Feature Generation Using Recurrence Quantification Analysis
With Application to Fault Classification

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Abstract—In this paper, a RQA-based approach is developed for feature generation from raw vibration data recorded from a rotating machine with five different conditions. The created features are then used as the inputs to a classifier for the identification of six bearing conditions. Experimental results demonstrate the ability of RQA to discover automatically the different bearing conditions using features expressed in the form of recurrence quantification measures. Furthermore, using RQA extracted features and traditional features with artificial neural networks (ANN) and support vector machines (SVM) have been obtained. This RQA-based approach is used for bearing fault classification for the first time and exhibits superior performance over other traditional methods.

Keywords—fault classification; feature generation; recurrence quantification analysis (RQA); machine condition monitoring (MCM)

I. INTRODUCTION

Machine condition monitoring (MCM) is an area which is gaining increasing importance in the manufacturing industry. Maintenance costs can be reduced significantly by monitoring health of machinery. Potentially disastrous faults can be detected early, while enabling the implementation of condition-based maintenance rather than periodic, or responsive maintenance. Several conventional methods have been used to analyze the vibration signal in order to extract effective features for bearing fault detection. These include statistical analysis [1], frequency analysis [2], and time-domain analysis [3].

Feature extraction is one of the most important factors in pattern recognition problems. The choice of features can greatly affect the performance of classification. Any generated features will often be refined to try to achieve the desired level of performance. In recent years, the application of recurrence plot (RP) to pattern recognition problem has become increasingly common. The recurrence plot provides a visualized description on the recurrence of conditions of deterministic dynamical systems [4]. Webber and Zbilut developed the recurrence quantification analysis (RQA) by computing an array of specific recurrence variables that quantify the deterministic structure and complexity of RP [5]. RQA is a useful tool which quantifies the mentioned structures in the RP systematically. By using RQA, it is possible to generate new features presented to the classifier from raw vibration signals, while improving the classification efficiency.

II. TRADITIONAL FEATURE GENERATION METHODS

Rolling element bearings are probably among the most widely used rotating machine components. It is of prime importance to be able to accurately detect the existence and severity of faults in machinery in certain areas of industry, as the machine may be safety or emergency-related in many cases. The five bearing conditions, each having their own distinguishing characteristics, are as follows. 1) normal bearing (NO); 2) inner race fault (IR); 3) outer race fault (OR); 4) rolling element fault (RE); 5) cage fault (CA).

In order to simulate commonly occurring faults in rotating machinery, experimental data was collected from a test rig (Fig. 1). The resultant vibrations in the horizontal and vertical planes were measured using two accelerometers. The output from the accelerometers was sampled at a rate of 10 kHz. Experimental datasets were formed by running this machine over a series of twelve different speeds and taking ten examples of data at each speed. Each example consists of 2048 data samples. This gives a total of 120 examples of each condition and a total of 600 raw data examples over six conditions to work with.

After evaluation and comparison, useful features are picked out for the further classification of different conditions. In this section, conventional features and a list of possibly useful features are described in detail.

![Diagram](image-url)

Figure 1. Machine test rig used in experiments

A. Conventional Measures

A number of statistically-based performance indicators exist, which provide single figure assessments of the
condition of rolling bearings. These give an indication of whether a bearing is in a state of distress, or within normal operating parameters, and show the degree of distress that a bearing is under. Conventionally, three most common measurements used are shock pulse (SP), crest factor (CF), and kurtosis.

B. Plain Statistics

A number of different statistical features were generated using moments and cumulants of the vibration data. The nth-order moment is defined by (1). The five statistical features used here are the five (first to fifth order) moments. These are stored in a matrix of size 5x600.

\[ m_k^{(n)} = \frac{1}{N} \sum_{i=1}^{N} x_i^n, \quad k = 1, 2, \ldots, 5 \]  

(1)

C. High and Low Filtering

The four statistical features were calculated on data filtered using an eighth-order Butterworth IIR high pass filter with a cut-off frequency of 129 Hz; this gave another 4x600 matrix. A low-pass filter with the same cut-off frequency was used on the same datasets, and gave a 4x600 matrix.

D. Normalization

The importance of normalization to both the efficiency and accuracy has been demonstrated [6]. The normalization in experiments is based on (2).

\[ f_i' = \frac{(f_i - m_f^{(n)})}{\sigma_f} \]  

(2)

where \( m_f^{(n)} \) is the mean value of the feature vector \( f \) and \( \sigma_f \) is the standard deviation of the feature vector \( f \).

III. FEATURE GENERATION USING RQA

Recurrence plots are graphical representations of sequences of data, which allows the detection of hidden dynamical patterns and nonlinearities inside the data. The structures of RP can be characterized by typology pattern (large scale) and texture pattern (small scale). Typology pattern describes RP globally, which includes homogeneous, periodic, drift and disrupted; texture pattern is the closer inspection of the RP which are single dots, diagonal lines as well as vertical and horizontal lines.

Analysis of the structure of RP can extract much information implied in vibration signal. Fig. 2 is the RP under conditions of NO and OR. From this figure we can find that the RPs of different conditions are distinguishing, but it is difficult to differentiate quantificationally.

![Recurrence plot (RP) under conditions of NO and OR](image)

The most important recurrence quantification measures which we used in this paper are briefly introduced as follows [7, 8]:

1) Recurrence rate (RR):

\[ RR = \frac{1}{N^2} \sum_{i,j} R_{ij} \]  

(3)

RR counts the black dots in the RP. It is a measure of the density of recurrence points in the RP.

2) Determinism (DET):

\[ DET = \frac{\sum_i |P(l)|}{\sum_i R_{ij}} \]  

(4)

Where \( P(l) \) is the histogram of the length \( l \) of diagonal lines. DET is the ratio of recurrence points that from diagonal lines (of at least length \( l_{min} \)) to all recurrence points.

3) Entropy of the diagonal line length (ENTR):

\[ ENTR = -\sum_{l_{min}}^l P(l) \ln P(l) \]  

(5)

ENTR is the Shannon entropy of the frequency distribution of diagonal lines in the RP. This measure is designed to quantify the complexity of the deterministic structure in the system.
4) \textbf{Ratio (RA)}:

\[ RA = \frac{DET}{RR} \]  

(6)

RA is the ratio of DET to RR, which is used to token the change of System.

5) \textbf{Laminarity (LAM)}:

\[ LAM = \frac{\sum_{v \in \text{vmin}} v P(v)}{\sum_{v \in \text{vmin}} v P(v)} \]  

(7)

Where \( P(v) \) is the histogram of the lengths \( v \) of the vertical lines. LAM is the ratio of recurrence points that form vertical lines (of at least length \( \text{vmin} \)) to all recurrence points.

Five RQA measures introduced above were used to represent different vibration patterns. All the measures were calculated from vibration signals of five conditions. To analysis the cluster distribution of these RQA measures under different conditions intuitively, two-dimensional scatter plots of some measures were generated as follows.

Fig. 3 is 2D scatter plots of the RQA measures based feature sets. The two coordinates represented unlike measures of one vibrant pattern. From the scatter plots, it can be found that the features with group of DET and ENTR or DET and RA are well clustered. The separability between classes under group of RR and DET or RA and LAM are low because the clusters for different classes overlap greatly. To improve the separability of the features, it is necessary to adopt classification to identify different bearing conditions.

IV. \textbf{PATTERN CLASSIFICATION AND COMPARISON}

A number of experiments were carried out to evaluate the discriminating ability of features generated by RQA and other classical features in term of classification performance, using ANN and SVM classifiers, respectively. The multilayer perceptron (MLP) is chosen here as the structure of the network. The MLP used consists of one hidden layer and one output layer, with the hidden layer having a logistic activation function and the output layer using a linear activation function. A nonlinear SVM classifier with polynomial kernel is employed for the classification task.

A. \textbf{Classification Results}

Table I shows the confusion matrix of the classification performance for five conditions, using 5 features generated by RQA and 12 neurons in ANN. Each row of this Table shows the associated classification results made by the MLP for a given condition. Each entry in the row shows what the perceived classification are, expressed as a percentage of the total number of cases for the condition. From Table I, it can be observed that condition NO and IR manage to achieve 100% accuracy, condition OR, RE and CA achieving 94.6%, 95.8 and 96.6%, respectively. It is also very clear from the Fig. 5 that most of the misclassifications occur between classes OR RE and CA.
TABLE I. CLASSIFICATION PERFORMANCE (%) FOR RQA/ANN

<table>
<thead>
<tr>
<th></th>
<th>NO</th>
<th>IR</th>
<th>OR</th>
<th>RE</th>
<th>CA</th>
</tr>
</thead>
<tbody>
<tr>
<td>NO</td>
<td>100</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>IR</td>
<td>0</td>
<td>100</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>OR</td>
<td>0</td>
<td>0</td>
<td>94.6</td>
<td>5.4</td>
<td>0</td>
</tr>
<tr>
<td>RE</td>
<td>0</td>
<td>0</td>
<td>3.4</td>
<td>95.8</td>
<td>0.8</td>
</tr>
<tr>
<td>CA</td>
<td>0</td>
<td>0</td>
<td>2.8</td>
<td>0.6</td>
<td>96.6</td>
</tr>
</tbody>
</table>

B. Comparison of Classification Performance

The classification performance results displayed in Table II were obtained using features generated by RQA and classical methods. Both ANN and SVM classifiers are utilized in order to see the capability of different feature sets over different classification algorithms. In this experiment, features are directly used as the inputs to classifiers without normalization. As listed in Table II, among classical methods, the five low-pass filter features perform the worst with around 32.7% success in SVM classifier, which is mainly due to large variation in values in the un-normalized data. This may be addressed by using the ideas in [9]. When RQA extracted features are used, the improvement is overwhelming in either ANN or SVM classifier. Overall, RQA produces much more robust features for classifiers and has the ability to perform well without normalizing the data.

With normalized data, this experiment examines the classification performance in each scenario by the same feature extraction methods used in the proceeding experiment. As shown in Table III, each scenario sees an improvement in classification performance, ranging from 0.1% to 58.4%, compared with those using un-normalized data. Evidently, two classifiers have much less difference in classification performance compared with those in the last experiment. It is interesting to see that the normalization does not seem to help the classification much in cases using RQA-extracted features while other features achieve better performance.

TABLE II. CLASSIFICATION SUCCESS WITH UN-NORMALIZED FEATURES

<table>
<thead>
<tr>
<th>Features Type</th>
<th>ANN Best perf. (%)</th>
<th>SVM Best perf. (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>5 Plain Statistical</td>
<td>87.2</td>
<td>90.8</td>
</tr>
<tr>
<td>5 High pass Filter</td>
<td>86.3</td>
<td>32.7</td>
</tr>
<tr>
<td>5 Low pass Filter</td>
<td>87.6</td>
<td>90.4</td>
</tr>
<tr>
<td>5 Conventional</td>
<td>96.3</td>
<td>97.2</td>
</tr>
</tbody>
</table>

TABLE III. CLASSIFICATION SUCCESS WITH NORMALIZED FEATURES

<table>
<thead>
<tr>
<th>Features Type</th>
<th>ANN Best perf. (%)</th>
<th>SVM Best perf. (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>5 Plain Statistical</td>
<td>89.2</td>
<td>89.7</td>
</tr>
<tr>
<td>5 Highpass Filter</td>
<td>90.4</td>
<td>92.8</td>
</tr>
<tr>
<td>5 Low pass Filter</td>
<td>91.3</td>
<td>91.1</td>
</tr>
<tr>
<td>5 Conventional</td>
<td>91.2</td>
<td>92.3</td>
</tr>
<tr>
<td>5 RQA generated</td>
<td>96.5</td>
<td>97.1</td>
</tr>
</tbody>
</table>

V. CONCLUSION

In this paper, quantitative analytical tool Recurrence Quantification Analysis (RQA) was used to analyze the vibration signals of rolling bearings under five conditions. RQA-based feature extractor is proposed for the generation of features from the raw vibration data for classification applied to the problem of rolling bearing fault classification. Summarizing the results from these two experiments, it can be said that when classical feature extraction methods are employed, the classification performance changes drastically with the variation of classification method and data, while RQA-generated features maintain a constantly high level of performance. The superior performance of RQA against other methods is clearly demonstrated through the overall classification success.

REFERENCES