Performance Analysis of Wavelet Thresholding Methods Using DTCWT for Denoising of Vibration Signals

Shivangi pawar1 Preety D Swami2
1,2Department of Electronics & Communication Engineering
1,2Samrat Ashok Technological Institute, Vidisha, India

Abstract— This paper presents a robust technique for denoising of vibration signals corrupted by Additive White Gaussian Noise. The proposed method uses Dual Tree Complex Wavelet Transform (DTCWT) and is very efficient due to its shift invariance property and reduced aliasing effect. While using DTCWT, we are comparing Different Threshold selections. The threshold value is selected using Universal, Rigrsure, Heursure and Minimaxi methods and is level adaptive. The best results are obtained by the threshold value selection using ‘Minimaxi’ threshold at low values of noise standard deviation and using ‘Universal’ threshold at higher values of noise standard deviation. Experiments are carried out on simulated vibration signals as well as on real time fault signal. The comparison of the results of the proposed methods using DTCWT for synthetic signal is done using the signal to noise ratio (SNR). Higher SNR is gained compared to traditional denoising method. For comparison of results of the real time signal, another statistical parameter ‘Kurtosis’ is chosen.

Key words: DWT, DTCWT, Thresholding, Minimaxi, Heursure, Rigrsure, Universal

I. INTRODUCTION

Modern machineries are one of the most important tools. Today industries can’t be imagined without machines. These machines play crucial role in manufacturing industries, reduce the labor work and time consumption. Rotary machine is a tool that contains different rotating parts such as rotors, bearings, gears etc. To achieve the appropriate goal, machines should be fault less. But due to presence of noise, faults are not detected correctly. Due to various reasons such as mechanical vibrations, stresses, inadequate lubricant and asymmetric loading, breakdown happens and different types of faults take place in machines. These faults foremost to slow or total stoppage in production and therefore economical loss and safety problems are faced by industries. To defeat these problems, some efficient and fast techniques are required that are able to not only detect faults, but also remove noise from the faulty signals. These vibration signals contain useful information to detect the faults [1-2]. To retrieve the characteristic fault frequencies of the vibration signal, denoising of signal is an essential pre-processing step.

For the past few years, many techniques have been developed in this field to detect faults such as the Fourier Transform (FT) [3-4] and the Short Time Fourier Transform (STFT) [4]. Fourier analysis has a serious drawback. Fourier Transform gives the complete information about the frequency content of the signal but the time information is missing. Thus using this transform it is not possible to identify that which frequency component exists at a particular time. Main Drawback of STFT is poor resolution. STFT creates constant resolution for a window and it is suitable for Quasistationary signals. STFT gives the information about both time and frequency of the signal, but the selection of window size is a big concern.

Due to this drawback, a transform is required which is able to give not only perfect time and frequency resolution of a spectral band but a particular spectral component without any limitation. Wavelet transform has now become approved that gives perfect time and frequency information of a signal under investigation. Wavelet transform can be basically categorized into Continuous Wavelet Transform (CWT) and Discrete Wavelet Transform (DWT). Main advantage of DWT over CWT is that it is comparatively faster, easier to implement and avoids redundancy. However DWT has some drawbacks such as lack of shift invariance and aliasing effect. To overcome these problems, in this paper, a robust technique for denoising of vibration signals are proposed that use DTCWT.

The paper organization is as follows: A short description of DWT and DTCWT is given in Section II that describes the functioning of the transforms. Section III presents the proposed denoising algorithm. In Section IV, comparisons of results and their analysis is done. Finally conclusions are given in Section V.

II. DWT AND DTCWT

A. DWT

In numerical analysis and functional analysis, a discrete wavelet transform (DWT) is any wavelet transform for which the wavelets are discretely sampled. As with other wavelet transforms, the key advantage over Fourier transforms is temporal resolution i.e., it captures both frequency and location information (location in time) [4-6].

In discrete wavelet transform, filters of different cutoff frequencies are used to analyze the signals at different scales. The signal is passed through a series of high pass filters to analyze high frequency components, and is passed through a series of low pass filter to analyze the low frequency components. This shows better in Fig.1. The amount of detail information present in the signal known as resolution of the signal, is changed by filtering operations, and the scale is changed by upsampling and downsampling operations. Downsampling a signal corresponds to reducing the sampling rate, or removing some of the samples of the signal whereas upsampling leads to increasing the sampling rate of a signal by adding some new samples to the signal.
with the lower DWT. When designed in this way, the DTCWT is nearly shift invariant, in contrast with the DWT. The perfect reconstruction property of the DTCWT is verified too. Its properties of approximate shift invariance, computational efficiency and perfect reconstruction makes it a good candidate for denoising signals. For $\psi_s(t)$ and $\psi_h(t)$ denoting two real valued wavelets used for lowpass and highpass filters respectively, the complex wavelet $\psi_c(t)$ is given by

$$\psi_c(t) = \psi_s(t) + j\psi_h(t)$$ (1)

Thus two real wavelets constitute a complex analytical wavelet which is supported on positive frequency axis.

1) Decomposition and Reconstruction of DTCWT

Since DTCWT is decomposed of two parallel wavelet transforms, the wavelet coefficient $d_{l}^{Re}(t)$ and scaling coefficient $c_{l}^{Re}(t)$ of the upper tree can be computed via inner product

$$d_{l}^{Re}(k) = 2^{l} \int_{-\infty}^{+\infty} x(t)\psi_{l}(2^l t - k) dt \quad l = 1 \ldots j$$

$$c_{l}^{Re}(k) = 2^{l} \int_{-\infty}^{+\infty} x(t)\phi_{l}(2^l t - k) dt$$

Where $l$ is scale factor and $j$ is maximum scales.

Similarly coefficient of lower tree can also be computed using $\psi_s(t)$ and $\phi_s(t)$ in place of $\psi_h(t)$ and $\phi_h(t)$

$$d_{l}^{Im}(k) = 2^{l} \int_{-\infty}^{+\infty} x(t)\psi_{l}(2^l t - k) dt \quad l = 1 \ldots j$$

$$c_{l}^{Im}(k) = 2^{l} \int_{-\infty}^{+\infty} x(t)\phi_{l}(2^l t - k) dt$$

The wavelet and scaling of the DTCWT coefficient can be given by combining the output of the dual tree as follows

$$d_{l}^{c}(k) = d_{l}^{Re}(k) + jd_{l}^{Im}(k) \quad l = 1 \ldots j$$

$$c_{l}^{c}(k) = c_{l}^{Re}(k) + jc_{l}^{Im}(k)$$

Furthermore, when other coefficients are set to zero, the scaling or wavelet coefficients can be individually reconstructed using the following equation

$$d_{l}^{c}(t) = 2^{(l-1)/2} \left[ \sum_{n} d_{l}^{Re}(n)\psi_{l}(2^{l} t - n) + \sum_{n} d_{l}^{Im}(n)\phi_{l}(2^{l} t - n) \right] \quad l = 1 \ldots j$$

and

$$c_{l}^{c}(t) = 2^{(l+1)/2} \left[ \sum_{n} c_{l}^{Re}(n)\phi_{l}(2^{l} t - n) + \sum_{n} c_{l}^{Im}(n)\psi_{l}(2^{l} t - n) \right]$$

Coefficients $d_l(t)$ and $c_l(t)$ are real and have equal lengths as the original signal $x(t)$, which are different from $d_{l}^{c}(k)$ and $c_{l}^{c}(k)$. For real tree, corresponding decomposed scaling coefficient (approximation) $c_{l}^{Re}(k)$ and wavelet coefficient (details) $d_{l}^{Re}(k)$ as well as the inverse transform between the two consecutive resolution levels 1 and $l+1$ can be derived by

$$c_{l+1}^{Re}(k) = \sum_{n} h_{o}(n - 2k)c_{l}^{Re}(n)$$

and

$$c_{l+1}^{Re}(k) = \sum_{n} h_{i}(n - 2k)\phi_{l}^{Re}(n)$$

Similarly for imaginary tree

$$c_{l+1}^{Im}(k) = \sum_{n} g_{o}(n - 2k)c_{l}^{Im}(n)$$

$$c_{l+1}^{Im}(k) = \sum_{n} g_{i}(n - 2k)\phi_{l}^{Im}(n)$$

and

$$c_{l+1}^{Im}(k) = \sum_{n} \tilde{g}_{o}(k - 2n)c_{l+1}^{Re}(n) + \sum_{n} \tilde{g}_{i}(k - 2n)\phi_{l+1}^{Im}(n)$$

Fig. 1: Block Diagram of Discrete Wavelet Transform at 3 level of decomposition

1) Drawbacks of DWT

a) The drawback with wavelets is that it oscillates between positive and negative values around the singularities.

b) Wavelet coefficients of decimated DWT are changed when input signal will be shifted in time.

c) Aliasing appears when wavelet coefficient is calculated i.e., it is unwanted checkerboard artifacts appear when edges are under an acute angle.

B. DTCWT

The dual-tree complex wavelet transform (DTCWT) is a comparatively recent enhancement to the discrete wavelet transform (DWT) with extremely important additional properties. It is nearly shift invariant and directionally selective in two and higher dimensions. The dual-tree complex wavelet transform is employed due to its property of approximate shift invariance that is extremely important in signal denoising. It generates complex coefficients by using a dual tree of wavelet filters to obtain their real and imaginary parts. This introduces limited redundancy (2m:1 for m-dimensional signals) and enable the transform to provide approximate shift invariance and directionally selective filters (properties lacking in the traditional wavelet transform) while maintaining the usual properties of perfect reconstruction and computational efficiency with good well-balanced frequency responses.

DTCWT contains two dual tree wavelet basis functions and due to this property the difficulty of lack of shift invariance, coefficient oscillation and aliasing effect do not occur [7-8]. It is very influential and efficient transform for multiple fault detection and noise reduction. DTCWT uses a dual tree of wavelet filters to find the real and imaginary parts of complex wavelet coefficients. The DTCWT of a signal is implemented using two critically-sampled DWTs in parallel on the same data. In this transform, two parallel DWTs with dissimilar lowpass-highpass filters are used for decomposition and reconstruction of signal and hence it is extremely directionally selective. For specially designed sets of filters, the wavelet associated with the upper DWT can be an approximate Hilbert transform of the wavelet associated
Fig. 2(a) and Fig. 2(b) shows block diagram of two stage DTCWT decomposition and two stage DTCWT reconstruction respectively[9-10].

Complex transform implemented in this way is no longer critically sampled, because two independent wavelet transforms are required. The benefits of complex wavelet transform actually depend on the spectrum of $\phi(t)$ being single sided. To have this property, it is required that the wavelet function $\psi_g(t)$ and $\psi_h(t)$ form the Hilbert Transform pair.

$$\psi_g(t) = H[\psi_h(t)]$$

Where $H[.]$ denotes the Hilbert transform operator. It is demonstrated that an orthogonal wavelet basis is the Hilbert transform of another orthogonal wavelet basis if and only if the associated scaling filter of the former is a half sample delayed version of the scaling filter of later, that is $g_0(n) \approx h_0(n - 0.5)$

III. PROPOSED WORK

Overlapping of undesirable, out of band frequencies with required frequencies of signal, causes distorted spectrum of signal and aliasing effect is introduced in the signal. Aliasing an effect that causes different signals to become almost identical or aliases of one another when sampled. It also refers to the distortion or artifacts that results when the signal reconstructed from samples is different from the original continuous signal. The inverse DWT cancels this aliasing, but only if the wavelet and scaling coefficients do not change. Any wavelet coefficient processing (thresholding, filtering, quantization) upsets the delicate balance between the forward and inverse transform, and introduce artifacts in the reconstructed signal. These types of signals cannot be filtered correctly and create serious impacts in many sensible applications. DWT avoids aliasing, only if the wavelet and scaling coefficients are not changed. However throughout filtering, thresholding or any other processing, coefficients deal with this step. These coefficients alter and aliasing is introduced in the signal. DTCWT have no such restriction and thus gives alias free spectrum of the signal.

A. Decomposition of Multiple Harmonic Signal

The aliasing of signals caused by DWT is established by generating a synthetic signal $s_1(t)$ having multiple harmonics, at a sampling frequency 2000Hz, given by

$$S_1(t) = 0.5\cos(2\pi \cdot 30t) + \cos(2\pi \cdot 150t) + 1.5\cos(2\pi \cdot 200t) + \cos(2\pi \cdot 300t) + 0.5\cos(2\pi \cdot 500t) \quad (18)$$

Where, $t \in [0,0.256]$. From the equation of this signal, it is clear that five frequencies are here in the signal, that are 30, 150, 200, 300 and 500Hz. Decomposition of this signal via DWT and DTCWT is shown in Fig. 3(a) and Fig. 3(b) respectively. The frequency information of the decomposed signals are obtained by computing their FFT. The FFTs of decomposed subbands are plotted in Fig. 3(c) and Fig. 3(d) for DWT and DTCWT respectively.

From the spectrum of subbands, DWT shows distorted frequency spectrum (Fig. 3(c)), in which unwanted frequency component such as 800 and 1000Hz are observed in d3, d2 and in d1 subbands, whereas these frequencies are not in the signal. On the other hand, spectrum of DTCWT (Fig. 3(d)) shows actual frequencies 30, 150 and 500Hz in a4, d1 and d4 subbands in that order and d2 and d3 subbands both show 200 and 300Hz frequencies. For DWT, identical wavelet (db8) is used for the decomposition of the signal. Thus it is clear that DTCWT do not suffer from aliasing. Also, in DWT the figure of lowest approximation coefficients is not as clear as in DTCWT.
subbands of DWT of Fig.3(a), (d) FFT of decomposed subbands of DTCWT of Fig.3(b)

B. Proposed Denoising Method

Noise suppression is an integral part of any signal processing task. For denoising of signal in the proposed work, initially the signal is decomposed using DTCWT which results in separate approximation and detail coefficients for every stage of decomposition. Threshold plays an important role in the denoising process. Finding an optimum threshold is a complicated process. Soft thresholding technique is used for such denoising processes normally.

1) Threshold Selection

Threshold selection is an important process which directly affects the quality of output denoised signal. In this paper, performances of four well-known standard threshold estimation methods are investigated for vibration signals corrupted by additive white Gaussian Noise. These four methods are briefly described as follows:

2) Universal Thresholding

The threshold values ($\lambda$) are calculated by universal threshold (square root log) method given by,

$$\lambda_j = \sigma_j \cdot \frac{2}{\log N_j}$$

(19)

Where, $N_j$ is the length of the noisy signal $j^{th}$ scale and $\sigma_j$ is the standard deviation at $j^{th}$ scale given by,

$$\sigma_j = \frac{\text{MAD}_j}{\text{median}[|\omega|]} \cdot \frac{0.6745}{0.6745}$$

(20)

Where, $\omega$ represent wavelet coefficient at scale $j$.

3) Minimaxi Thresholding

This method finds threshold ($\lambda$) using Minimax principle. It uses a universal threshold to yield Minimax performance for mean square error against an ideal procedure. The Minimax principle is used in statistics to design estimators. Since the de-noised signal can be assimilated to the estimator of the unknown regression function, the Minimax estimator is the option that realizes the minimum, over a given set of functions of the maximum Mean Square Error (MSE). This procedure finds optimal thresholds [12]. The threshold is given by,

$$\lambda = \begin{cases} \sigma(0.3936 + 0.1829 \log_2 N) & N \geq 32 \\ 0 & N < 32 \end{cases}$$

(21)

Where, $\sigma = \text{median} \left[ \frac{|\omega|}{0.6745} \right]$ and $\omega$ is the wavelet coefficient vector at unit scale and $N$ is the length of signal vector. In this method, the threshold value will be selected by obtaining a minimum error between wavelet coefficient vector of noise signal and original signal.

4) Rigrsure Thresholding

It is a soft threshold evaluator of unbiased risk. Suppose $W = [\omega_1, \omega_2, ..., \omega_N]$ is a vector consists of the square of wavelet coefficients from small to large. Select the minimum value $r_0(b^{th})$ from risk vector, which is given as,

$$R = \{ r_k \}_{k=1,2,..N} = \frac{N-2l+1}{N} \sum_{k=1}^{l} \omega_k$$

(22)

as the risk value. The selected threshold is $\lambda = \sigma_d \omega_b$ where, $\omega_b$ the $b^{th}$ squared wavelet coefficient (coefficient at minimum risk) chosen from the vector $W$ and $\sigma$ is the standard deviation of the noisy signal.

5) Heursure Thresholding

Threshold is selected using a combination of universal and Rigrsure methods. If the signal to noise ratio is very small, the rigrsure method’s estimation is poor. In such case, fixed form threshold of universal method gives better threshold estimation [13]. Let threshold obtained from universal method is $\lambda_1$ and threshold obtained from Rigrsure is $\lambda_2$ then Heursure gives the threshold given by,

$$\lambda = \begin{cases} \lambda_1 & A > B \\ \min(\lambda_1, \lambda_2) & A \leq B \end{cases}$$

(23)

Where, $A = \frac{N-s}{N}$ and $B = \left( \log_2 N \right)^{1/2} \sqrt{N}$. The $N$ is length of wavelet coefficient vector and $s$ is the sum of squared wavelet coefficients given as $s = \sum_{i=1}^{N} \omega^2_i$.

Threshold determination is an important problem. A small threshold may yield a result which may be noisy and large threshold can cut significant part of signal thus losing the important details of the signal.

6) Thresholding

Thresholding is used to filter the noisy signal. For better results, proper thresholding method is required to be used, which not only eliminates the noise but also sustains the original information of the signal. Thresholding is performed on high frequency component i.e. detailed coefficient of wavelet transform, as it is more affected by noise. Approximation coefficients contain low frequency components, hence are less affected by noise. Thresholding is performed at each level of decomposition. Detailed coefficients are compared with the threshold value and are modified accordingly. After reconstruction, denoised signal can be obtained. For proper smoothing, appropriate threshold value has to be chosen. If it is too small, noise cannot be eliminated properly and if it is large it will remove original signal information along with noise. In this paper soft thresholding is used which is discussed below.

7) Soft Thresholding

In this thresholding, if the signal contains noise than it is not removed totally, but its amplitude is reduced by some amount as shown by the mathematical expression

$$x = \text{sign} \times \max(0,|x| - T)$$

(24)

Where, ‘$\times$’ is a noisy wavelet coefficient and ‘$T$’ is threshold. Soft thresholding shrinks the coefficients above the threshold in absolute value and has some advantages. It makes algorithms mathematically more obedient. Sometimes, pure noise coefficients may pass the hard threshold and appear as annoying “blips” in the output. Soft thresholding shrinks these false structure.

IV. EXPERIMENTS AND RESULTS

A. Denoising of Simulated Faulty Signal

Faulty bearings can be seen as a series of impulses. Furthermore, noise is always present when these signals are captured with the help of accelerometers. In this work, a faulty signal is simulated and noisy signals are generated by adding Additive White Gaussian Noise of a variety of standard deviations. The simulated signal is represented by,

$$s(t) = 0.4 \sum_{i=1}^{n} \delta(t-111) + \sum_{k=1}^{N} \text{rand}(1) \exp(-0.12(t-t')) \sin(2\pi f_0 t')$$

(25)

Here, $t \in [0, 1023]$ is the no. of samples, $t'$ shows a delay of 204.8 seconds and $f_0 \in [0, 0.5120-1/Fs]$, where $1024/Fs=0.5120$. The sampling frequency (Fs) of signal is 2000Hz.
For conducting tests, noisy signals are generated by addition of noise levels of 0.01, 0.02, 0.04, 0.08, 0.2 & 2 noise standard deviation. The noisy signals are denoised by applying the thresholding methods on the DTCWT coefficients. The threshold value is selected using Universal, Rigrsure, Heursure and Minimaxi methods on DTCWT coefficient.

Quantitative Results are shown in table 1. The threshold value is selected using Universal, Rigrsure, Heursure and Minimaxi method and is level adaptive, that is, for every stage a different threshold is chosen. The best results are obtained where the threshold value is selected using ‘Minimaxi’ for low values of noise standard deviation and ‘Universal’ for higher values of noise standard deviation. Fig.4 shows simulated faulty signal, Noisy signal with noise Standard deviation 0.02 and denoising results of Threshold value selected using Universal, Rigrsure, Heursure and Minimaxi methods on DTCWT coefficient.

Table 1: SNR values of the denoised signal for values of noise standard deviation

<table>
<thead>
<tr>
<th>STANDARD DEVIATION</th>
<th>THRESHOLD</th>
<th>UNIVERsal</th>
<th>RIGRSURE</th>
<th>HEURSURE</th>
<th>MINIMAXI</th>
</tr>
</thead>
<tbody>
<tr>
<td>( \sigma = 0.01 )</td>
<td>Snr_noisy</td>
<td>18.8790</td>
<td>18.8790</td>
<td>18.8790</td>
<td>18.8790</td>
</tr>
<tr>
<td></td>
<td>Snr_den</td>
<td>17.6656</td>
<td>20.6811</td>
<td>17.6656</td>
<td>21.2935</td>
</tr>
<tr>
<td>( \sigma = 0.02 )</td>
<td>Snr_noisy</td>
<td>12.8584</td>
<td>12.8584</td>
<td>12.8584</td>
<td>12.8584</td>
</tr>
<tr>
<td>( \sigma = 0.04 )</td>
<td>Snr_noisy</td>
<td>6.8378</td>
<td>6.8378</td>
<td>6.8378</td>
<td>6.8378</td>
</tr>
<tr>
<td></td>
<td>Snr_den</td>
<td>9.9701</td>
<td>8.5669</td>
<td>9.9701</td>
<td>12.1114</td>
</tr>
<tr>
<td>( \sigma = 0.08 )</td>
<td>Snr_noisy</td>
<td>0.8172</td>
<td>0.8172</td>
<td>0.8172</td>
<td>0.8172</td>
</tr>
<tr>
<td></td>
<td>Snr_den</td>
<td>5.9008</td>
<td>2.6421</td>
<td>5.9008</td>
<td>6.8970</td>
</tr>
<tr>
<td>( \sigma = 0.2 )</td>
<td>Snr_noisy</td>
<td>-7.1416</td>
<td>-7.1416</td>
<td>-7.1416</td>
<td>-7.1416</td>
</tr>
<tr>
<td></td>
<td>Snr_den</td>
<td>0.8324</td>
<td>-4.5960</td>
<td>0.8324</td>
<td>-0.2429</td>
</tr>
<tr>
<td>( \sigma = 2 )</td>
<td>Snr_noisy</td>
<td>-27.1416</td>
<td>-27.1416</td>
<td>-27.1416</td>
<td>-27.1416</td>
</tr>
</tbody>
</table>

Table 1: SNR values of the denoised signal for values of noise standard deviation
B. Denoising of Real Time Faulty Signal

The present denoising algorithm is also experienced on real time faulty signal. The real time faulty signal is taken from CWRU bearing data Center [14]. Reliance electric motor with torque transducer, dynamometer and control electronics constitutes the test arrangement. This signal contains defect in inner race at fan end side. The sampling frequency of the signal is 12000Hz. Diameter of inner race is .007 inches and load is 1 HP. For this signal input SNR is not known, thus to compare the results, statistical parameter known as kurtosis [15],[16] is calculated, and is given by the equation

\[ \text{Kurtosis}(x) = \frac{E(x - \mu)^4}{\sigma^4} \]  \hspace{1cm} (26)

here \( \mu \) and \( \sigma \) are mean and standard deviation of signal\( (x) \). The kurtosis for noisy signal and denoised signal using DTCWT for various threshold value selected Universal, Rigrsure, Heursure and Minimaxi are shown in Fig.5. This shows better performance of DTCWT with Universal thresholding as compared to Minimaxi thresholding.

Fig. 4(a): Simulated faulty signal \( S_2(t) \), (b) Noisy signal with noise standard deviation 0.02, Denoising results by Threshold value selection using Universal, Rigrsure, Heursure and Minimaxi in (c), (d), (e), (f) respectively.

Fig. 5(a): Noisy signal with fault at inner race, (b), (c), (d), (e) Denoising results by Various Thresholds selected using Universal, Rigrsure, Heursure and Minimaxi thresholds respectively.
V. CONCLUSION

A comparison of denoising of vibration signals affected with various noise levels by employing different threshold calculated using universal, rigrsure, heursure and minimaxi has been introduced in this paper. In the proposed work, DTCWT is used as it is shift invariant and do not introduce aliasing. By applying this method to practical signals, it is observed that the proposed denoising method removes noise more effectively and the denoised signal retains the original shape of signal after eliminating the noisy content. While using DTCWT, we are comparing different threshold selections. The conclusion can be drawn from the study, The best performance for simulated faulty signals the threshold value selection using ‘Minimaxi’ threshold at low values of noise standard deviation and using ‘Universal’ threshold at higher values of noise standard deviation. The best results are obtained when the threshold value is selected using ‘Universal’ on DTCWT for Real time faulty signal. Future work proposes testing and improving the algorithm for different load values and for various gears and rotary parts.

REFERENCES

[14] Image denoising with an optimal threshold and neighbouring window Zhou Dengwen *, Cheng Wengang Department of Computer Science and Technology, North China Electric Power University, 2 Beinong Road, Changping District, Beijing 102206, China.