Using a Model Matching Method for Rolling Bearing Fault Determination

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Abstract. This paper mainly introduces the model matching method in fault determination of an application, first before applying the model matching method for characteristics of principal components analysis, reducing their dimensions to improve the performance.

1. Introduction

Rolling bearing is part of the mechanical and electrical equipment in the worst working conditions, plays in the mechanical and electrical equipment to withstand the load and deliver the payload, whether its running normal directly affects the performance of the entire machine. In General, the disintegration of complex, precision mechanical and electronic devices should not be checked, as one of the important parts of the bearing, was demolished after the diagnosis of the damage is not allowed, which also caused technical difficulties in monitoring and fault diagnosis of bearings. Based on the principal component analysis (PCA) model matching method is a simple and effective method of rolling bearing fault judgment has a certain application.

2. Model matching method based on PCA

2.1 PCA reduction principle

Principal component analyses (Principal Component Analysis, PCA), multiple variables by linear transformations to elect a number of less important variables in a multivariate statistical analysis. Also called principal component analysis. In the actual project, in order to analyze problems, often a lot of variables associated with this (or factor) because every variable information reflected to varying degrees in the subject. Principal components analysis is first by K. Pearson on the introduction of non-random variable, thereafter H. Hotelling this method is extended to the cases of random vectors. Message size is usually measured by the sum of squares of deviation or variance.

Principal component analysis is to find the original number has certain dependencies (such as p), reassembled into a new set of integrated indicators unrelated to each other instead of the original target. Main components analysis, is study multiple variable between correlation a multiple statistics method, research how through minority several main components to reveals multiple variable between of internal structure, that from original variable in the export minority several main components, makes they as more to retained original variable of information, and each other between non related. Usually mathematics Shang of processing is will original p a index for linear combination, as new of integrated index. The classic approach is to use F_1 (choose the first linear combinations, the first comprehensive index) the variance expression, the Var (F_1) higher, say F_1 contains more information. Therefore all linear combinations of F_1 is the variance of the books in the maximum, so that F_1 is the first principal components. If first main components not enough to representative original p an index of information, again consider selected F_2 that selected second a linear combination, to effective to reflect original information, F_1 has some information on not need again appeared in F_2 in the, with mathematics language expression is requirements Cov (F_1, F_2) = 0, is said F_2 for second main components, and so on can structure out third, and fourth,......, subsection P a main components.

2.2 Model matching method

Model matching method is compared to a standard template and unknown samples to see if they are the same or similar. Model matching method includes two categories and multiple categories. The General steps are as follows:

Feature extraction of the treated samples, the feature vector X;

Calculating eigenvector x samples and template vector X_1, $X_2 \cdot\cdot\cdot$, X_C distance between D_1, ..., D_C; If $D_i=\min\{D_j\}$,j=1,2,...,C, and $D_i < \varepsilon$, is awarded the sample X is classified as class i, is recorded as; If all D_i (i=1, 2, ..., C) is greater than ε, then rejected.

3. Algorithm implementation

Based on the MATLAB platform 39 you have extracted 12-dimensional feature samples the classifier is trained, afterwards using the trained classifier to other 14 12-dimensional to determine the characteristics of samples, and to evaluate performance.

3.1 Algorithm

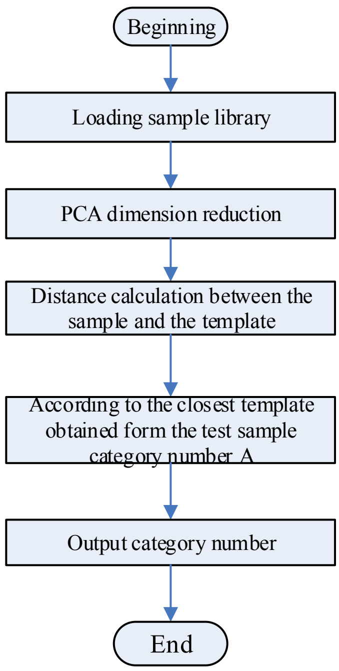

Fig.1 Algorithm flow chart

3.2 Principal component selection and sample distribution

Sample library with PCA after operation, the first principal component contributes to 93%, the first two principal components contributed to 97%, the first three principal components contributes to 98%.

Based on the first three principal components observed sampling distribution is shown in Figure 2, can see normal samples and samples distribution centers nearly coincide, so the algorithm based on Euclidean distance of Center method does not apply.

Contribution is 1% the third principal component (Figure 2 (a) for the z-coordinate) distinction between samples is not working. So take the first two main consists of dimension reduction features, the total contribution rate threshold is set to 95%.

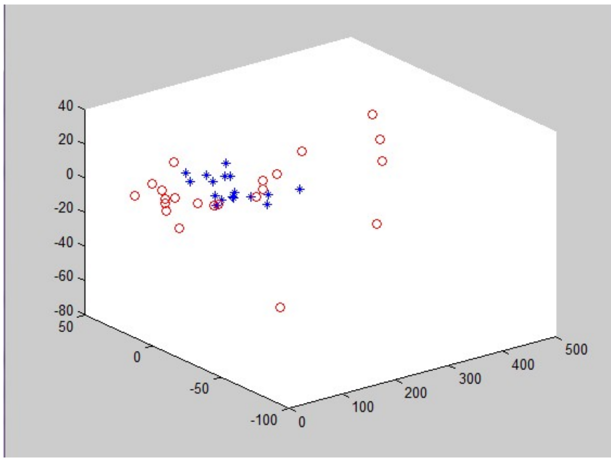

Fig.2 (a) The first three principal components distribution

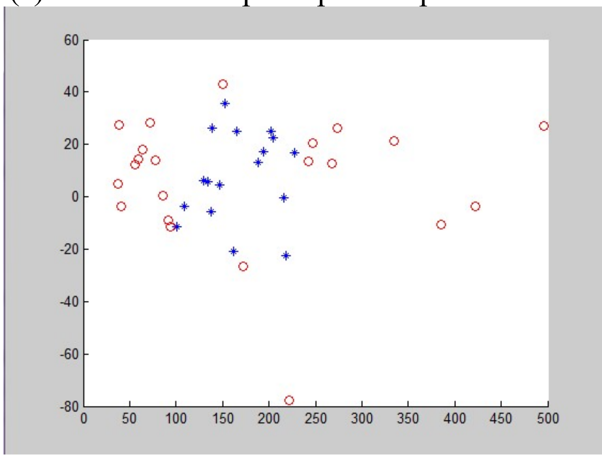

Fig.2 (b) The first two principal components distribution

4. Conclusion

Run the result is shown in Figure 3.

Through this experiment, PCA analysis of selected data for dimension reduction and classification using model matching method, reduce the amount of computation and storage.

The first two principal components results in Figure 3, classifier testing results are correct, the first three principal components results in Figure 4, classifier testing results is 92.86%, again: contributed to 1% the third principal component samples of the distinction no longer plays an active role.

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Command Window
 1 th test results for 0 should be 0 test results correct
 2 th test results for 0 should be 0 test results correct
 3 th test results for 0 should be 0 test results correct
 4 th test results for 1 should be 1 test results correct
 5 th test results for 0 should be 0 test results correct
 6 th test results for 0 should be 0 test results correct
 7 th test results for 0 should be 0 test results correct
 8 th test results for 0 should be 0 test results correct
 9 th test results for 0 should be 0 test results correct
 10 th test results for 0 should be 0 test results correct
 11 th test results for 0 should be 0 test results correct
 12 th test results for 0 should be 0 test results correct
 13 th test results for 1 should be 1 test results correct
 14 th test results for 1 should be 1 test results correct
 Completed 14 times test, The accuracy is 100.000000%
fx >>
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Fig. 3. Results after running

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Command Window
 1 th test results for 0 should be 0 test results correct
 2 th test results for 0 should be 0 test results correct
 3 th test results for 0 should be 0 test results correct
 4 th test results for 1 should be 1 test results correct
 5 th test results for 0 should be 0 test results correct
 6 th test results for 0 should be 0 test results correct
 7 th test results for 0 should be 0 test results correct
 8 th test results for 0 should be 0 test results correct
 9 th test results for 0 should be 0 test results correct
 10 th test results for 0 should be 0 test results correct
 11 th test results for 0 should be 0 test results correct
 12 th test results for 0 should be 0 test results correct
 13 th test results for 1 should be 1 test results correct
 14 th test results for 0 should be 1 test results error
 Completed 14 times test, The accuracy is 92.857143%
fx >>
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Fig.4. The first three principal components of operating results

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