Advanced Engineering Forum *Online: 2011-12-22*
ISSN: 2234-991X, Vols. 2-3, pp 761-764
doi:10.4028/www.scientific.net/AEF.2-3.761

A Character of Rotating Machinery Defined Based on KICA

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Key words: KICA, fault diagnosis, rotating machinery

Abstract. This research aims at defining a character of rotating machinery—KIC, that the typical rolling bearing and gear failure modes can be effectively identified by using the character. Firstly, A correlation coefficient matrix is composed by the correlation coefficient between two-two independent component derived from kernel independent component (KICA). Then the KIC is defined by the correlation coefficient matrix. Experimental results show that the KIC has a good effect for identifying the bearing and gear fault modes, so it can be used as sensitive character for rotating machinery fault diagnosis.

Introduction

In modern times, rotating machinery covers a broad range of mechanical equipment and plays an important role in industrial application. Fault diagnosis and degradation assessment for rotating machinery are critical to maintain the normal operation of equipment, whose purpose is to analyze the relevant external information to judge the condition of the inaccessible internal components so as to decide if the bearing needs to be replaced or not [1]. Vibration analysis-based method is the most principal and effective method for bearing monitoring, and consists of two most important aspects (1) feature extraction (2) condition identification and fault diagnosis.

Effective feature extraction for fault diagnosis is still an ongoing research issue. The common techniques perform feature extraction from the waveforms in the time, frequency or time-frequency domain, and the extracted features include statistical quantities (e.g., mean value, root mean square value, skewness, kurtosis, crest factor, etc.), energy or entropy of different frequency bands obtained via wavelet/wavelet packet decomposition or empirical mode decomposition , fractal dimension [9], and so on. These waveform-based feature extraction methods always need to combine with failure mechanism to implement fault diagnosis. However, failure mechanism is a complicated process. At the same time, these features are sensitive to different faults and degradation stages, but none of them consistent enough to be used as a sole indicator of spall size.

Kernel Independent Component Analysis (KICA) is a non-linear method for blind source separation (BSS) advanced recently [2-4]. The approach is more robust than other ICA algorithms with regards to variations in source densities, degree of non-Gaussianity, and presence of outliers. So it is particularly appropriate in situations where little is known about the underlying sources [5-7]. This research aims at defining a character of rotating machinery——KIC, that the typical rolling bearing and gear failure modes can be effectively identified by using the character.

Theory

Kernel ICA is a new approach to the ICA problem based not on a single nonlinear function, but on an entire function space of candidate nonlinearities. F-correlation is defined as the maximal correlation between random variables, using reproducing kernel Hilbert space ideas, then an ICA contrast function can be based on the computation of a canonical correlation in function space. Finally, canonical correlation analysis (CCA) can be carried out efficiently in an RKHS by making use of the "kernel trick" [8-9]. The diagram of KICA process is shown in Fig. 1.

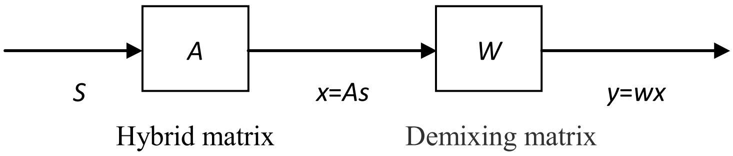

Fig. 1. The diagram of KICA process

Form the derivation process of KICA, it can be found that the independent components obtained after the hybrid matrix ***X*** pass though the demixing matrix ***W***, what the demixing matrix ***W*** plays the role of a filter. The structure of ***W*** is constituted by the the structure of ***X.*** The matrix whose structure similar with ***X*** can be decomposed to independent components passing though ***W***, but other structure matrixs may not have the same effect. It is well known that the independent components are uncorrelated with each other, so the correlation coefficient can be used to identify if a certain matrix can be decomposed to independent components passing though ***W,*** then, identify if the matrix similar with ***X***.

There is an example. Four channel bearing vibration signals with normal mode [x1,x2,x3,x4] is performed KICA, the demixing matrix $W_{bearing\_normal}$ and the independent components [y_1,y_2,y_3,y_4] are obtained. The correlation coefficient of random vector y_i and y_j can be described as follows:

$$r_{ij} = \frac{E\{[y_i - E(y_i)][y_j - E(y_j)]\}}{\sqrt{D(y_i)}\sqrt{D(y_j)}} \tag{1}$$

The four channel bearing vibration signals with normal mode is taken as template signal and the demixing matrix $W_{bearing\_normal}$ is taken as the template filter. Random signals of normal bearing and bearing with outer race defect are taken to pass through $W_{bearing\_normal}$. The correlation coefficient matrixs $R = [r_{ij}]_{4\times4}$ are shown as follows:

$$R_{normal} = \begin{bmatrix} 1.0000 & 0.1616 & 0.0618 & 0.0369 \\ 0.1616 & 1.0000 & 0.1756 & 0.0390 \\ 0.0618 & 0.1756 & 1.0000 & -0.0231 \\ 0.0369 & 0.0390 & -0.0231 & 1.0000 \end{bmatrix} \quad R_{outer} = \begin{bmatrix} 1.0000 & 0.4850 & -0.2454 & -0.2643 \\ 0.4850 & 1.0000 & 0.1038 & -0.2125 \\ -0.2454 & 0.1038 & 1.0000 & -0.1805 \\ -0.2643 & -0.2125 & -0.1805 & 1.0000 \end{bmatrix}$$

R_{normal} is corresponding bearing with normal mode and R_{outer} is corresponding bearing with outer race fault . It can be found that the correlation coefficient of R_{normal} is smaller than R_{outer} .Because the signals of outer race fault bearing is different with the template. According to this case, The character KIC can be defined as follows:

$$KIC = \sqrt{\sum_{i=1}^{n}\sum_{j=1}^{n}(1 - r_{ij})^2} \tag{2}$$

Experimental

Experiments were performed on Machinery Fault Simulator (MFS) from SpectraQuest, Inc. shown in Fig. 2. It can simulate most of faults that commonly occur in rotating machinery, such as misalignment, unbalance, resonance, roller bearing faults, gearbox faults, and so on.The simulator has a range of operating speeds up to 6000 rpm. In this work, the simulator is composed of a motor, a coupling, a testing roller bearing fitted on the left of the shaft near the motor, a working roller bearing on the other side, a bearing load and a shaft. The MFS provides a bearing fault kit consisting of one inner race defect, one outer race defect, one with ball defect, and one combination of defects for performing experiments and studying bearing fault diagnosis, and provides one chipped tooth and one missing tooth for performing experiments and studying gear fault diagnosis.

Fig. 2. Machinery Fault Simulator

The shaft rotating speed was obtained by a laser speedometer. Acceleration signals were measured using the Dewetron 16 channels data acquisition system and the IMI 603C01 accelerometers. The data was stored in .mat format for further Matlab operation.

Results and discussion

The four channel bearing vibration signals with normal mode is taken as template signal and the demixing matrix $W_{bearing\_normal}$ is taken as the template filter. Four channel bearing vibration signals with normal , inner race defect, ball defect and outer race defect are taken for analyzed respectively. The values of KIC are shown in Tab1. 50 samples are taken from four bearing defective modes respectively. The values of KIC are plot and shown in Fig. 3. It can be found that the KIC has a good effect for identifying the bearing fault modes, so it can be used as sensitive character for rolling bearing fault diagnosis.

The four channel gear vibration signals with normal mode is taken as template signal and the demixing matrix W_{gear_normal} is taken as the template filter. Four channel gear vibration signals with normal , chipped tooth defect and one missing tooth defect are taken for analyzed respectively. The value of KICs are shown in Tab2. 50 samples are taken from three gear defective modes respectively. The values of KIC are plot and shown in Fig. 3. It can be found that the KIC has a good effect for identifying the gear fault modes, so it can be used as sensitive character for gear fault diagnosis.

Table 1 The KIC values of rolling bearing

Mode \ Samples	1	2	3	4	5	6	7	8	9	10
Normal	3.73	3.83	3.91	3.82	3.71	3.79	3.88	3.81	3.91	3.78
Inner race defect	2.94	2.98	3.03	2.91	2.94	2.96	2.97	3.06	2.83	3.08
Outer race defect	2.13	2.12	2.15	2.17	2.13	2.01	2.13	2.17	2.08	2.17
Ball defect	3.56	3.55	3.53	3.54	3.55	3.51	3.59	3.50	3.55	3.51

Table 2 The KIC values of gear

Mode \ Sample	1	2	3	4	5	6	7	8	9	10
Normal	4.05	4.10	4.08	4.12	4.11	4.08	4.12	4.08	4.10	4.10
Chipped tooth	3.94	3.92	3.93	3.89	3.95	3.95	3.99	3.98	3.89	3.88
Missing tooth	3.64	3.71	3.69	3.71	3.67	3.71	3.70	3.65	3.65	3.63

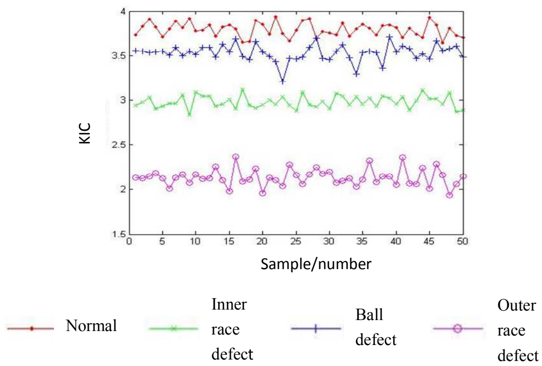

Fig. 3. Compare with the KIC values of roller bearing with four different defective mode

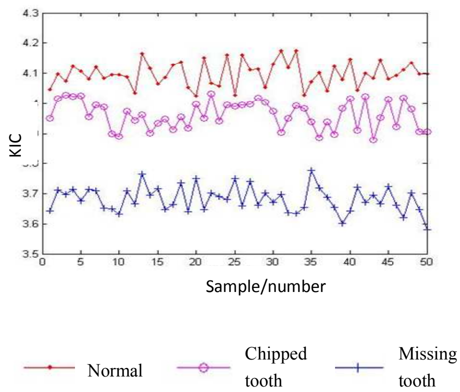

Fig. 4. Compare with the KIC values of gear with three different defective mode

Conclusion

The KIC has a good effect for identifying the bearing and gear fault modes, so it can be used as sensitive character for rotating machinery fault diagnosis.

Acknowledgements

This work is supported by the national natural science foundation of China (51105138), the aid program for science and technology innovative research team in higher educational institutions of Hunan province, the cultivating program for the industrialization of research findings in higher education institutions of Hunan province(10CY008), the CEEUSRO special plan of Hunan province (2010XK6066) .

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