Vibration-Based Anomaly Detection Using FLAC Features for Wind Turbine Condition Monitoring

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Key words: Wind turbine condition monitoring, Anomaly detection, Time-frequency analysis, Unsupervised learning, Gaussian mixture models.

Abstract
We present a method for detecting anomalies in vibration signals of wind turbine components. The predominant characteristics of wind turbine vibration signals are extracted by applying a time-frequency feature extraction method based on Fourier local autocorrelation (FLAC) features. For anomaly detection, one-class classification based on an unsupervised clustering approach is applied in consideration of the wind turbine’s dynamic operating conditions and environment. To validate the proposed system, we conducted experiments using the vibration data of actual 2 MW wind turbines. The results showed the effectiveness of using the FLAC features, particularly in the case of the low-speed main bearing where the conventional method with traditional features cannot detect the anomalies.

1 INTRODUCTION

Wind energy is one of the most important renewable energy sources and has gained much attention due to the recent energy crisis. However, as wind turbines become increasingly large and more complex in order to provide reliable power generation, their maintenance and repair becomes more difficult. The focus of this research carried out under Japan’s national “Smart Maintenance for Wind Energy” project is the development of a reliable and cost-effective condition monitoring system (CMS) to maintain the availability and improve the reliability of wind turbines. The main task of CMS is to detect mechanical failures at an early stage such that maintenance can be carried out in a timely manner. Typical condition monitoring techniques for wind turbine include vibration analysis, acoustic emission, oil analysis, strain measurement, ultrasonic analysis, and thermography [1]. One of the more popular tools in the condition monitoring of rotating machinery is vibration analysis.

In this paper, we describe a method for detecting anomalies in the vibration signals of wind turbine components. The system developed here is based on artificial intelligence approaches that achieve multi-dimensional data analysis without deep knowledge about the mechanical behavior. The key modules that influence the performance of the detection system are feature extraction and unsupervised learning. For feature extraction, which is the main contribution of this work, the predominant characteristics of the wind turbine vibration signals are extracted by applying Fourier local autocorrelation (FLAC) features. This feature extraction method was originally developed for audio processing such as sports highlight
detection [3] and indoor health monitoring [4]. At the anomaly detection stage, we employ an unsupervised clustering approach based on Gaussian mixture models (GMMs) in consideration of the wind turbine’s dynamic operating conditions. As in one-classification problems, the feature vectors extracted from the normal (healthy) vibration signals are used to estimate the normal GMM parameters. Then, the input vibration signals are investigated by calculating the anomaly score based upon the log-likelihood function of the distribution.

In the following sections, we first explain the details about the proposed system based on the FLAC feature extraction and the GMMs. We then present the results of experiments using the vibration data of actual 2 MW wind turbines. Finally, we describe the conclusion of presented work.

2 METHODOLOGY

Figure 1 shows an overview of the developed anomaly detection system for condition monitoring of a wind turbine. The system is based on an unsupervised learning approach, and the vibration data collected under normal conditions are considered and processed in the training phase. Since the main task of this kind of anomaly detection system is to construct classifiers when only one class is well sampled and well characterized by the normal condition data, it is essential to use advanced and sophisticated feature extraction techniques.

In this paper, we introduce a time-frequency feature extraction method for computing local autocorrelations on complex Fourier values from vibration signals. For training, we apply GMMs to deal with the varying operating conditions of the wind turbine data. The rationale and techniques for each process are described as follows.

2.1 Data selection

In general, vibration signals from wind turbine components working in an actual environment are nonstationary or nonlinear since they are affected by various and dynamic...
operating conditions. In order to reduce the influence of the operating conditions, applying data selection or filtering before the main processing is useful in practice. For the selection criteria, several variables from supervisory control and data acquisition systems can be used [5]. For example, if the actual recorded power output is zero or the wind speed is outside the predefined range for a certain duration, the vibration signals collected within that duration are rejected. In this work, the rotational speed of the main shaft are used as a selection criterion.

2.2 Feature extraction

In condition monitoring and health diagnosis, extracting the representative features or indicators that reflect the actual health status is very important and affects the overall detection performance. In the literature on vibration signal processing, various features in the time and frequency domain have been proposed [6]. Here, we introduce a time-frequency feature extraction method based on the local autocorrelation of complex short-time Fourier spectra into vibration-based anomaly detection. The FLAC features are combined with the conventional feature values in vibration signal analysis such as RMS, kurtosis, and crest factor, and the dimensionality-reduced feature vectors are generated by principal component analysis.

2.2.1 Conventional features

For the conventional features, time-domain statistical measures commonly used for vibration analysis are calculated. For the input data vector \( x_i, i = 1, 2, 3 \ldots, N \), seven measures extracted from the waveform are defined as follows:

\[
RMS = \sqrt{\frac{\sum_{i=1}^{N} x_i^2}{N}}
\]  

(1)

\[
Crest Factor = \frac{\max(|x_i|)}{\sqrt{\frac{1}{N} \sum_{i=1}^{N} x_i^2}}
\]  

(2)

\[
Kurtosis = \frac{\sum_{i=1}^{N} (x_i - \bar{x})^4}{(N - 1)\sigma^4}
\]  

(3)

\[
Skewness = \frac{\sum_{i=1}^{N} (x_i - \bar{x})^3}{(N - 1)\sigma^3}
\]  

(4)

\[
Peak – Peak Amp. = \max(|x_i|) - \min(|x_i|)
\]  

(5)

\[
Clearance Factor = \frac{\max(|x_i|)}{\sqrt{\frac{1}{N} \sum_{i=1}^{N} |x_i|^2}}
\]  

(6)

\[
Impulse Indicator = \frac{\max(|x_i|)}{\frac{1}{N} \sum_{i=1}^{N} |x_i|}
\]  

(7)

Furthermore, frequency-domain statistical measures based on envelope analysis are included in the conventional features. Here, five measures are extracted from the envelope
spectrum: RMS, crest factor, crest factor in the low-frequency range, and maximum peak in the low-frequency range and its frequency index.

In the anomaly detection system, the above conventional features are extracted at every short-time interval (frame) using a sliding window method, and are concatenated with the following FLAC features for each frame.

2.2.2 Fourier local autocorrelation features (FLAC)

The prototype of FLAC is the higher-order local autocorrelation (HLAC), which is well developed for extracting the spatial information in the field of computer vision and has been widely utilized and extended for motion analysis as Cubic HLAC (CHLAC). The FLAC features were initially proposed for representing acoustic signals and have been proved to work effectively for modeling unstructured sounds with wide variations [3][4].

Firstly, vibration signals are transformed to a complex spectrum by short-time Fourier transform and a series of frame sequences of short-time spectra are obtained. Let time and frequency be denoted by $t$ and $\nu$, respectively, and the complex spectrogram be $f(r)$ at the position $r = (t, \nu)$. We develop the local autocorrelation function to deal with the complex values:

$$x_{t,\nu}(\mathbf{a}) = f^*(r) f(r + \mathbf{a})$$

where $\mathbf{a}$ is a displacement vector indicating local neighborhoods and $f^*$ denotes the complex conjugate of $f$. We limit the $\mathbf{a}$ to within a $2 \times 2$ region on the time-frequency plane since the local neighborhoods are assumed to be highly correlated, as well as to comply with the complex autocorrelation formula. The combination patterns of $\mathbf{r}$ and $\mathbf{r} + \mathbf{a}$ are shown in Figure 2, producing five-dimensional feature vectors. The complex values $f(r)$ and $f(r + \mathbf{a})$ are represented by $A e^{-j\theta}$ and $B e^{-j\varphi}$, where $A$ and $B$ are magnitudes and $\theta$ and $\varphi$ are phases. The FLAC feature is described by:

$$x_{r,\mathbf{a}} = Ae^{-i\theta} Be^{i\varphi} = AB^{i(\varphi-\theta)}$$

This feature value is based on the multiplication of magnitudes and the difference of phases. By considering such correlation of complex values, we can extract joint features of the magnitudes as well as those of phases that are robust to phase shift. Note that each feature pattern in Figure 2 encodes significant dynamic feature on the time-frequency plane. The FLAC features are extracted at the entries $(t, \nu)$. For each frame $(t)$, we concatenate all feature values to construct the (long) FLAC feature vector. In practice, a filterbank procedure is applied before extracting the FLAC features in order to reduce the dimensionality in frequency domain. Ye et. al [3] reported that the FLAC features are more effective for describing acoustic characteristics than cepstrum-based features such as MFCC commonly used in audio processing.
2.3 Anomaly detection based on Gaussian mixture models

The task of anomaly or novelty detection is simply to recognize that test data differ in some respect from the data that are available during training. This can be defined as one-class classification, in which a model is constructed to describe normal condition data, and is typically applied to situations where there is insufficient data corresponding to abnormalities [7][8]. In anomaly detection for a complex mechanical system such as wind turbine components, there is a wide variety of characteristics in the data even when collected in normal (healthy) condition due to the various operating states of components and the environmental conditions. We therefore study the use of clustering-oriented approach based on GMMs.

GMMs estimate the probability density of the target (normal) class, given by a training dataset. Here the target class is modeled using a mixture of K Gaussians; in other words, the characteristics of the normal vibration data are represented by K clusters. The GMM probability density function (pdf) can be defined as a weighted sum of Gaussian component densities as given by the equation:

$$ p(x|\theta) = \sum_{i=1}^{K} w_i g(x|\mu_i, \Sigma_i) $$  \hspace{1cm} (10)

where $x$ is a D-dimensional data vector, $w_i$ is the mixture weight of $i$th component. Each component density is a D-variate Gaussian function as follows:

$$ g(x|\mu_i, \Sigma_i) = \frac{1}{(2\pi)^{D/2}|\Sigma_i|^{1/2}} \exp \left\{ -\frac{1}{2}(x - \mu_i)'\Sigma_i^{-1}(x - \mu_i) \right\} $$  \hspace{1cm} (11)

with the mean $\mu_i$, and the covariance matrix $\Sigma_i$. The complete GMM is parameterized by the mean vectors, covariance matrices and mixture weights from all component densities, and the parameters $\theta = \{w_1, \mu_1, \Sigma_1, ..., w_K, \mu_K, \Sigma_K\}$ are optimized using the EM algorithm. We define the anomaly score of an input data vector $x'$ as a likelihood $-\ln p(x'|\theta)$. In classification process, we apply a threshold selection method utilizing the confidence measure for GMM pdfs, which is used to estimate the reliability of a classification result [9].
The confidence measure is estimated from the pdf density quantile, and a threshold which includes a certain proportion of the total probability mass is selected [9].

3 EXPERIMENTS

To investigate the effectiveness of the methodology, we conducted detection experiments by using vibration data obtained from actual wind turbines.

3.1 Description of dataset

In the “Smart Maintenance for Wind Energy” project, CMS data including the vibration signals of the main components have been continuously measured and collected from 41 2MW-class wind turbines actually working in Japan. The data measurements have been taken by NTN, a member of the project, using their own CMS product [10][11] installed in the 41 wind turbines. In this study, we examined two cases where faults appeared during the measurement period. The dataset is outlined in Table 1. The sampling frequency of the vibration signals is 25.6 kHz. In Case 1, there were signs of damage at the input side of the generator. In Case 2, the main bearing failed and was replaced during the period. It is reported that the latter case, in particular, is a more challenging task due to the difficulties in detecting very low speed rolling elements [12]. For training of the normal-state models, we used two months of the historical data for each case. In Case 2, the training period was set after the replacement of the main bearing and the data before the replacement were evaluated as shown in Figure 6.

<table>
<thead>
<tr>
<th>Component</th>
<th>Case 1</th>
<th>Case 2</th>
</tr>
</thead>
<tbody>
<tr>
<td>Rotation speed</td>
<td>2013.0 (rpm)</td>
<td>19.4 (rpm)</td>
</tr>
<tr>
<td>Period</td>
<td>Aug/8/14–Sep/15/15</td>
<td>Nov/1/14–Jul/31/15</td>
</tr>
<tr>
<td>Period (training data)</td>
<td>Feb/12/15–Apr/12/15</td>
<td>Apr/15/15–Jun/15/15</td>
</tr>
</tbody>
</table>

3.2 Results and discussion

As the experimental results for the generator (Case 1), the trend in RMS values as a traditional signal processing method is shown in Figure 3 and the detection results of the developed system are shown in Figure 4. To investigate the effectiveness of the feature extraction methods, we conducted two detection experiments as shown in Figure 4. In Case 1, all of the results indicate that at around Jul/10/2015, the anomaly score started rising above the threshold calculated with the normal-state model. According to the envelope analysis of the vibration signal of Jul/10/2015, the peak values of the spectrum were actually found at the corresponding fault frequency. This suggests that the incipient fault of the generator bearing can be detected with our system. Note that even traditional signal processing such as RMS could potentially detect the fault because this case is a high speed rolling element, as shown in Figure 3.
Figure 3: Time series of RMS of vibration signals in Case 1

Figure 4: Results of the proposed system in Case 1
Next, we describe the experimental results for the main bearing (Case 2). As shown in Figure 5, any signs corresponding to faults could not be found with the time series of RMS values. This indicates that the traditional signal processing or feature extraction method has difficulty detecting faults in the vibration signals of a very low speed rolling element. As shown in Figure 6-(1), anomaly detection with only the conventional features was also not able to detect the faults; namely, almost all of the anomaly scores were below the threshold for the entire period. On the other hand, by using anomaly detection with the FLAC features, the anomaly scores were obviously higher than the threshold before the damaged main bearing was replaced at the beginning of April 2015. The FLAC features are extracted from both the time and frequency domains and they characterize more temporal dynamic features in both time and in a wide range of frequencies for representing the vibration signals. This leads to the improved anomaly detection performance.

![Figure 5: Time series of RMS of vibration signals in case 2](image-url)
4 CONCLUSIONS

In this paper, we presented a vibration-based anomaly detection method for wind turbine condition monitoring. At the feature extraction stage, we applied a time-frequency feature extraction method based on FLAC features in combination with commonly used conventional vibration features. At the anomaly detection stage, we employed an unsupervised clustering approach based on GMMs. The experiments using actual wind turbine data showed the effectiveness of using the FLAC features even in the case of a very low speed main bearing.

Figure 6: Results of the proposed system in Case 2
ACKNOWLEDGEMENTS
This paper is based on results obtained from a project commissioned by the New Energy and Industrial Technology Development Organization (NEDO).

REFERENCES