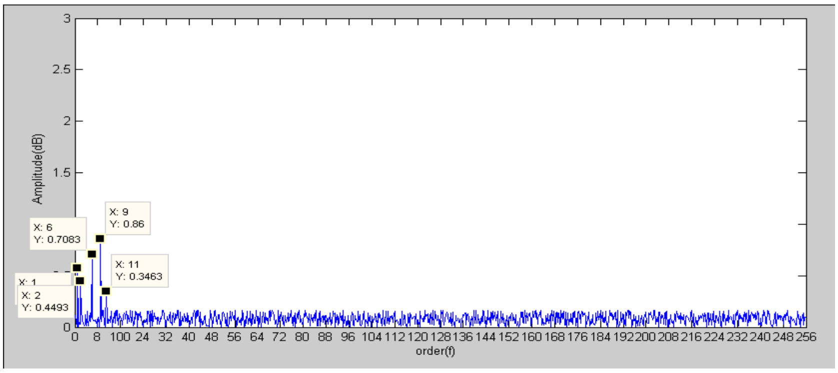


Fig. 4. The order cepstrum of normal condition.

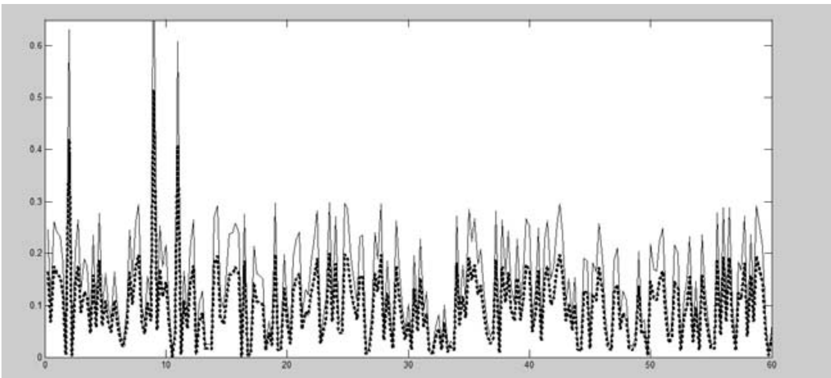


Fig. 5. The detection result using extremal curve.

4.2. The Gear Misalignment of the Automotive Transmission

The order cepstrum of misalignment is shown in Fig. 6. The amplitude in Fig. 6 exceeded the amplitude in Fig. 4 apparently. The peak occurs in gear mesh order as well as its second harmonic and third harmonic. The time domain characteristic values and the frequency domain characteristic values extracted by signal processing are shown in Table 6 and Table 7 respectively. Input the characteristic values vector into the SVM model, the output is "2". It indicates that the defect of gear misalignment exists in the transmission.

4.3. The Surface Machining Error of Gear of the Automotive Transmission

The order cepstrum of surface machining error is shown in Fig. 7. In Fig. 7 the peak appears in the gear mesh order and its second harmonic. In addition to this, the "ghost line" can also be seen between the gear mesh order and the second harmonic and between the second harmonic and the third harmonic as well. The "ghost line", as a frequency component in power cepstrum, is a periodic component produced by defect appeared during processing. The time domain characteristic values and the frequency domain characteristic values extracted by signal processing are shown in Table 8 and Table 9 respectively. Input the characteristic values vector into the SVM model, the output shows "3", which represents the defect of surface machining error of the gear.

Table 6. The time domain characteristic values.

Code	X_1	X_2	X_3
Value	1.9810	0.4165	4.7563

Table 7. The frequency domain characteristic values.

Code	X_4	X_5	X_6	X_7
Value	0.5621	0.5786	0.9609	1.0716
Code	X_8	X_9	X_{10}	X_{11}
Value	0.1526	0.8106	0.8852	0.0153
Code	X_{12}	X_{13}	--	--
Value	1.9810	0.9235	--	--

Table 8. The time domain characteristic values.

Code	X_1	X_2	X_3
Value	1.5321	0.3643	4.2056

Table 9. The frequency domain characteristic values.

Code	X_4	X_5	X_6	X_7
Value	0.9275	0.7910	0.5394	0.9764
Code	X_8	X_9	X_{10}	X_{11}
Value	0.2017	0.7546	0.1058	0.0247
Code	X_{12}	X_{13}	--	--
Value	0.7368	0.8298	--	--

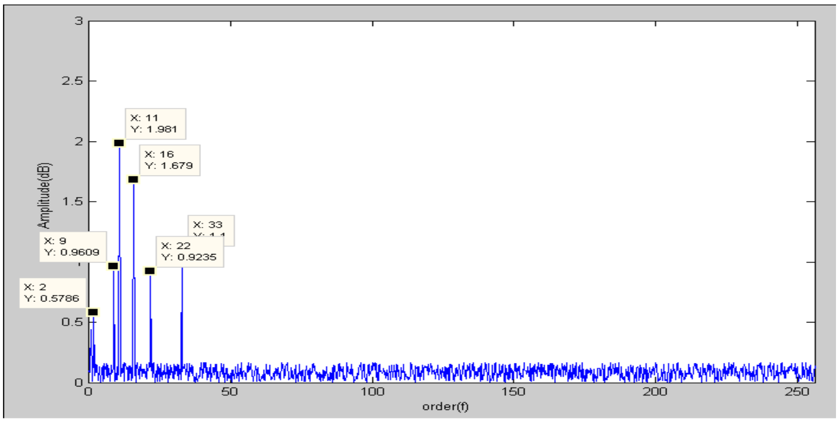


Fig. 6. The order cepstrum of gear misalignment.

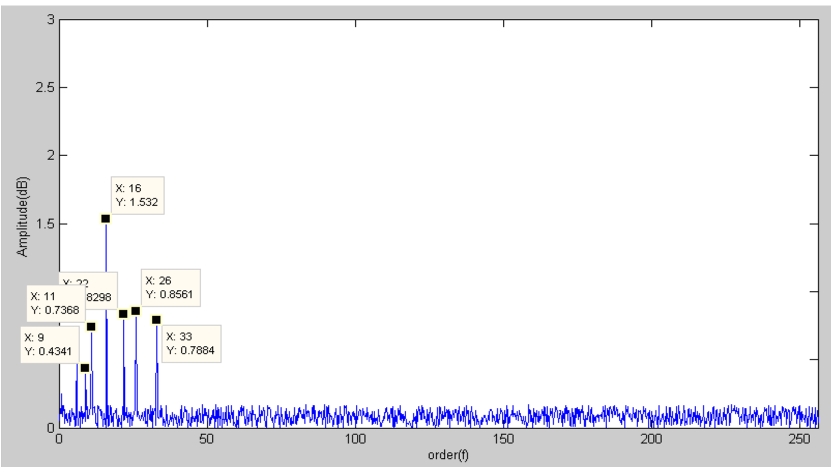


Fig. 7. The order cepstrum of surface machining error of gear.

5. Conclusions

In this paper, a method integrating order cepstrum, SVM and extremal curve for automotive transmission quality detection has been proposed. Based on the method, a hybrid diagnosis system has been built. Tests for automotive transmission fault diagnosis have been done under three conditions include: the normal condition, the gear misalignment, and the surface machining error of gear. The results presented in this paper show that in the signal processing stage, aliasing has been avoided, periodicities have been found clearly, and the periodic component has been simplified to a single spectral line by using order cepstrum. Besides, the quality detection has been accomplished using SVM and extremal curve which overcome the weakness of the conventional methods that it is not able to produce the true result if sufficient samples are not available. In addition to this, new fault samples acquired by means of extremal curve can enrich the SVM model. It can be concluded that the method proposed can be used in the field of automotive transmission quality detection with satisfactory result.

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Important Dates:

Mai, 15th: Full manuscript
June 1st: Notification of acceptance/rejection
July 1st: Final submission + early registration deadline
August 1st: Last possible payment for inclusion in proceedings

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