A New HFRT Algorithm Based on Maximal Overlap Discrete Wavelet Packet Transformation

Hong-Tao Zhang and Jian-Ming Liao

Abstract—The high frequency resonant technique (HFRT) algorithm is a popular technique for fault-detection and is widely applied in mechanism systems and industrial constructions. In this paper, a new HFRT algorithm based on maximal overlap discrete wavelet packet transformation (MODWPT) is developed. By the simulation test for soil embedded pipes fault-detection, it is shown that the performance of newly proposed HFRT algorithms is more sensitive to early defects than the traditional HFRT methods based on the Hilbert transform.

Index Terms—Fault-detection, high frequency resonant technique, maximal overlap wavelet packet transforms, soil embedded pipe.

1. Introduction

Known as an envelop power spectrum analysis, envelop detection, or demodulated resonance analysis [1], the high frequency resonance technique (HFRT) is a traditional method for extracting repetitive low level fault related vibrations in the presence of high background noise levels and is widely applied in the fault-detection for mechanism systems and industrial constructions. The maintenance industry has adopted HFRT as one of the main tools in the condition monitoring program for early bearing fault-detection at present [2],[3]. Generally, the traditional HFRT is based on the Hilbert transforms (HT), or the fast Fourier transform (FFT). However, there are two limitations as follows:

1) The HFRT demands on knowledge of the resonance frequency range where the defect generated impulses is more pronounced with respect to normal system vibrations;

2) Due to the overlap of each transient component, a traditional HFRT may not be able to identify each defect, when there are multiple defects developed at the same time.

Taking these limitations into account, we develop a new HFRT algorithm based on maximal overlap discrete wavelet packet transformation (MODWPT). In this algorithm, we make full use of the “Wavelet coefficients usable for analysis of variance”, and “Shift invariant transformation” in MODWPT [4]. By the simulation test in fault-detection for soil embedded pipes, the performance of newly proposed HFRT algorithms based on MODWPT is more sensitive to early defects than the traditional HFRT methods based on the Hilbert transform (HT).

2. The New HFRT Algorithms Based on MODWPT

The algorithm includes two stages: resonant frequency band selection, and the mainly algorithm. The frequency band selection is based on the measurement of signal energy using MODWPT, root mean square (RMS) [5] and Spikeness using kurtosis [6]. The mainly algorithm is similar to the traditional HFRT algorithm.

2.1 Resonant Frequency Band Selection

Due to the bearing impact resonance, the extraction of high-frequency transients is vital to HFRT for defect detections. It is desired to select the resonance frequency range which results in the best signal to noise ratio for demodulating bearing defect frequencies. In order to isolate the bearing transients from other signal components, the objective of this section is to identify a resonance frequency band with the best signal to noise ratio. The selected packet can then be used for the main process.

Our resonance frequency band selection algorithm integrates a resonance frequency band selection criterion with the MODWPT. The criterion includes three steps based on the signal energy which adopt the RMS and Spikeness using kurtosis. The procedure can be described in the following steps, as shown in Fig.1:

1) Wavelet packet transformation of signals: the vibration signal measured from an accelerometer is decomposed by MODWPT [5]. The step results in a complete wave packet tree and the wavelet coefficients for each packet are denoted as \( \omega_{i,j} \).

2) Screening with kurtosis: first of all, the kurtosis can be defined as follows:

\[
\lambda = \frac{1}{T \sigma^4} \int_0^T [x(t) - \mu_x]^4 dt
\]  

(1)

where \( \mu_x \) is the signal mean, \( \sigma \) is the signal standard deviation, and \( T \) is the duration of the signal. Using (1) the kurtosis \( \lambda_{i,j} \) of \( \omega_{i,j} \) can be obtained.
All the packets with $\lambda_{i,j}$ greater than a threshold value $\partial$ are passed to step 3).

3) Packet selection from RMS change: for each of the packets from step 2), we calculate the RMS changes with respect to the previous measurement or the measurement of a normal condition. We then claim the packet with maximum RMS change as the best approximate packet HFRT analysis.

$$\text{SNR} = \frac{\left| \omega(t) \right|^2}{\left| y(t) - \omega(t) \right|^2} \quad (3)$$

where $y(t)$ is the response signal, and $\omega(t)$ is the noise. This is the ration of the expected induced harmonics energy to the total noise. In the following work, we will define $\text{SNR}=1$.

To extract impulsive components form the synthetic signal, we use a level 4 MODWPT using 16th order Daubechies wavelet; the procedure can be referred in [7] in detail.

### 3.1 The Result of the MODWPT

By the simulation test, the result of the MODWPT is shown in Table 1.

<table>
<thead>
<tr>
<th>Fre</th>
<th>0</th>
<th>0.025</th>
<th>0.05</th>
<th>0.075</th>
<th>0.1</th>
<th>Kur</th>
</tr>
</thead>
<tbody>
<tr>
<td>10000</td>
<td>$\checkmark$</td>
<td>$\checkmark$</td>
<td>$\checkmark$</td>
<td>$\checkmark$</td>
<td>$\checkmark$</td>
<td>3.16</td>
</tr>
<tr>
<td>8758</td>
<td>—</td>
<td>—</td>
<td>—</td>
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<td>$\checkmark$</td>
<td>2.94</td>
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<tr>
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<td>$\checkmark$</td>
<td>$\checkmark$</td>
<td>—</td>
<td>—</td>
<td>—</td>
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<td>$\checkmark$</td>
<td>—</td>
<td>—</td>
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<td>—</td>
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<td>$\checkmark$</td>
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<td>—</td>
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<td>$\checkmark$</td>
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<td>$\checkmark$</td>
<td>$\checkmark$</td>
<td>$\checkmark$</td>
<td>3.10</td>
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<tr>
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<td>—</td>
<td>$\checkmark$</td>
<td>—</td>
<td>$\checkmark$</td>
<td>$\checkmark$</td>
<td>2.68</td>
</tr>
</tbody>
</table>

Note: The Kur in Table 1 is kurtosis [7] And Fre represents frequency.

In Table 1, “$\checkmark$” means the packet have a noticeable pulse train, that is to say, it represents the impulsive component generated by pipe defect, “—” means no.

### 3.2 The Result of HFRT Using MODWPT

To be brief, we use some features to investigate the performance: pulse localization tracking, pulse amplitude tracking, peak rise time, background noise suppression, against noise interference, separation of adjacent pulses, demodulate fault frequency. When the $\text{SNR}$ is 1, the performance of the algorithm is shown in Table 2.

From the table, we can obtain that:

1) The algorithm based on MODWPT is very sensitive to early defect signals.

2) When the adjacent pulses are close to each other, the algorithm can give good time resolution.

3) The algorithm based on MODWPT give the better background noise suppression for the given smooth and denoising parameters than the algorithm based on HT.

4) The algorithm based on MODWPT outperforms the HT for extracting the fault related frequency components, and sidebands.

The HFRT based on the MODWPT takes advantage of wavelet packet signal processing with denoising process to efficiently demodulate fault related frequency components for the purpose of early defect detections, therefore, this algorithm outperform HT when $\text{SNR}$ is 1.
Table 2
The Performance of the algorithm

<table>
<thead>
<tr>
<th>Features</th>
<th>Hilbert Performance (%)</th>
<th>MODWPT Performance (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Pulse localization tracking</td>
<td>86.16</td>
<td>95.34</td>
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<tr>
<td>Pulse amplitude tracking</td>
<td>85.47</td>
<td>96.43</td>
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<td>Peak rise time</td>
<td>85.74</td>
<td>70.43</td>
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<tr>
<td>Background noise suppression</td>
<td>71.47</td>
<td>97.33</td>
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<tr>
<td>Against noise interference</td>
<td>73.12</td>
<td>95.19</td>
</tr>
<tr>
<td>Separation of adjacent pulses</td>
<td>71.14</td>
<td>85.73</td>
</tr>
<tr>
<td>Demodulate fault frequency</td>
<td>70.19</td>
<td>98.31</td>
</tr>
</tbody>
</table>

4. Conclusions

The algorithm takes full advantages of the wavelet packet signal processing with denoising process to efficiently demodulate fault related frequency components from sampled pipe spectra for the purpose of the early pipe defect detection, and can give the better rise time and pulse localization tracking for fault detection.

References


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