Optimization of time domain features for rolling bearing fault diagnostics

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Abstract

The main objective of this paper is the determination of an optimal parameter set for the generation of features from an acceleration time signal of a bearing vibration with different fault sizes. The derived features based on an advanced analysis of statistical characteristics calculated from parts of the time signal considering the impact impulse response. The properties of the decay of vibration due to its impulse likely excite during rolling up the rolling elements on defect bearing races are to be captured. Therefore, vibration peaks in the time signal are located and applied for the process of feature generation. The free parameters examined here are the cut-off frequencies of the bandpass filter for a signal filtering and the amplitude threshold value for the definition of such peaks. The selection of the features and determination of the parameters are executed on the basis of the classification evaluation. The approach is exposed by the example of the diagnosis of artificially brought in damage in passenger car wheel bearings. The results are very promising, because in a test rig signals obtained from damaged rolling bearings could be separated from the normal fault-free operation and other fault classes without any classification error.

1. Introduction

In condition monitoring and fault diagnostic the use of time and frequency domain features is a common technique. The monitoring process has been improved continuously over the last years, because new signal pre-processing techniques have been introduced. Due to the high number of possible features and different ways of feature generation a kind of framework for the feature selection process is required.

As damage is categorized by making a comparison with stored reference values being characteristic for a certain damage class, the reference values used here based on features which are generated from the acceleration time signal of the bearing. This feature values are representing the learning samples assembling points or areas in a multidimensional space. Each of them belongs to a specific state. The values of the generated features of the signal to be assigned are positioned in this feature space and the distance from the predefined damage categories is calculated. Assigning a signal to a damage class that is the minimum distance away in the feature space is performed by a classifier, where predefined metrics could be used.
According to a wrapper approach\textsuperscript{(4)} the classification result using the learning samples for all states is evaluated. The idea suggested in this paper is to use only parts of the time signal which stand in close relation to possible bearing faults. In this approach several statistical features of the time domain based on detected peaks of the original signal are generated. The features values will change when other filter bandwidths or amplitude thresholds are selected. All this leads to the determination of an optimized feature set for a given classifier by adapting all pre-processing parameters (Figure 1), which influence the feature values.

\begin{figure}
\centering
\includegraphics[width=\textwidth]{figure1.png}
\caption{Wrapper for feature selection}
\end{figure}

The feature generation becomes part of the feature selection process. This means for statistical moments like kurtosis as a well known diagnosis parameter, that the current value has to be marked with the related filter band\textsuperscript{(5)}.

\section{2. Feature Selection}

\subsection{2.1 Time domain feature generation}

Filtering is a suitable method to extract the interesting part of the signal which contains the desired information. The effect of different filter bandwidths on the feature performance at various damage stages is presented in a couple of publications for kurtosis for instance. In a first step of signal pre-processing the time signal is normalized with the root mean square (RMS) to eliminate the signal energy and the influence of the signal pathway from the source of vibration to the sensor. That would be a useful technique to transfer established classification parameters to other rigs or applications and achieve a significant independency from varying loads. Since the acceleration time signal and the
root mean square have the same physical unit, the filtered and normalized signals are non-dimensional (Figures 4 and 5).
The proposed peak features based on a peak detection algorithm which separate the local extremum of the signal referring to a impact pulse response from the remaining signal components. A peak is defined as an event in the time signal which satisfy the criterion, that a local maximum with an amplitude over a predefined threshold exists\(^{(6,7)}\).

Based on the proposed processing procedure some statistical analyses are performed and used as features (Table 1). In this approach 47 features are extracted and examined most of them peak features but in addition also some classical bearing fault indicators to benchmark their behaviour. Nevertheless only the two bold marked peak features should be discussed in this paper to demonstrate the principle ideas of the work.

During the steps of

- bandpass filtering and normalizing of the original signal and
- threshold depending peak detection

the cut-off frequencies of the bandpass filter and the threshold for the peak detection are varied as parameters of the feature selection process. The filtering is executed by a fifth order Butterworth bandpass filter in four filter bandwidths 1-10 kHz, 10-20 kHz, 20-30 kHz and 30-40 kHz. The threshold was varied from 0 to 10 in integers which refer to the non-dimensional value of the filtered and normalized signal. Other signal processing methods like higher order derivatives\(^{(8,9)}\) could be used for feature optimisation the same way but are not subject of the present investigation.

### Table 1. List of feature

<table>
<thead>
<tr>
<th>feature definition</th>
<th>formula</th>
<th>feature number</th>
</tr>
</thead>
<tbody>
<tr>
<td>number of peaks</td>
<td>[ \bar{N} ]</td>
<td>3</td>
</tr>
<tr>
<td>RMS of peaks</td>
<td>[ \bar{x}<em>{\text{Peak}} = \sqrt{\frac{1}{N} \sum</em>{n=1}^{N} x_{n,\text{Peak}}^2} ]</td>
<td>4</td>
</tr>
<tr>
<td>standard deviation of peaks</td>
<td>[ \sigma = \sqrt{\frac{1}{N} \sum_{n=1}^{N} (x_{n,\text{Peak}} - \bar{x}_{\text{Peak}})^2} ]</td>
<td>6</td>
</tr>
<tr>
<td>RMS of peak distance</td>
<td>[ \bar{\delta}<em>{\text{posi Peak}} = \sqrt{\frac{1}{N} \sum</em>{n=1}^{N} \delta^2_{\text{posi Peak}}} ]</td>
<td>15</td>
</tr>
</tbody>
</table>

2.2 Classification benchmark

The evaluation of the feature parameter setting which is shown in Figure 1, is made by evaluating the classification rate when using the learning samples of all measured states. In fact this is a proper way for maximising the performance by using a given classifier. Various work is done in the field of pattern recognition\(^{(10,11,12,13)}\) and feature selection\(^{(14,15,16,17)}\). A classifier is chosen being able to decide in case of even fuzzy affilia-
tion\(^{(14)}\) to the considered classes and respecting the composition of the feature formed scatter plots. In this paper the rate or the classification accuracy of reclassification (correct classified samples / total number of samples) is calculated for two features at a time and should be a key feature to evaluate the performance of classification. A reclassification rate of 1 indicates that all samples are correct classified and 0 that none of them could be classified correctly. Relevant values are situated in the interval \([0.5\ 1]\).

3. Experimental results

3.1 Failures

A fault of interest in passenger car wheel bearings could be false brinelling. It is a typical fault due to small vibrations in non rotating roller bearings for instance while transporting a car by railway. While the force for a false brinelling fault is necessarily not high, a bearing race with indentations from shock load is called brinelling. For our investigations one bearing was damaged by a cyclic load according to the operating conditions. To generate some other faults sizes, the damage structures were artificially brought in by eroding them width wise into the outer race of the disassembled passenger car wheel bearing (Figure 2). Their extension in depth was quite small as shown in Table 2.

<table>
<thead>
<tr>
<th>Table 2. Examined fault sizes</th>
</tr>
</thead>
<tbody>
<tr>
<td>Bearing</td>
</tr>
<tr>
<td>averaged depth [µm]</td>
</tr>
<tr>
<td>averaged width [µm]</td>
</tr>
</tbody>
</table>

Figure 2. Failures
3.2 Vibration measurement

Faults of small dimensions in rolling bearings are causing high frequency vibrations when being passed by the rolling elements due to the impact pulse response. For the present investigations an accelerometer is used to measure the time signal in the frequency range up to 40 kHz. A high sample rate of $2^{17}$ (131 072) is used for data acquisition to record 50 time signals for each class. Each sample has a duration of 0.5 seconds, $2^{16}$ (65 536) data points in the time signal, in order to generate the learning data for the pattern recognition algorithm used below. To record the high frequency range the sensor is placed directly on the outer ring by gluing to overcome problems associated to mounting. The experience indicates clearly, that recording the time signals for diagnostic, using frequencies above 25 kHz, without verifying the surface to sensor contact by observing the frequency spectrum will result in significant lower detection accuracy. The presented experimental data were measured by applying a radial load on the bearing at 1000 revolutions per minute on a test rig. Looking at the signal structure in Figure 3 the faulty bearings are simply observable. Especially the time signal for fault E2 shows the typical signature of a faulty bearing. But features used in an automatic pattern recognition procedure for condition monitoring should be correlated with the fault and being robust to changes of surrounding conditions in order to avoid misclassifying and being qualified for an early detection.

![Figure 3. Original time signals](image-url)
3.3 Influence of parameter setting

Referring to the peaks in Figures 4 and 5 the peak distribution (red crosses) could be characterised by several statistical features concerning amplitude and deviation. As seen in Figure 4 the RMS-value of the peaks for a good and a faulty bearings do not differ significantly at a threshold of 0. Increasing the threshold to a value of 3 would blank out the noisy peaks, which have no fault relation. So the RMS of the peaks of the faulty bearing should be significantly higher in respect to the undamaged bearing. Filtering the signals of Figure 4 in a bandwidth of 10-20 kHz increases the peak value of the normalized signal and emphasises the impact related content at a threshold of 3. In this manner, it is expected that the RMS and the standard deviation should also increase. Comparing Figures 4 and 5 the best way getting distinguishable peak features is filtering and threshold rising.

Figure 4. Peak detection, filter bandwidth: 1-40 kHz
The classification evaluation of the undamaged bearing class and the small eroded defect class is shown in Figure 6 for two filter and two thresholds. With varying threshold (th) the reclassification rate of the learning sample regarding the combination of two features at a time differs. For this investigation no cross validation or other techniques to improve the generalisation capability of the classifier is used. The classification algorithm generates a class specific membership function and possess an inherent generalisation. In the following plots feature 4 is the RMS of the peaks and feature 6 is the standard deviation of the peaks. Regarding the reclassification rate for feature 4 and 6 for all threshold and bandpass filter combinations as shown in Table 3, it is evident that thresholds up to 3 seem to be a good choice for the filter bandwidth of 10-20 kHz. The good evaluation of both features at this bandwidth can be traced back to the scatter plots where the severability of the two classes is obvious. Scatter plots displaying feature 4 and 6 at different filter bandwidths are showing an optimum for 10-20 kHz in Figure 7. And the influence of the threshold is displayed in Figure 8 where the factorisation of the class midpoints of both features for a threshold of 2 is at a maximum.
Table 3. Reclassification rate along all possible parameter variations for feature 4 and 6

<table>
<thead>
<tr>
<th>Threshold</th>
<th>1-10 kHz</th>
<th>10-20 kHz</th>
<th>20-30 kHz</th>
<th>30-40 kHz</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>1</td>
<td>1</td>
<td>0.78</td>
<td>0.73</td>
</tr>
<tr>
<td>1</td>
<td>1</td>
<td>1</td>
<td>0.70</td>
<td>0.62</td>
</tr>
<tr>
<td>2</td>
<td>0.99</td>
<td>1</td>
<td>0.76</td>
<td>0.60</td>
</tr>
<tr>
<td>3</td>
<td>0.91</td>
<td>1</td>
<td>0.54</td>
<td>0.67</td>
</tr>
<tr>
<td>4</td>
<td>0.67</td>
<td>0.57</td>
<td>0.50</td>
<td>0.61</td>
</tr>
<tr>
<td>5</td>
<td>0.85</td>
<td>0.57</td>
<td>0.51</td>
<td>0.60</td>
</tr>
<tr>
<td>6</td>
<td>0.73</td>
<td>0.62</td>
<td>0.53</td>
<td>0.56</td>
</tr>
<tr>
<td>7</td>
<td>0</td>
<td>0.68</td>
<td>0</td>
<td>0.54</td>
</tr>
<tr>
<td>8</td>
<td>0</td>
<td>0.68</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>9</td>
<td>0</td>
<td>0.77</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>10</td>
<td>0</td>
<td>0.77</td>
<td>0</td>
<td>0</td>
</tr>
</tbody>
</table>

Figure 6. Reclassification rate
Figure 7. Scatter plots of features, different bandpass filter cut-off frequencies

Looking at the scatter plots of the other eroded defect (E1) and the false brinelling (FB) an optimum of filter bandwidth and threshold for separation could be achieved. Seemingly this optimum is fault specific. In real world applications one has to integrate the parameter optimisation in an automatically driven process. Nevertheless the optimal parameter setting for this specific application consisting of a bandpass with cut-off frequencies 10 and 20 kHz and the threshold of 2 could be used for classifying good and small eroded defect condition.

4. Conclusions

In this paper the influences of fault related impact pulse indicating parameter like bandpass filter cut-off frequency and amplitude threshold in feature generation using peak features have been presented. Basic conditions and functioning during possible condition monitoring applications is presented. An optimal parameter set for the process of feature extraction and selection could be identified with a new software tool, which allows a systematic change of relevant parameters of the pre-processing of the time signal. This efficiency of the technique has to be proven in other real world applications but the classification accuracy and reliability obtained so far is very promising. On the
hand the investigations show clearly that the process of feature generation in condition monitoring could be a very complex issue, if advances methods should be applied.

![feature plots](image.png)

**Figure 8.** Scatter plots of features, different thresholds

### References


