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A Statistical Feature utilising Wavelet Denoising and Neighblock Method for Improved Condition Monitoring of Rolling Bearings

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Rolling element bearings are of great importance in industrial applications as well as in critical applications in transport. Signal processing techniques can enhance the ability of bearings condition monitoring to identify faults during operation. In this work, state of the art signal denoising techniques are applied for condition monitoring of roller bearings. In particular wavelet denoising with NeighBlock threshold technique is applied in vibration waveforms. A standard data base for lifelong operation of roller bearings is used for the tests. The condition monitoring efficiency of a statistical feature is assessed taking into account both raw and denoised bearing vibration signals. A brief assessment shows that such a signal denoising technique can evidently improve the remaining useful life estimation as well as the change point detection of the structural health of the asset.

1. Introduction

Maintenance strategies for rotating machinery are generally shifting from preventive maintenance to Condition Based Maintenance (CBM). CBM techniques have gained significant interest in academic literature. On the contrary, CBM techniques are not equally widespread outside academia. Industry and air transport are still reluctant to incorporating new and possibly costly CBM systems. The fact is, however, that an appropriate CBM system, when applied to –a preferably large or critical- mechanical asset can substantially lower the maintenance cost, compared to traditional methods as stated by Byington and Garga (2001). Rolling element bearing failures are very common in industry. As stated by Ocak and Loparo (2005) the most common failure of an induction motor is bearing failure, followed by stator winding failures and rotor bar failures. CBM is generally based in monitoring of a statistical feature derived from vibration recordings on the bearing case. The feature is useful as long as i) it correlates well to any sudden change in the structural integrity of the mechanical asset or ii) it has monotonic trend and therefore can be utilised for remaining useful life estimation of the asset. This statistical feature can very frequently exhibit irregular patterns that cannot correlate well with any gradual or sudden structural degradation. These patterns may be attributed to temperature fluctuations of the lubricant or various forms of bearing structural degradation that suddenly arise and smooth out with the long term operation of the machine. This work is dedicated in improving diagnostics and remaining useful life estimation applying an advanced wavelet denoising technique on classical CBM statistical features. In section 2 the wavelet denoising with Neighbouring blocks technique is presented. In section 3 the effect of this technique is explored on data derived from a bearing wear data base (Nectoux et al. 2012). In section 4 the results are discussed and in section 5 few conclusions are drawn and summarised.

2. Wavelet Denoising

Suppose we need to extract an unknown signal f from a noisy dataserie $s(t_i)$

$$s(t_i) = f(t_i) + e(t_i) \tag{1}$$

where t_i is the discrete time and $e(t_i)$ is an additive noise component. The noise component is most often assumed a zero mean gaussian process with variance σ^2 and its samples are considered independent and identically distributed (i.i.d.). Kernel estimators or spline estimators can be applied in order to smooth out the noisy portion of the mixture. However they cannot handle well local signal structures. Fourier based signal processing can also dispose of a portion of the noisy component. This is done by applying linear filters at particular frequency bands. This method however is not efficient when the Fourier spectra of the signal and that of noise overlap. Wavelet transform is the approximation of a function or signal, in mean square terms, with another function called a mother wavelet and DWT is its discrete form. In practical signal processing, the discrete version of wavelet transform is often employed by discretizing the wavelet dilation and translation parameters. The procedure becomes even more efficient if dyadic values of these parameters are used. Practically relevant to dyadic DWT is multi-resolution analysis (MRA) described by Mallat (1999). MRA is a time efficient digital signal processing method which is connected to the theory of filter banks. It yields a tree structure for the signal decomposition that splits the signal into segments with different frequency resolutions. Figure 1 depicts a 2 level DWT tree. Each "branch" comprises of two mirror filters, a low pass (LP) and a high pass (HP) filter.

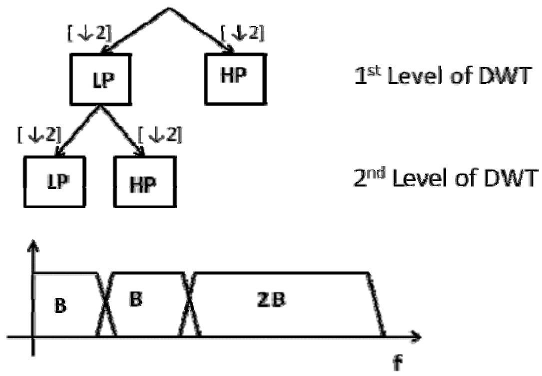

Figure 1: A graphic representation of DWT

The technique proposed by Donoho is based on the idea of thresholding the wavelet coefficients at each wavelet decomposition level. Those wavelet coefficients that have small absolute value are considered noisy coefficients. On the other hand, coefficients having large absolute value are considered as important information. The act of removing the small absolute value coefficients and reconstructing the signal should produce a signal with less noise which would yield a good approximation of the original signal f (Eq. 1). The wavelet denoising (or wavelet shrinkage) technique is in general as follows:

1) Split the signal into segments with different frequency resolution via DWT

$$\tilde{\mathbf{\Theta}}=\mathbf{W}\bullet\mathbf{Y} \qquad (2)$$

Where **W** is the DWT matrix, $\mathbf{Y}=\{y_1,y_2\dots y_n\}$ is the original signal and $\tilde{\mathbf{\Theta}}=\tilde{\theta}_{i,j}$ is the wavelet coefficient i of the j decomposition level.

2) Apply an appropriate threshold to the high frequency components of $\tilde{\Theta}$ known in literature as the details

$$\hat{\theta}_{i,j}=\beta_{i,j}\bullet\tilde{\theta}_{i,j} \qquad (3)$$

Where $\beta_{i,j}$ is a shrinkage factor for the coefficient i at level j.

3) Reconstruct the denoised signal using the inverse DWT formula

$$\hat{\mathbf{Y}}=\mathbf{W}^{-1}\bullet\hat{\mathbf{\Theta}} \qquad (4)$$

The expert should choose a wavelet basis as well as the depth of levels of decomposition in order to form the decomposition procedure of Eq. (1) and a threshold method as described in Eq. (3).

2.1 Thresholding with neighbouring blocks method

Cai and Silverman (1998) has proposed an interesting threshold method. In that method the shrinkage factor at Eq. (3) is not applied at each coefficient at each level. On the contrary it is applied in a group of successive coefficients and the threshold is calculated within adjacent blocks of coefficients. The method resembles a sliding window that calculates a threshold value within a neighbourhood and applies this threshold in the central block of this neighbourhood of coefficients. More analytically

1) Perform DWT of Eq. (2) with a certain wavelet basis and number of levels of decomposition in order to acquire the wavelet coefficients
2) At each level of decomposition, group the wavelet coefficients into disjoint blocks $\mathbf{b}_{i,j}$ of length $L_0 = \lceil (\log n)/2 \rceil$. Each block is extended by an amount of $L_1 = \max(1, \lceil L_0/2 \rceil)$ points in each direction to form overlapping blocks $\mathbf{B}_{i,j}$ of length $L = L_0 + 2L_1$.
3) Within each block indexed i at level j, $\mathbf{b}_{i,j}$, estimate the coefficients via the shrinkage rule of Eq. (3). The shrinkage factor $\beta_{i,j}$ is chosen with reference to the coefficients of the larger block $\mathbf{B}_{i,j}$

$$\beta_{i,j} = \max(0, (1 - \lambda L\sigma^2 / S^2)) \tag{5}$$

Where k=1,2.., L_1 is the index of each data point within the bigger block $B_{i,j}$,

$S^2 = \sum_{(j,k)\in B_{i,j}} \tilde{\theta}_{j,k}$ and σ^2 is the variance of the extended block and λ=4.5053.

The latter method is shown to outperform other older threshold criteria such as Rigsure, NisuShrink and others (Cai and Silverman 2000).

3. Case Study: lifelong bearing data

The problem with rolling element bearing data is that due to the industrial maintenance policies bearings are usually replaced well before critical break down, thus the scarcity of real life lifelong bearing data. Several lifelong bearing data bases that are acquired from experimental test rigs can be accessed through internet. These have been used within the academia to test Remaining Useful Life (RUL) as well as diagnostic methods and models. The most recent known to the authors is the data base of PRONOSTIA (Nectoux et al. 2012). The data comprise of several lifelong bearing test histories with varying load and rotating frequencies. Vibration data are recorded from two axes once every 10 s. The vibration waveform sampling rate is 25,6 Khz and each waveform is 0.1 s long (2.560 samples per vibration ASCII file). Each tested bearing is considered broken when the vibration signal amplitude overpasses 20g.

3.1 Statistical feature extraction

The most common way to apply and assess diagnosis and RUL strategies is through statistical feature extraction and monitoring. Such features may be derived from time domain (rms, kurtosis, crest factor..) frequency domain (kurtosis, skewness, frequency with maximum amplitude), wavelet domain (rms or some other statistic of a particular wavelet resolution band) and others can be found in literature. The best feature for RUL estimation is the one that correlates well with the gradual degradation of the roller bearing under consideration and it should be monotonic. Diagnosis on the other hand is based on picking the change point in the operation of the mechanical asset. The better the correlation of a feature change point with the actual structural deterioration change point, the better. Figure 2 depicts extracted vibration waveform rms plotted against the time evolution of each experiment. Such a variable is frequently used for RUL and diagnostic purposes. However there variables contain significant trends and change points that can neither correlate with actual health status or with a gradual degradation mechanism. Take for instance Figure 2a and b, where few regions have been marked. These regions possibly correspond to different physical processes. Region 1 coincides with the beginning of the experiment and exhibits a sudden (Figure 2a) or gradual change (Figure 2b) in trend. This trend can most certainly be attributed to change in lubricating oil temperature or smoothing out of the virgin groove of the rolling bearing. In any case this run-in period differs from experiment to experiment (as is evident in Figures 2a, b) and can affect the training efficiency of an expert system. Moreover, other mechanisms that can possibly be attributed to slight bearing faults, which are not “fatal” but disappear with the course of the experiment, can have their toll on the CBM feature trend. Region 2, as noted in the figure, probably depicts a slight fault in the bearing that appears and disappears, contaminating the trend of the CBM feature and obscuring the on-line change point analysis for bearing diagnosis. Region 3 is the only part of each plot that can directly and without any reluctance be correlated to the fatal flaw that results in the final break down of the asset.

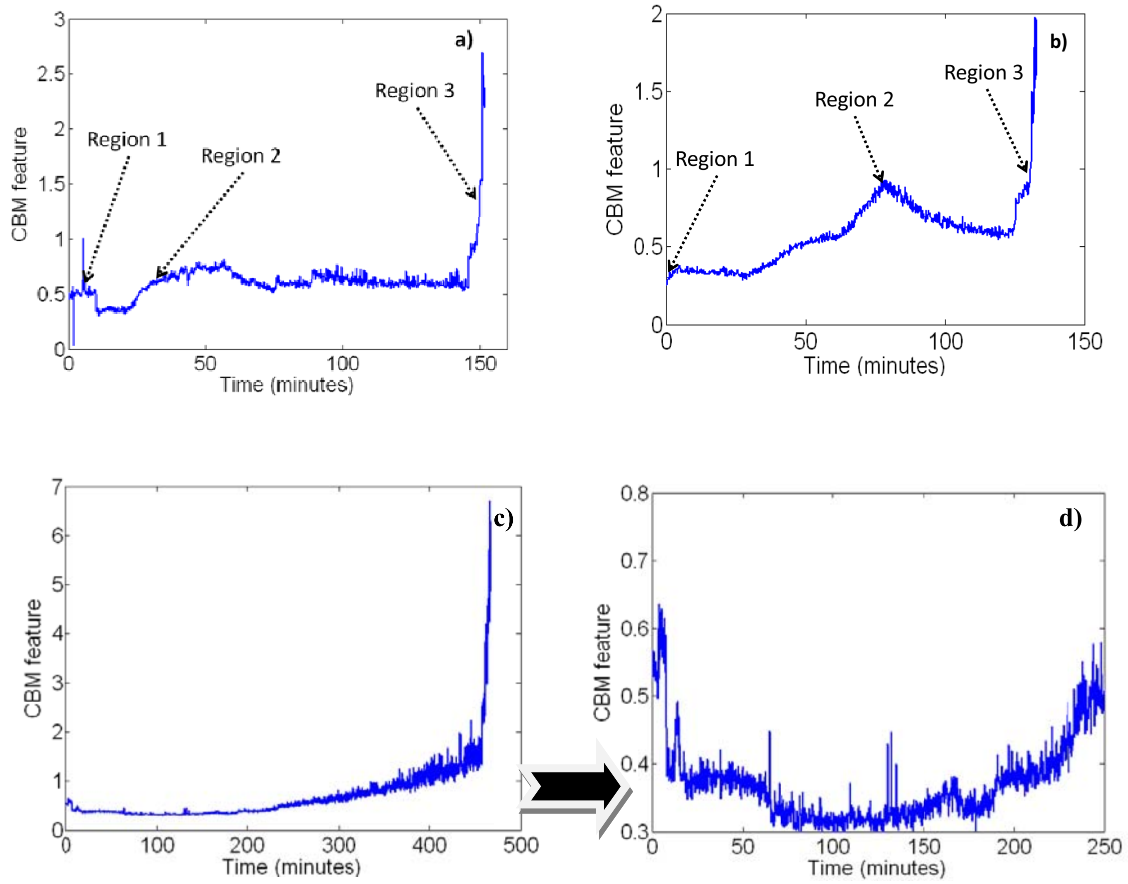

Figure 2: Time evolution of rms for three bearing failure histories derived from PRONOSTIA data base. Figure 2d is a zoom in Figure 2c.

Few outliers in the beginning of the experiment can be treated either with a short moving average filter or with some kind of outlier handling (Roulias et al. 2012). Similar remarks can be made for a number of other features that the authors had the time to extract from PRONOSTIA data base (some of which are briefly reported in the beginning of this paragraph) but not the space to depict in this paper. Since these irregular patterns exist in a vast variety of features a simple feature fusion (a feature level fusion technique for mechanical asset has been proposed by the authors in Loutas et al. 2011) may not be sufficient to improve either the health-change-point detectability or the RUL estimation capability of the CBM scheme. Similar remarks can be made for all six lifelong histories from PRONOSTIA data base that were analyzed by the authors but due to space restrictions are not depicted in this paper.

3.2 Application of waveform denoising to the extracted CBM features

The denoising process of paragraph 2.1 is applied to each vibration recorded ASCII file. ‘db10’ wavelet basis is chosen as a wavelet basis. The authors have experimented with a vast variety of wavelet bases but no significant changes were noted among them concerning the extracted feature timeline. Moreover, concerning Eq. (5), the median absolute deviation (MAD) of the extended block is used as a more robust dispersion estimator instead of the sample standard deviation. The NeighBlock thresholding scheme was applied to all detail wavelet coefficients. The results on the extracted feature (rms) are as follows. The depth (number of levels) of DWT is chosen as follows. The similarity of actual remaining useful life function to CBM feature is assessed qualitatively. This similarity measure is chosen to be the absolute correlation coefficient ρ, 0<ρ<1 where ‘1’ implies identity and ‘0’ implies irrelevance (to be more precise, absolute correlation coefficient zero means that one of the two components of the comparison is white noise). In Table 1 several cases are taken into account. Case 1 is derived from raw waveform data, case 2, 3, 4 and 5 are the cases concerning denoising with one, two, three and four levels of decomposition.

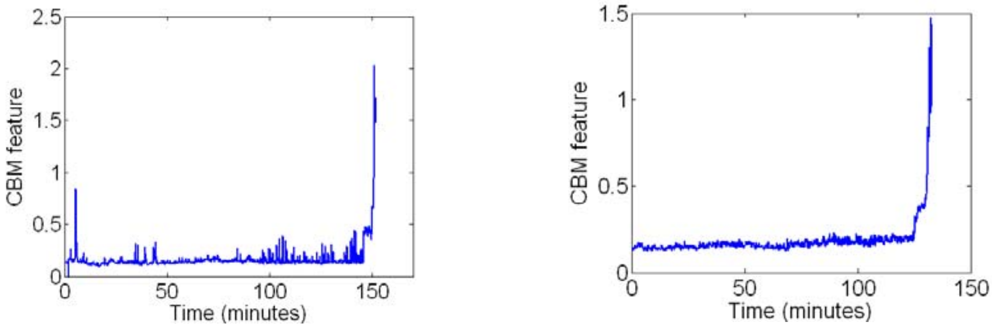

Figure 3a, b: The extracted features after the wavelet denoising performed on the original vibration recordings compared to Figures 2a, b respectively

The best similarity measure is succeeded with the three levels of decomposition as shown in Table 1. Thus the best RUL estimation feature is derived from case 3 scenario. The same case is applied to every lifelong bearing history under consideration.

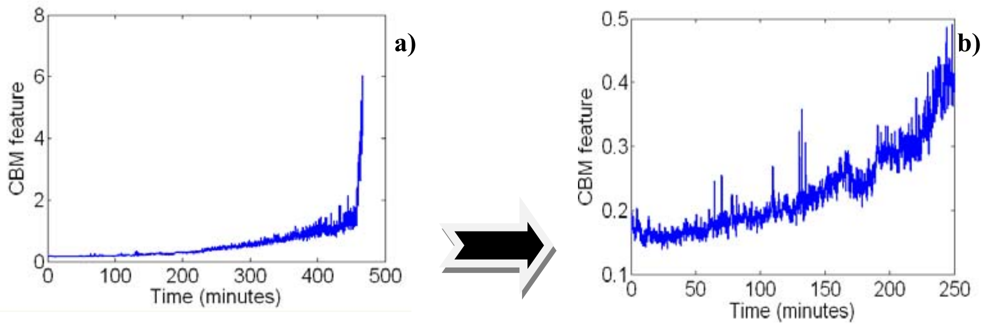

Figure 4a, b: The extracted feature after the wavelet denoising performed on the original vibration recordings, compared to Figure 2c and 2d respectively.

Table 1: Selecting the depth of the DWT decomposition.

	Case 1	Case 2	Case 3	Case 4	Case 5
Correlation coefficient	0.6813	0.6784	0.7123	0.7506	0.7402

4. Discussion

Figure 3a and b shows the extracted rms value from the wavelet denoised vibration signals. First of all, the irregular run-in-period trend at the beginning of each experiment has largely been eliminated. The picture is much clearer concerning the improvement from Figure 2b to Figure 3b where the final health status change point is completely distinguishable from the rest of the experiment. The only issue seems to be several outliers that exist especially in Figure 3a. This seems to be no big issue, since an additional on-line, feature-level pre-processing (Roulias et al. (2012)) can eliminate these irregularities. In Figure 2d the trend is very irregular and bath tub shaped. Comparing Figure 2c and d with Figures 4a and 4b makes it clear that wavelet denoising improves the robustness of CBM. On the other hand, Figure 4b shows an improved picture compared to Figure 2d. An almost monotonic trend is now distinguishable. It is evident that RUL estimation can be improved and become more robust taking as input this feature. The latter statement can be sustained also by Table 1 and noting the increase in correlation from Case 1 to Case 4.

This short procedure can be summarized in the following flow chart (Figure 5).

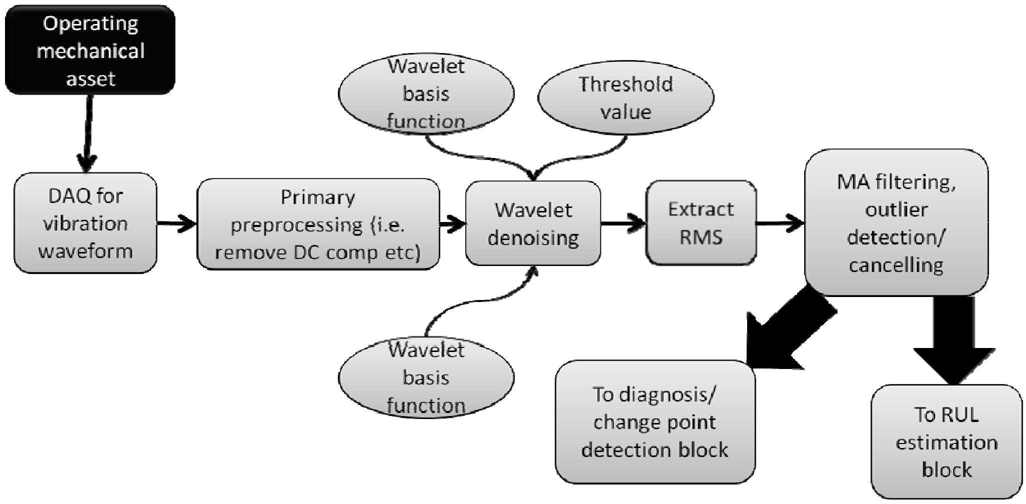

Figure 5: The proposed feature extraction scheme

5. Conclusion

This work proposes a new CBM feature for robust monitoring of rolling element bearings based on vibration sensor monitoring. This is the rms value of the wavelet denoised vibration waveform. This has several advantages. First of all it can easily be applied for on-line monitoring. Second, it improves substantially the structural health change-point detection capability of the rms. Third it substantially improves the RUL estimation capability of the rms. As a next stage the authors are going to apply this feature for RUL estimation as well as change point detection and assess quantitatively the improvement of such estimation for various RUL models. Moreover, the reason for this effective smoothing via wavelet denoising is going to be investigated.

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