ICSV13 - Vienna
The Thirteenth International Congress on Sound and Vibration
Vienna, Austria, July 2-6, 2006

DISCRETE WAVELET-BASED THRESHOLDING STUDY ON ACOUSTIC EMISSION SIGNALS TO DETECT BEARING DEFECT ON A ROTATING MACHINE

Yanhui Feng*, Suguna Thanagasundram, Fernando S. Schlindwein**

University of Leicester, Department of Engineering, Leicester LE1 7RH, UK
yf12@le.ac.uk* fss1@le.ac.uk**

Abstract

A five stage "Roots and Claw" dry vacuum pump is a typical kind of quasi-steady state high speed rotating machine. The research using the novel Acoustic Emission measurement and Wavelet technique aims to develop advanced detection methods for dry vacuum pumps to prevent pumps' failure. In this paper, the denoising problem of Acoustic Emission signal is studied by using Discrete Wavelet Transform thresholding methods. The Donoho-Johnstone threshold method and parameter method are studied and compared. The Birgé-Massart strategy outperforms other estimators in our case. The denoised Acoustic Emission signals enable detection of the defect and identification of the type of bearing defect. Care has to be taken on selecting the wavelet basis properly to reduce bias and error. The study shows that the Discrete Wavelet Transform-based thresholding method is suitable for bearing defect detection of rotating machines using Acoustic Emission signals.

INTRODUCTION

A five stage "Roots and Claw" dry vacuum pump is a typical kind of quasi-steady state high speed rotating machine. Its reliability is crucial to the semiconductor industry and a typical failure might cost over £100,000. The rolling element bearing catches our attention since the major problems in dry vacuum pumps are caused by this kind of failures. Rolling element bearing is the most commonly used machine part of rotating machines and its failure can be disastrous. Intensive research has focused on developing advanced bearing defect detection methods based on acoustic and vibration measurements. Each bearing element has a characteristic rotational frequency. When a particular defect happens on the bearing element, energy on that rotational frequency will increase. This characteristic bearing defect frequency can be calculated from the known geometry information of bearing and its speed [1]. Different acoustic and vibration measurement methods for bearing defect detection are also reviewed in the same reference [1].

Acoustic emission (AE) describes the phenomena that result in structure borne elastic waves being generated by rapid energy released from localised sources. AE signal is a high frequency signal, normally over 20 kHz but can be bounded to lower values depending on application. AE is becomeing more and more popular in condition monitoring of rotating machine for its high sensitivity. Mba [2] used Acoustic Emission to detect and identify bearing and gearboxes defects. Choudhury and Tandon [3] used Acoustic Emission for detection of defects in rolling element bearings.

When defects appear on bearings, wide bandwidth periodic AE bursts can be observed. Then the task of bearing fault detection can be performed by finding out whether the AE bursts are periodic and whether they correspond to one of the characteristic bearing defect frequencies for identifying the type of bearing defect. The denoising and enhancement of AE signals is importance for it can reveal the occurrence of these bursts. The reduction of the number of signal coefficients can also greatly reduce the workload of post-analysis; particularly important since the sampling rate for AE signals is usually very high (~200 kSPS). The AE signals are highly non-stationary for their amplitude and frequency fluctuate. In this case, adaptive schemes are needed.

The application of Wavelet Transform for bearing defect detection has caught attention recently. Wavelet techniques are more suitable for transient analysis. Peng [4] presented a comprehensive review on the application of wavelets in machine condition monitoring and fault diagnostics. Qiu [5] proposed a two-step optimization process. Liu [6] studied the adaptive harmonic Wavelet transform. When using Discrete Wavelet Transform, its computation efficiency ensures its applicability on real-time implementations. The thresholding scheme based on Discrete Wavelet Transform is more attractive for it handles noise adaptively at different levels. Discrete Wavelet Transform firstly decomposes signals at different levels. At each level, noise is estimated robustly. Then the denoising threshold is estimated by using different estimators. Two main families of threshold methods are: Donoho-Johnstone methods (Square2log, Heursure, SURE and Minimax) and parameter methods proposed by Birgé-Massart (Birgé-Massart strategy and penalized method).

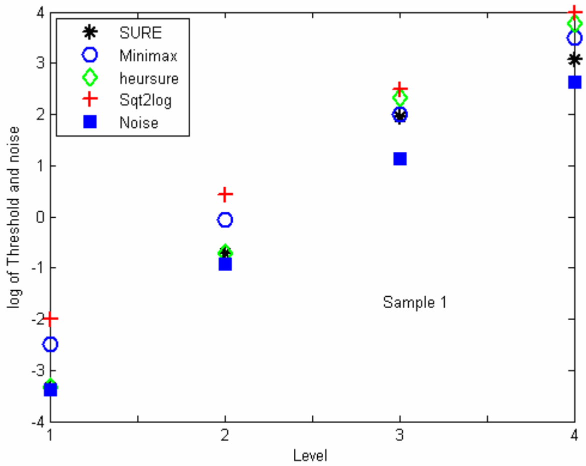
In this paper, these main families of thresholding methods based on Discrete Wavelet Transform are studied in order to investigate their nonlinear behaviour at different levels. The first study aims to find out the relationship of the four estimators of Donoho-Johnstone threshold methods. The second study is to investigate the parametric thresholding method proposed by Birgé and Massart. Finally, the periodicity of the denoised signals is studied to investigate their suitability for bearing defect frequency detection.

EXPERIMENTAL METHODS

A five stage “Roots and Claw” dry vacuum pump with empty load was used as test bed. A known defected bearing was mounted at its high vacuum side. The speed of pump was set at 105 Hz (6300 rev min^{-1}) and the inlet pressure was set at 0 mbar. An AE transducer (PAC R3α) was firmly held at the surface of the pump house to capture AE signals in the radial direction. The AE signals were sent to an amplifier with gain of 1000 and then a band pass filter (10 *kHz*-50 *kHz*) before being digitized by a 16-bit NI Analogue to Digital Converter (ADC). The frequency response of the transducer and filter is chosen as to complement that of the ADXL acceleration transducer also used in our research. The AE signals were sampled at the rate of 200 *kHz*. The analysis was conducted off line on the platform of Matlab and LabView.

RESULTS AND DISCUSSION

The AE signals were separated into frames of samples for analysis. Each frame corresponding to 10^{-2} s included 2000 data points. In this section, the default option of DWT for all the estimators is chosen as level dependent. Signals were decomposed by 4-levels DWT (bior3.9). The biorthogonal wavelet is used because the linear phase and symmetry features are important in signal detection. Wavelet coefficients from Level 1 to 4 correspond to four frequency bands D1 (50 *kHz*~100 *kHz*), D2 (25 *kHz* ~50 *kHz*), D3 (12.5 *kHz* ~25 *kHz*) and D4 (6.25 *kHz* ~12.5 *kHz*). The thresholding was conducted at wavelet coefficients on different levels. The purpose of the first study aims to find out the relationship of four estimators of Donoho-Johnstone threshold methods. The four estimators are Square2log (also Universal), Minimax, Heursure and SURE. Figure 1 (Left) and Figure 2 show the thresholds and noise (note: logarithmic scale) estimated in three typical frames. The original signal is noisy and it is not easy to separate the AE bursts. See Figure 1(Right) for Sample 1. The denoised signals of Sample 1 are shown in Figure 3. It is shown that Sqt2log outperforms the other three estimators.



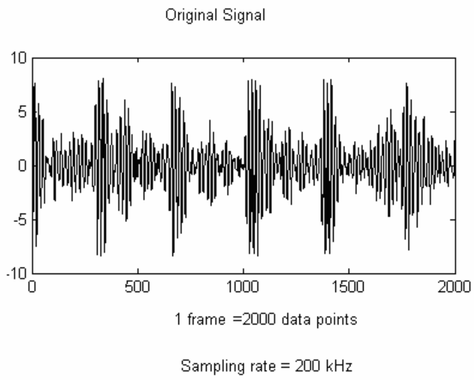


Figure 1 – Left: Estimated Thresholds and noise (log) for Sample1; Right: The original signal

All the estimators are adaptive to the noise. For different AE signals, Sqt2log always selects the highest thresholds and SURE is the most conservative threshold estimator always selecting the lowest thresholds. Table 1 summarizes the observation of the sequence of estimated thresholds by using these four estimators.

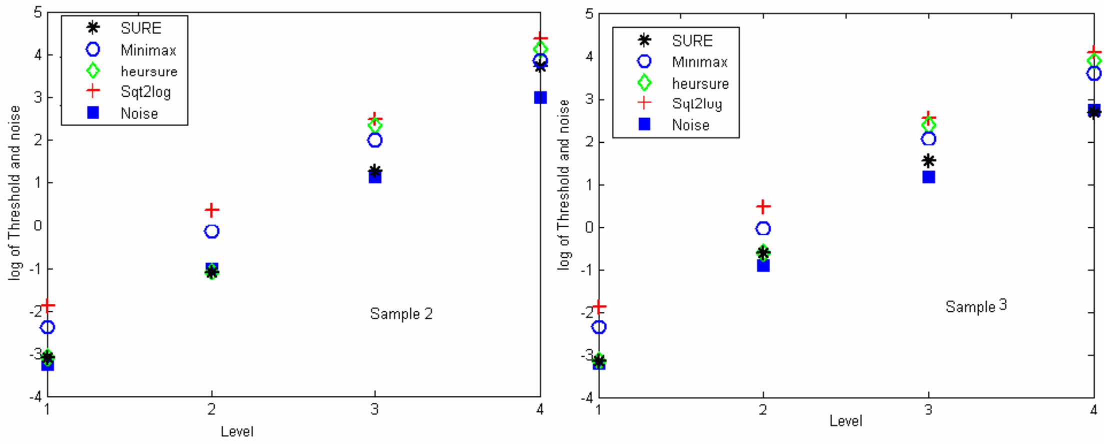


Figure 2 –Estimated Thresholds and noise (log) for Sample2 and 3

Table1 – Sequence of selected thresholds at different levels

	Sequence of selected thresholds by using four estimators
Level 1	Sqt2log>Minimax>heursure(=SURE)>noise
Level 2	Sqt2log>Minimax>noise; heursure=SURE
Level 3	Sqt2log>heursue>Minimax>noise; heursure$\neq$ SURE
Level 4	Sqt2log>heursue>Minimax>noise; heursure$\neq$ SURE

The sequence of Sqt2log, Minimax and noise is kept as the same at different levels in all the cases. The estimated thresholds to noise ratios of Sqt2log and Minimax are equally at different levels. For Sqt2log, signals with SNR over 1.36 were kept. For Minimax, signals with SNR over 0.87 were kept.

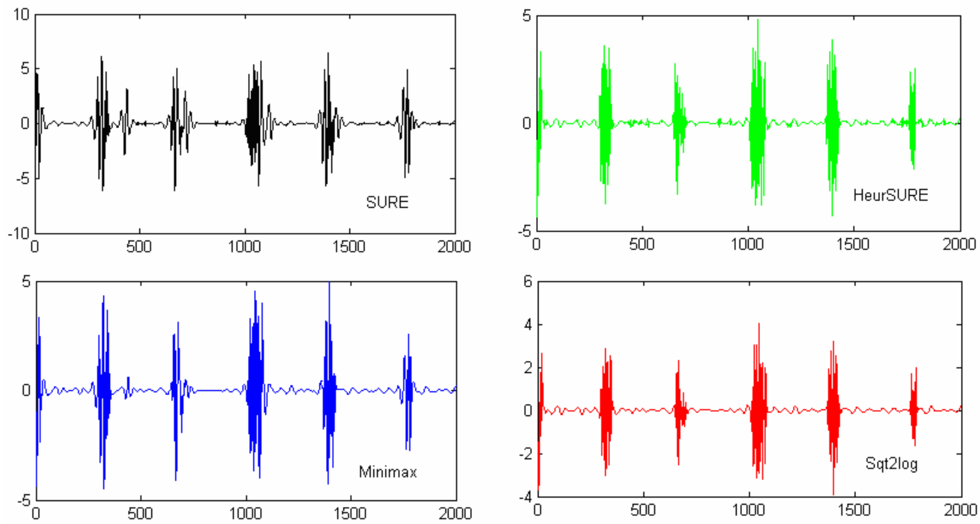


Figure 3 –Denoised signal of Sample 1

Heursure selects the same thresholds as SURE at lower levels 1 and 2 while at higher levels 3 and 4, it chooses higher thresholds. It keeps more coefficients than Sqt2log and Minimax at low levels 1 and 2. See Figure 4 for illustration of denoised coefficients of

Sample 1 at different levels. All the estimators tend to keep more coefficients at low levels 1 and 2 when SNR is high at these levels. The denoised signals (see Figure 3) are mainly dominated by the coefficients at levels 1 and 2, which explain why Sqt2log outperforms the other three estimators.

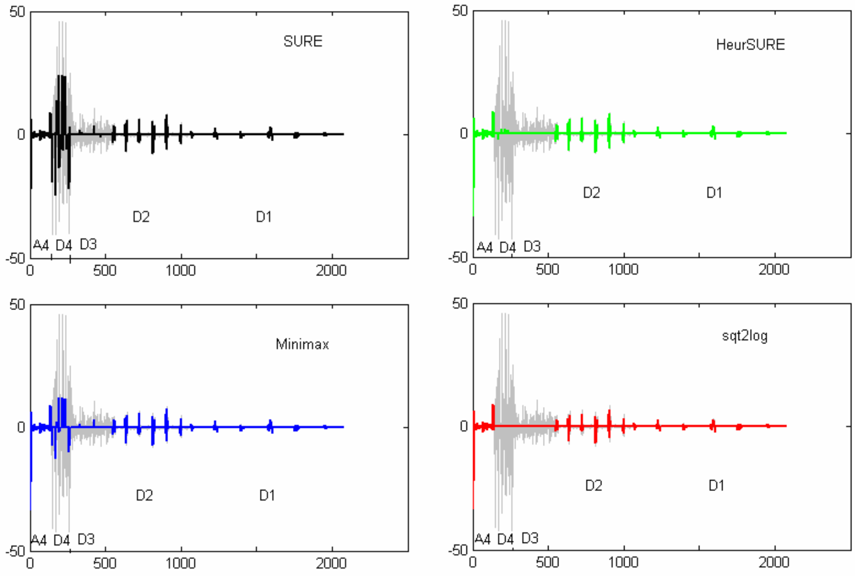


Figure 4 –Denoised coefficients at different levels

The second study is to investigate the parametric thresholding method proposed by Birgé and Massart, including Birgé-Massart strategy and penalized method. Figure 5 shows the estimated thresholds and noise of Sample 1 using Birgé-Massart strategy.

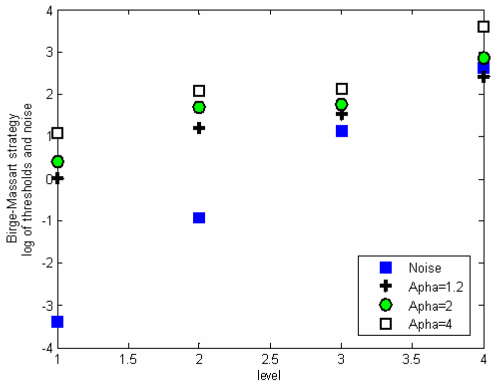


Figure 5 –Estimated Thresholds and noise (log) for Sample1 using Birgé-Massart strategy

The thresholds selected by Birgé-Massart strategy are also adaptive to the noise. The estimated thresholds increase by the parameter Alpha. But Birgé-Massart strategy is very strict at low levels 1 and 2, only the signals with SNR over 3.5 remain, even choosing the smallest Alpha=1.2 at level 1. The estimator tends to keep more coefficients at high levels 3 and 4 and is more flexible than Donoho-Johnstone threshold methods at higher levels for one can easily control thresholds by changing Alpha. Denoised Signals are shown in Figure 6. Denoised coefficients of Sample 1 at different levels are shown in Figure 7. The estimator tends to keep more coefficients at higher levels 1 and 2. Satisfactory denoising is achieved for Alpha=4.

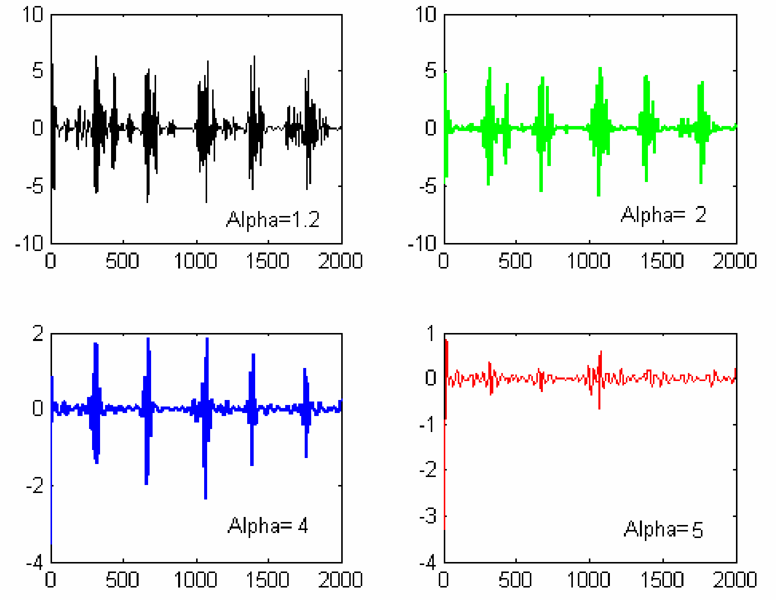


Figure 6 –Denoised signal of Sample 1 using Birgé-Massart strategy Alpha=1.2, 2, 4, 5

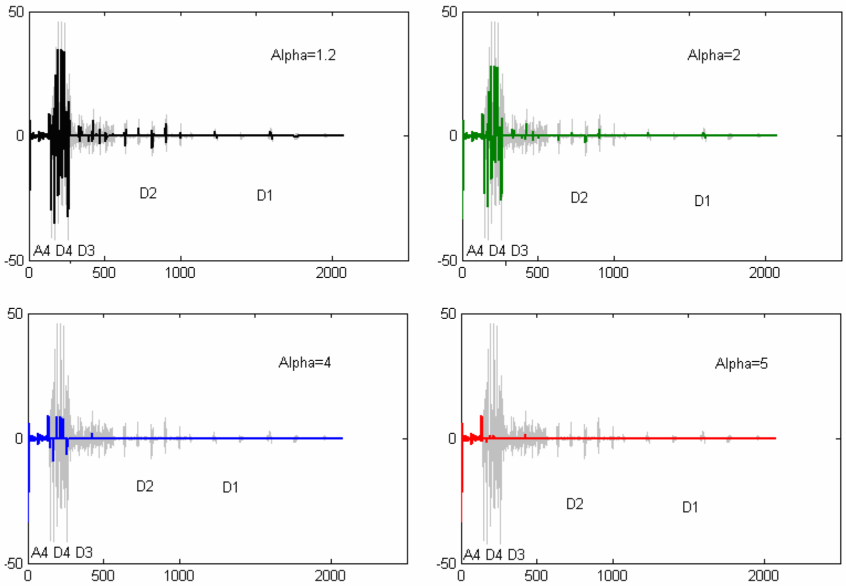


Figure 7 –Denoised coefficients at different levels using BM strategy Alpha=1.2, 2, 4,5

The estimated thresholds using penalized method at level 1 are showed on Figure 8 (Left). Other thresholds estimated by Donoho-Johnstone method are also given for comparison. As known before, the Birgé-Massart strategy chooses thresholds higher than 0 at level 1, which are the highest estimated threshold. In this case, Minimax and Sqt2log correspond to Alpha 3 and 7.6, which are both the high penalized factors (Alpha 2.5 to 10 are defined to be high penalized factors). The denoising affect using penalized method is not obvious in our case even when Alpha=10, see Figure 8 (Right). The reason is that penalized method underestimates the noise level at higher levels.

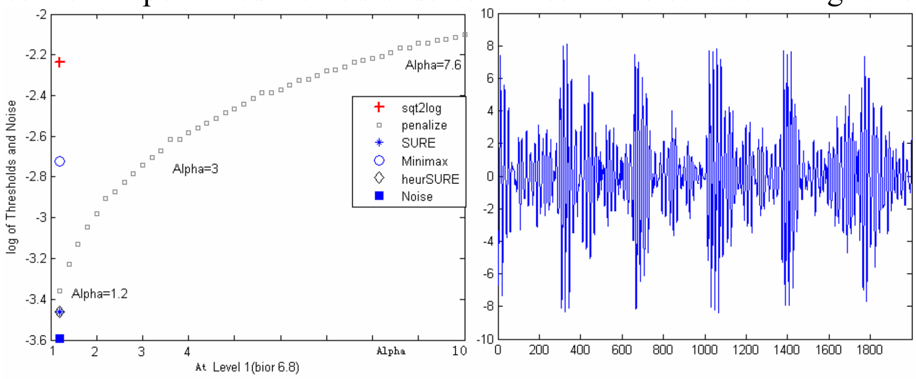


Figure 8 –Left: Estimated Thresholds and noise (log) for Sample1 using Penalized method Alpha[1.2, 10] at level 1; Right: Denoised signal using Penalized method Alpha=10

In the following section, the periodicity of denoised AE signals is studied in order to investigate their suitability for bearing defect frequency detection.

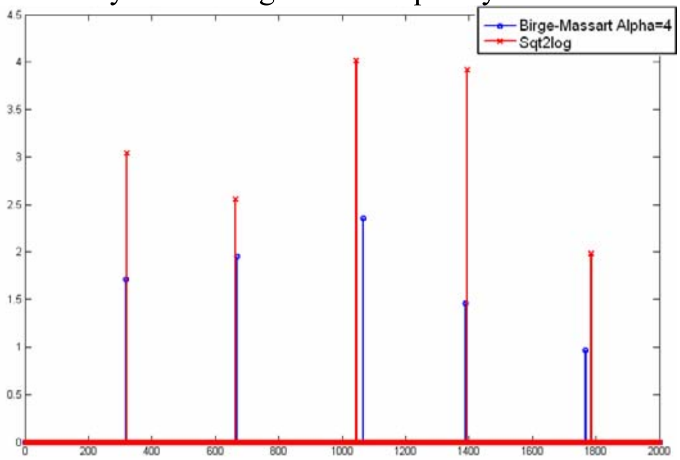


Figure 9 – Peaks of denoised signals (absolute value) using bior3.9 Wavelet

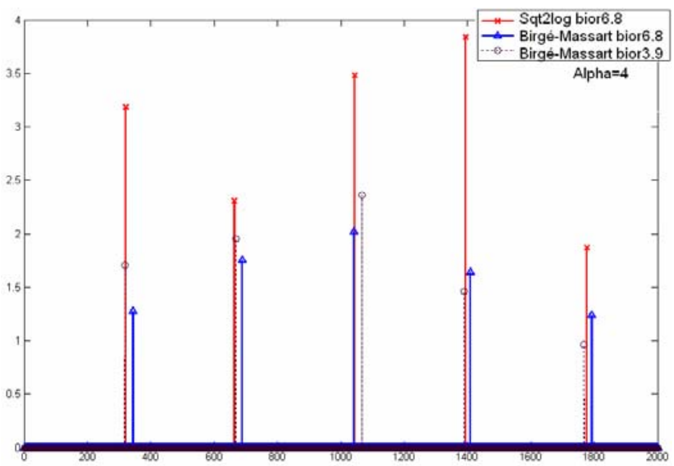


Figure 10 – Peaks of denoised signals (absolute value) using bior6.8Wavelet

The peaks of the denoised signals Sample 1 (absolute value) are picked up as Figure 9 and Figure 10. The amplitudes of peaks of Sqt2log are higher than those estimated by the Birgé-Massart strategy. The periodicity of the peaks is very obvious. Table 2 gives the detailed positions of peaks, the average periods (unit in data points) and errors.

Table2 – Peaks location of denoised signals

PeakPosition		Peak 1	Peak 2	Peak 3	Peak 4	Peak 5	Ave Period	Error
bior 3.9	Sqt2log	320	663	1045	1394	1785	369	4.85%
	Birgé-Massart Alpha=4	319	669	1068	1390	1767	361	7.87%
bior 6.8	Sqt2log	320	664	1044	1394	1776	364	4.71%
	Birgé-Massart Alpha=4	337	689	1041	1409	1793	364	3.64%

The characteristic defect frequency is 550 *Hz*. So the corresponding period value is 363.64 when sampling rate is set to 200 *kHz*. All the estimated average periods from Table 2 are close to 363.64 and Birgé-Massart gets the best performance for less bias. Moreover, basis bior6.8 is more suitable in this case for its estimated periods have less bias and error.

CONCLUSIONS

In this paper, Acoustic Emission signal denoising problem is studied based on Discrete Wavelet Transform thresholding methods. The denoised Acoustic Emission signals allow detection of the defect and identification of the type of bearing defect. The Donoho-Johnstone threshold method and parameter method are studied. The penalized method is not suitable for broadband AE signal adaptive denoising. SURE is the most conservative thresholding estimator. Birgé-Massart strategy selects very high thresholds at low levels 1 and 2. Birgé-Massart strategy outperforms other estimators. Care has to be taken on selecting wavelet basis properly to reduce the bias and error.

REFERENCES

[1] N. Tandon, A. Choudhury, "A review of vibration and acoustic measurement methods for the detection of defects in rolling element bearings," Tribology International 32(1999) 469-480.

[2] D. Mba, "Prognostic opportunities offered by acoustic emission for monitoring bearings and gearboxes, " 12th International Congress on Sound and Vibration, 2005.

[3] A. Choudhury, N. Tandon,, "Application of acoustic emission technique for the detection of defects in rolling element bearing," Tribology International 33(2000) 39-45.

[4] Z.K.Peng, F.L.Chu, "Application of wavelet transform in machine condition monitoring and fault diagnostics: a review with bibliography," Mechanical Systems and Signal Processing (2004) 18, 199-221.

[5] Hai. Qiu, J.Lee, J. Lin, G. Yu, "Wavelet filter-based weak signature detection method and its application on rolling element bearing prognostics," Journal of Sound and Vibration 289 (2006) 1066-1090.

[6] B. Liu "Adaptive harmonic wavelet transform with applications in vibration analysis," Journal of Sound and Vibration 262 (2003) 45-64.