Gearbox Fault Diagnosis Based on Polynomial Chirplet Transform and Support Vector Machine

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Abstract: In order to effectively extract gearbox signal features from complex vibration signals with interference from small samples and diagnose faults, this article proposes a gearbox fault diagnosis method based on polynomial chirplet transform and support vector machine. Firstly, via the polynomial chirplet transform for time-frequency analysis of vibration signals, a set of transformation kernel parameters that can centrally and accurately represent the time-frequency characteristics of the vibration signal are proposed as features to distinguish different states of the gearboxes. Secondly, this research combines the transform kernel parameters with time-domain and frequency-domain features to form feature vector groups. Then we use the feature vector group as the input set of the support vector machine to classify the feature vector group and obtain the state judgment of gearbox vibration signals. It's found that transformation kernel parameters have a significant positive effect on improving the accuracy of model faults diagnosis after multiple experimental comparisons and this algorithm has generalization.

1 INTRODUCTION

Gearbox fault diagnosis (Zhuang Ye, 2021), as a current research hotspot, attracts widespread attention in multiple fields, and gearbox is a mechanical device widely used in mechanical equipment to increase output torque or change motor speed. In recent years, algorithms based on feature extraction and pattern recognition have been widely used for gearbox fault diagnosis. Using time-frequency analysis methods such as short-time Fourier transform and wavelet transform to process the original signal, and the obtained time-frequency images were used as the input set of the neural network to form a gearbox fault diagnosis model (Yiwei Cheng - Jianhua Zhou) based on a combination of non parametric time-frequency analysis methods and machine learning methods. However, the non parametric time-frequency analysis methods (Anand Parey, 2019), such as short-time Fourier transform, wavelet transform, and Wigner-Ville distribution, have time-frequency resolution independent of the signal. It is prone to errors when reflecting the time-frequency characteristics of complex signals, and the extracted features do not yield relatively accurate pattern recognition results. In addition, the application of neural networks in intelligent fault diagnosis (Zhuang Ye - Mingjing Yao) requires a large amount of fault data, but in reality, collecting a large amount of fault data can sometimes be cumbersome and difficult.

The parameterized time-frequency analysis methods (Yang Yang, 2013) construct a matching transform kernel function for the signal model and iteratively select the appropriate transform kernel parameters to obtain a high-precision and cross term interference free time-frequency representation, which is beneficial for analyzing non-stationary signals and extracting useful information. In parameterized time-frequency analysis methods, polynomial chirplet transform (PCT) essentially uses polynomial functions to approximate the true time-frequency characteristics of the signal, thereby obtaining an accurate time-frequency representation of the polynomial phase signal. According to the Weierstrass approximation theorem, any continuous function on a closed interval can be uniformly approximated by a polynomial series. Therefore, compared to other parameterized time-frequency analysis methods, polynomial chirplet transform is suitable for analyzing non-stationary signals with finite and short lengths. Support vector machine (SVM) is a commonly used machine learning algorithm. Support vector machine adopts the principle of structural risk minimization to select models, therefore it has strong generalization ability.

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In addition, support vector machine adopts the principle of maximizing interval to classify samples, so it can effectively handle small sample data (Bin Li, 2019).

On the basis of the above analysis, this article studies the problem of gearbox fault diagnosis. Using polynomial chirplet transform for time-frequency analysis of vibration signals, a set of transformation kernel parameters that can centrally and accurately represent the time-frequency characteristics of vibration signals was proposed as features to distinguish different states of gearboxes. Analyze the time-domain and frequency-domain, and combine the extracted time-domain and frequency-domain features with the transformation kernel parameters to form a feature vector group. Using the feature vector group as the input set of support vector machine, a gearbox fault diagnosis model based on PCT and SVM is obtained. Compare and analyze the model accuracy obtained from the feature vector groups before and after adding transformation kernel parameters, and conduct generalization experiments on the gearbox fault dataset publicly available at Southeast University.

2 POLYNOMIAL CHIRPLET TRANSFORM

2.1 Definition of Polynomial Chirplet Transform

Generally, for the analytical signal $\mathrm{z(t)}$ of the frequency modulation signal $\mathrm{s(t)}$, let the transform kernel function

$$\kappa_{\mathrm{P}}(\mathrm{t}) = \sum_{\mathrm{i}=2}^{\mathrm{n}+1} \mathrm{c}_{\mathrm{i}-1}\mathrm{t}^{\mathrm{i}-1}$$

Here $\{\mathrm{c}_1, \mathrm{c}_2, \mathrm{c}_3, \ldots, \mathrm{c}_\mathrm{n}\}$ is the polynomial coefficients, which is the transformation kernel parameters. The definition of polynomial chirplet transform is as follows:

$$PCT_S(t_0, \omega; \mathrm{c}_1, \mathrm{c}_2, \mathrm{c}_3, \ldots, \mathrm{c}_\mathrm{n}) = \int_{-\infty}^{+\infty} z(\tau)\Psi^{\mathrm{R}}_{\mathrm{c}_1,\mathrm{c}_2,\mathrm{c}_3,\ldots,\mathrm{c}_\mathrm{n}}(\tau)\Psi^{\mathrm{S}}_{\mathrm{t}_0,\mathrm{c}_1,\mathrm{c}_2,\mathrm{c}_3,\ldots,\mathrm{c}_\mathrm{n}}(\tau)g_\sigma^*(\tau - t)exp(-j\omega\tau)d\tau$$

$$\Psi^{\mathrm{R}}_{\mathrm{c}_1,\mathrm{c}_2,\mathrm{c}_3,\ldots,\mathrm{c}_\mathrm{n}}(\tau) = \exp\left(-\mathrm{j}\sum_{\mathrm{i}=2}^{\mathrm{n}+1}\frac{1}{\mathrm{i}}\mathrm{c}_{\mathrm{i}-1}\tau^{\mathrm{i}}\right)$$

$$\Psi^{\mathrm{S}}_{\mathrm{t}_0,\mathrm{c}_1,\mathrm{c}_2,\mathrm{c}_3,\ldots,\mathrm{c}_\mathrm{n}}(\tau) = \exp\left(\mathrm{j}\sum_{\mathrm{i}=2}^{\mathrm{n}+1}\mathrm{c}_{\mathrm{i}-1}\mathrm{t}_0^{\mathrm{i}-1}\tau\right)$$

$\mathrm{g}_\sigma(\mathrm{t})$ is a Gaussian window function with a time window of σ,

$$\mathrm{g}_\sigma(\mathrm{t}) = \frac{1}{2\sqrt{\pi\sigma}}\exp(-\frac{\mathrm{t}^2}{4\sigma})$$

2.2 Parameter Estimation of Polynomial Chirplet Transform

According to the mathematical definition of polynomial chirplet transform, by selecting appropriate transformation kernel parameters $\{\mathrm{c}_1, \mathrm{c}_2, \mathrm{c}_3, \ldots, \mathrm{c}_\mathrm{n}\}$, the transformation kernel function matches the time-frequency characteristics of the signal more closely. So, the higher the concentration of the representation of time-frequency, the more accurate the representation of the time-frequency characteristics of the signal. From the above, it can be seen that the selection of transformation kernel parameters $\{\mathrm{c}_1, \mathrm{c}_2, \mathrm{c}_3, \ldots, \mathrm{c}_\mathrm{n}\}$ determines the analytical performance of the polynomial chirplet transform method, which in turn affects its accuracy in characterizing the time-frequency characteristics of non-stationary signals. Therefore, suitable transformation kernel parameters can be used as features of vibration signals for fault diagnosis and detection research. In summary, estimating the appropriate transformation kernel parameters $\{\mathrm{c}_1, \mathrm{c}_2, \mathrm{c}_3, \ldots, \mathrm{c}_\mathrm{n}\}$ is crucial for the study of gearbox fault diagnosis.

Polynomial chirplet transform utilizes a polynomial function to iteratively approximate the time-frequency characteristics of signals, thereby obtaining suitable polynomial transformation kernel parameters. Based on this idea, a method for parameter estimation has been developed based on the definition of polynomial chirplet transform. Without losing generality, it is assumed that the time-frequency characteristics of the signal are any function of time $\mathrm{IF}(t)$. In the i-th iteration process, polynomial chirplet transform is first used to obtain the time-frequency representation of the signal, i.e.

$$PCT_S(t_0, \omega; \mathrm{c}_1, \mathrm{c}_2, \mathrm{c}_3, \ldots, \mathrm{c}_\mathrm{n}) = \int_{-\infty}^{+\infty} z(\tau)\Psi^{\mathrm{R}}_{\mathrm{c}_1,\mathrm{c}_2,\mathrm{c}_3,\ldots,\mathrm{c}_\mathrm{n}}(\tau)\Psi^{\mathrm{S}}_{\mathrm{t}_0,\mathrm{c}_1,\mathrm{c}_2,\mathrm{c}_3,\ldots,\mathrm{c}_\mathrm{n}}(\tau)g_\sigma^*(\tau - t)exp(-j\omega\tau)d\tau$$

Among them, $\kappa_{\mathrm{P}_i}(\mathrm{t})$ is the transformation kernel function defined by parameters P_i when the number of iterations is 1. Make $\mathrm{P}_0 = 0$. When using initialization kernel parameters to match the time-frequency characteristics of signals, the effect is poor. Therefore, further iterative optimization of polynomial kernel parameters is needed.

The position of the ridge in the time-frequency representation of a signal can represent its time-frequency feature $\mathrm{IF}(t)$, and under noise conditions, the energy of the signal is mainly concentrated near the ridge. Therefore, by performing peak detection along the time axis in the time-frequency representation of the signal, the corresponding ridge position can be obtained. Call it the approximate time-frequency characteristic of the signal $\widetilde{IF}_i(t)$.

The approximate time-frequency feature $\widetilde{IF}_i(t)$ obtained from the i-th iteration is

$$\widetilde{IF}_i(t) = \underset{\omega}{\operatorname{argmax}}\{|PCT_S(t,\omega;P_i)|\}$$

Using the least squares method and the necessary conditions for finding extreme values of multivariate functions to fit and approximate the approximate time-frequency characteristic curve,

$$\tilde{P}_i = \min_{P_i} \sum \left[\overline{\overline{IF}}_i(t) - \widetilde{IF}_i(t)\right]^2$$

Where $\overline{\overline{IF}}_i(t)$ is the polynomial fitting curve of the approximate time-frequency characteristics after the i-th iteration. $\tilde{P}_i$ is the estimated value of the transformation kernel parameter in the i-th iteration. If $P_i = \tilde{P}_i$, then the new transformation kernel function is

$$\kappa_{P_i}(t) = \overline{\overline{IF}}_i(t)$$

The judgment basis for iteration termination is

$$\Lambda_i = mean \int \frac{|\widetilde{IF}_i(t) - \widetilde{IF}_{i-1}(t)|}{|\widetilde{IF}_i(t)|} < \alpha \qquad (1)$$

When $i = 1, \widetilde{IF}_{i-1}(t) = 0$.

3 EXPERIMENTATION

3.1 Dataset Introduction

In order to verify the feasibility of this method, during the operation of the gearbox, vibration signals were collected by installing an acceleration sensor for gearbox fault diagnosis. This article collected vibration signals of the gearbox under 5 different states, namely normal state and 4 fault states, with a sampling frequency of 6.4kHz. Select 20 sets of experimental data from different states for gearbox fault diagnosis.

3.2 Model Design

Time frequency analysis can further extract effective information from signals. Perform time-frequency analysis on each group of data using polynomial chirplet transform. The basis for terminating the iteration is shown in equation (1). The threshold is set to 1%. Extract the optimal transformation kernel parameters corresponding to each group of data separately. Taking the first set of data in fault state 4 as an example. Fig. 1 shows the time-frequency analysis and polynomial fitting effect when using the initialization transformation kernel parameters (i.e. *P*=0). In fact, it is the short-time Fourier transform. Due to noise interference, the position of the ridge line deviates greatly from the true time-frequency characteristics.

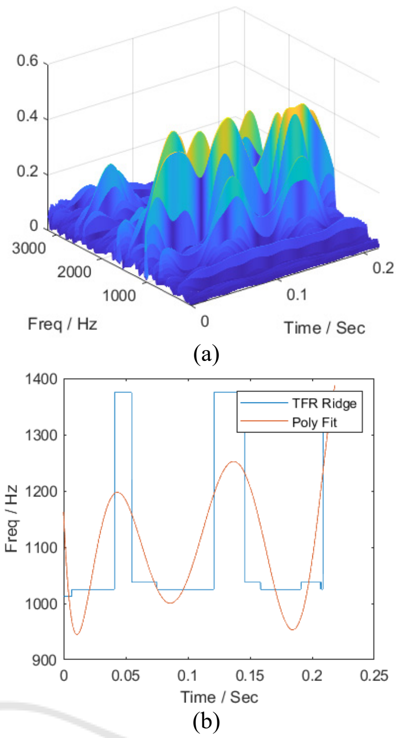

Figure 1. Initial time-frequency representation and polynomial fitting effect diagram.

Until the end of the iteration cycle, as shown in Fig. 2, the aggregation of time-frequency representation has been greatly improved, and the fitted polynomial curve is very close to the time-frequency characteristics of the signal.

At this point, polynomial chirplet transform accurately characterizes the time-frequency characteristics of the signal. Therefore, the transformation kernel parameters at this time can be extracted as a set of features for this group of signals.

In order to demonstrate the effectiveness of transforming kernel parameters in gearbox fault diagnosis, experiments were conducted to extract time-domain and frequency-domain features. Compare and analyze the accuracy of model classification before and after adding kernel parameters to the feature vector group. As the Box-plot is not affected by outliers, it can accurately and stably depict the discrete distribution of data, and visually display the distribution of each group of data. Therefore, Box-plot was used to filter out 12 commonly used features (Yajing Xiao, 2019) in fault diagnosis, including maximum, variance, average frequency, etc. Take the variance of the signal as an example. There are significant differences in the variance distribution range of each group's data under different states in Fig. 3. Therefore, it is feasible to use variance as a feature to distinguish different state data.

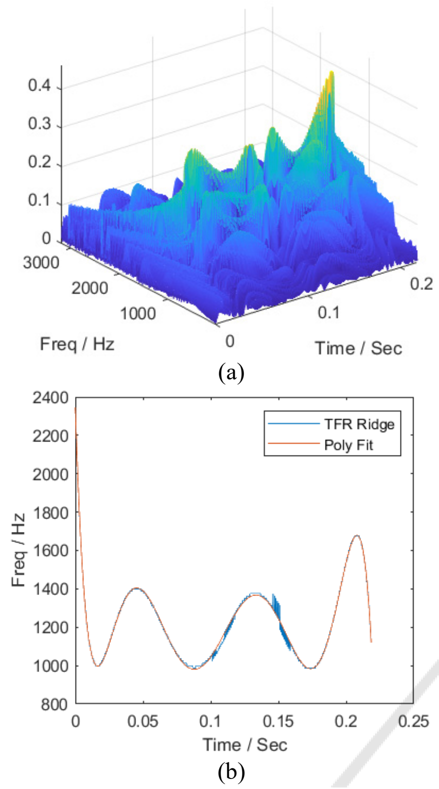

Figure 2. The optimal time-frequency representation and polynomial fitting effect diagram when reaching the threshold.

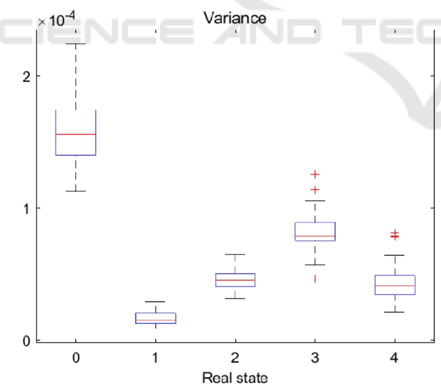

Figure 3. Box-plot of variance.

From this, the feature vector group of the gearbox vibration signal is obtained. Taking data one under normal conditions as an example. Its feature vector group is shown in Table 1. Preprocess the feature vector group. Using feature vector groups as input sets for support vector machine, a gearbox fault diagnosis based on PCT and SVM was established as shown in Fig. 4.

Table 1. The feature vector group of the first set of data in normal state.

Number	Time Domain Features		Frequency domain features		Transform kernel parameters
1	Waveform factor	1.2587256	Root mean square of frequency	1732.1435	1.088673E+03
2	Root mean Square	0.0317237	Center of gravity frequency	1539.9500	1.019567E+05
3	Minimum value	-0.094641	Average frequency	0.0009844	-5.757793E+06
4	Maximum value	0.1042190			1.283804E+08
5	Peak value	0.1988596			-1.399988E+09
6	Skewness	0.0348320			7.905804E+09
7	Kurtosis	2.9740948			-2.213817E+10
8	Variance	0.0010068			2.423154E+10
9	Margin	9.3294435			

Using the model obtained in Fig. 4, classify the feature vector groups. In order to observe the classification ability of the model in more detail, a confusion matrix is used to represent the classification results. As shown in Fig. 5, the horizontal axis represents the model's prediction of the state of the gearbox, while the vertical axis represents the true state of the signal. 0 represents normal state, 1 represents fault state one. The (0,0) coordinate value represents that the predicted state of the model is normal, and the true state of the signal is also normal, which means that the classification is accurate. The (1,0) coordinate value represents that the predicted state of the model is fault one, and the true state of the signal is normal, which means that the classification is incorrect. And so on.

From the figure, it can be seen that before adding transformation kernel parameters to the feature vector group, the accuracy of this model in state classification is 95%. After adding transformation kernel parameters to the feature vector group, the accuracy of this model in state classification is 100%.

3.3 Generalization Experiment

To further verify the universality of this method, this article uses the publicly available gearbox dataset from Southeast University (Chao Chen, 2020) for experiments. This dataset contains two sub datasets: bearing data and gear data. This article selects gear data, which includes normal state and four fault states, namely Chipped tooth, Missing tooth, Root fault and Surface fault. The speed load configuration is set to 20-0. Take the Y-direction vibration signal of

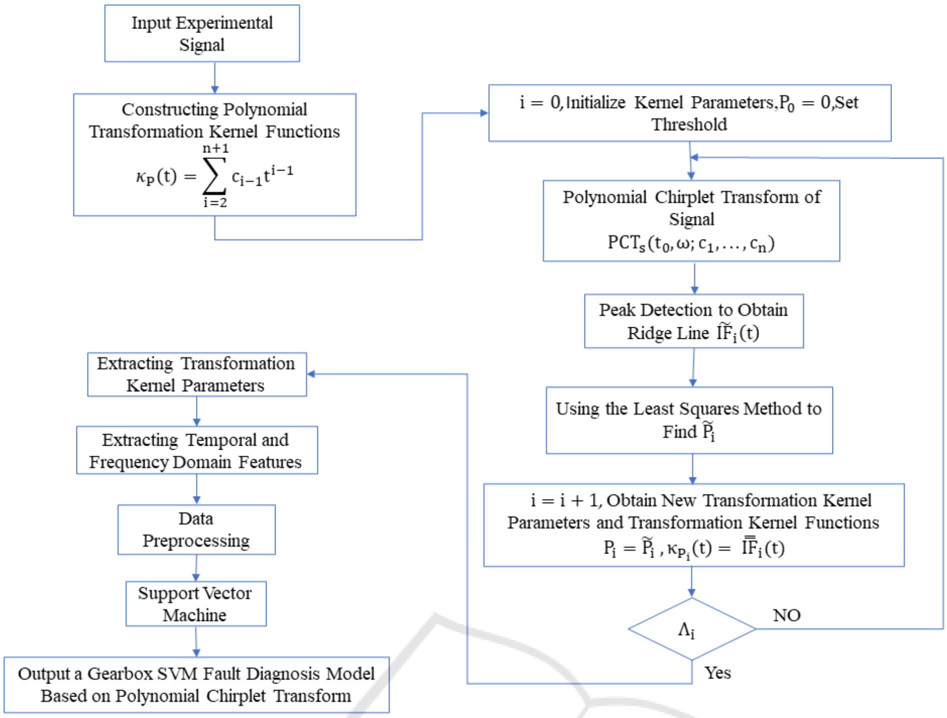

Figure 4. The gearbox fault diagnosis based on polynomial chirplet transform and support vector machine.

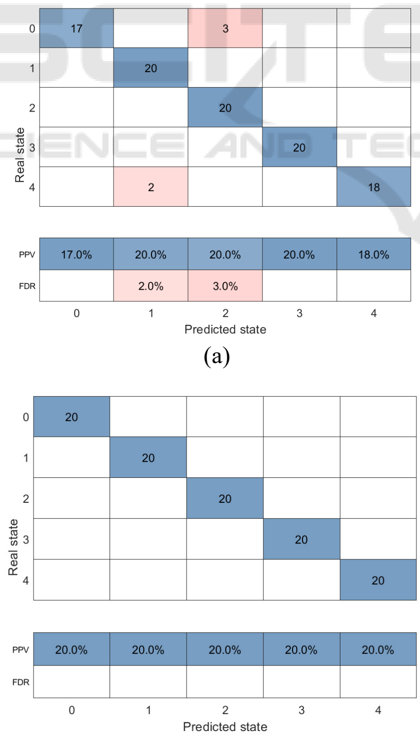

Figure 5. The confusion matrix before and after adding kernel parameters to the feature vector group.

the planetary gearbox as experimental data, take 1024 sampling points as sample length, and take 40 sets of samples for each state as the original dataset.

From the Fig. 6, it can be seen that the accuracy of the gearbox fault diagnosis based on PCT and SVM on this dataset is 98.5%, which performs well. This result verifies the generalization of the model on different datasets.

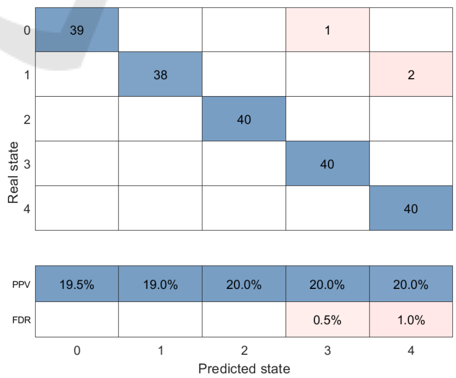

Figure 6. The classification effect on the gearbox fault dataset of Southeast University.

4 CONCLUSION

This article proposes a gearbox fault diagnosis method based on PCT and SVM. By studying the application of polynomial chirplet transform in time-frequency analysis, a set of features that can distinguish different states of gearboxes, namely transformation kernel parameters, has been proposed. Through comparative analysis, it can be concluded that this method can more effectively identify and classify different states of gearboxes. In addition, this article verified the generalization of the model on the gearbox fault dataset publicly available at Southeast University.

This method can accurately reflect the time-frequency characteristics of complex signals, and the extracted feature vector group containing transform kernel parameters can obtain more accurate pattern recognition results. In addition, this method is suitable for small sample experimental data and has low requirements for server configuration. Therefore, when using this method for fault diagnosis, it is easy to quickly collect data and perform fault diagnosis.

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