Vibroarthrographic Signals De-Noising Using Wavelet Subband Thresholding

S. H. Rahangdale, A. K. Mittra

Abstract*—Externally recorded knee-joint vibroarthrographic (VAG) signals bear diagnostic information related to degenerative conditions of cartilage disorders in a knee. The VAG technique is passive and can be used for long term monitoring. In order to improve the diagnostic capabilities of VAG, robust signal processing techniques are needed for de-noising of the signals. Traditional de-noising techniques apply a linear filter to remove the noise and interference from the VAG signals. These methods have certain limitations for the non-stationary VAG signals. In this paper, an improved technique for de-noising of VAG signals is presented. The acquired VAG signals are decomposed, de-noised and reconstructed by utilizing matlab wavelet transform toolbox. The proposed approach improves the signal to noise ratio (SNR) of these signals. The presented technique can be used in pre-processing stage of all VAG based knee joint monitoring and screening of articular cartilage pathology.

Index Terms*—Wavelets, de-noising, vibroarthrographic signal, knee-joint.

I. INTRODUCTION

The knee joint vibration signals are referred to as vibroarthrographic or VAG signals. Vibroarthrographic signals could be used to develop a non-invasive tool for monitoring and screening of articular cartilage pathology. Detection of knee-joint pathology at an early stage is important so that appropriate treatment can stop or slow down the degenerative process and facilitate extended functionality of the affected knee joint. VAG signals are non-stationary due to the fact that the quality of the knee-joint surfaces coming in contact may not be the same from one angular position to another during articulation of the joint[1]-[3].

VAG signals are contaminated by various noise during their acquisition. Denoising is an important problem that must be addressed before carrying out further analysis of signal. The random noises uncorrelated with VAG signals can be approximated by additive white Gaussian noise. The effect of denoising of VAG signals has direct influence on the sequential job such as malfunction analysis, diagnosis and recognition [4].

Filtering of noise from VAG signals may help in extracting and identifying significant TF features useful in screening applications [5]. In circumstances where the SNR of a signal is not known a priori, optimal linear filtering techniques such as Wiener filtering may not be the best solution. In such cases, approaches based on signal decomposition using orthogonal or non-orthogonal bases may be an interesting alternative. This paper is an attempt to automatically denoise VAG signals using wavelet transform.

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S. H. Rahangdale, Department of Electronics Engineering, Manoharbhai Patel Institute of Engineering & Technology, Gondia, India.

Dr. A. K. Mittra, Department of Electronics Engineering, Manoharbhai Patel Institute of Engineering & Technology, Gondia, India.

Wavelet transform has been proved to be a successful tool for analysis of VAG signals because of its good localization properties in time and frequency domain. Different wavelet based methods are used for denoising VAG signals. Method based on shrinkage of wavelet coefficients are very popular for estimation of VAG signals. In these methods noisy VAG signals is decomposed into approximation and detail coefficients by applying discrete wavelet transform. The decomposed coefficients are then thresholded for removal of noise from the signal. The thresholded coefficients are reconstructed to obtain the denoised version of VAG signal.

The rest of the paper is organized as follows. In section 2, Wavelet Transform and Discrete Wavelet Transform are briefly introduced. Section 3 describes the method used for de-noising of the VAG signals. Section 4 discusses the results of implementation of the proposed method. Finally, section 5 summarizes the conclusions drawn from previous sections.

II. BRIEF INTRODUCTION TO THEORY OF WAVELET TRANSFORM

The transform of a signal is just another form of representing the signal. It does not change the information content present in the signal. The WT provides a time-frequency representation of the signal. It uses multi-resolution technique by which different frequencies are analyzed with different resolutions. It is capable of representing signals in different resolutions by dilating and compressing its basis functions. The major advantage of the WT is that it has a varying window size, being broad at low frequencies and narrow at high frequencies, thus leading to an optimal time-frequency resolution in all frequency ranges [6]. The main idea of wavelet analysis is to measure the degree of similarity between the original waveform x(t) and the basic function of the WT also called the mother wavelet, through wavelet coefficients computation. The calculation process is performed on shifted version of the mother wavelet thus moving along the time, and on stretched or compressed version of the mother wavelet thus varying the frequency [7]. The continuous wavelet transform (CWT) is defined as the convolution between the original signal x(t) and a wavelet $\psi_{a,b}(t)$.

$$\mathrm{CWT}\ (a,b) = \int_{-\infty}^{+\infty} x(t)\,\overline{\psi_{ab}}(t)dt \quad (1)$$

$$= \frac{1}{\sqrt{a}}\int_{-\infty}^{+\infty} x(t)\,\psi\left(\frac{t-b}{a}\right)dt \quad (2)$$

Where x(t) is the input signal, a is the scaling factor, b is the translation parameter and Ψ(t) is the transforming function called mother wavelet. The mother wavelet is given by:

$$\psi a,b = \frac{1}{\sqrt{a}}\,\psi\left(\frac{t-b}{a}\right) \quad (3)$$

The DWT coefficients are usually sampled from the CWT on a dyadic grid, choosing parameters of translation $b = n*2^m$ and scale $a = 2^m$. The mother wavelet in DWT is defined as:

$$\psi_{m,n}(t) = \frac{1}{\sqrt{2^m}} \psi\left(\frac{t - n2^m}{2^m}\right) \quad (4)$$

DWT analyzes the signal by decomposing it into its coarse and detail information, which is accomplished by using successive high-pass and low-pass filtering operations, on the basis of the following equations:

$$y_{high}(k) = \sum_n x(n).h(2k - n) \quad (5)$$

$$y_{low}(k) = \sum_n x(n).l(2k - n) \quad (6)$$

Where $y_{high}(k)$ and $y_{low}(k)$ are the outputs of the high-pass and low-pass filters with impulse response h and l, respectively, after up sampling by 2.

In CWT, the signals are analyzed using a set of basic functions which relate to each other by simple scaling and translation. In the case of DWT, a time-scale representation of the digital signal is obtained using digital filtering techniques. The signal to be analyzed is passed through filters with different cutoff frequencies at different scales.

The DWT, which is based on sub-band coding, is found to yield a fast computation of wavelet transform. It is easy to implement and reduces the computation time and required resources. The DWT is computed by successive low-pass and high-pass filtering of the discrete time-domain signal as shown in figure 1. This is called the Mallat algorithm or Mallat-tree decomposition. Its significance lies in the manner it connects the continuous-time multiresolution to discrete-time filters. In the figure, the signal is denoted by the sequence $x(n)$, where n is an integer. The low pass filter is denoted by $l(n)$ while the high pass filter is denoted by $h(n)$. At each level, the high pass filter produces detail information; cD, while the low pass filter associated with scaling function produces coarse approximations; cA.

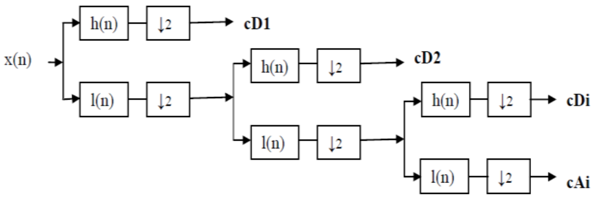

Fig.1. Multi-level wavelet decomposition tree.

With the application of this approach, the time resolution becomes arbitrarily good at high frequencies, while the frequency resolution becomes arbitrarily good at low frequencies. The filtering and decimation process is continued until the desired level is reached. The maximum number of levels depend on the length of the signal. The DWT of the original signal is then obtained by concatenating all the coefficients, cA and cDs, starting from the last level of decomposition.

After the wavelet decomposition, the noise in a signal can be further removed by wavelet de-noising. There are two methods which can be adopted to remove the noise using wavelet de-noising. The first method is forced de-noising. This method turns high frequency coefficients to zero in wavelet decomposition structure. After reconstruction the results of this method are smooth. But there is a chance of loosing the useful high frequency parts of the original signal. The second method is threshold de-noising. This method gives the value of threshold based various thresholding algorithms like Universal threshold, Rigorous Sure threshold and Minimax threshold [8]. In these methods the high frequency coefficients of wavelet decomposition are decided by the value of threshold. The threshold based de-noising improves the de-noised results significantly. These de-noised decomposition coefficients are then reconstructed using wavelet reconstruction.

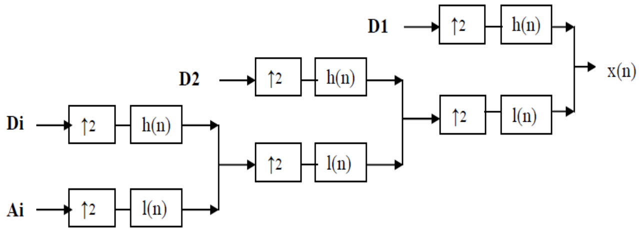

Fig.2. Multi-level wavelet reconstruction tree.

Figure 2 shows the reconstruction of the original signal from the wavelet coefficients. Basically, reconstruction is the reverse process of decomposition. The approximation and detail coefficients at every level are upsampled by two, passed through the low pass and high pass synthesis filters and then added to get the reconstructed signal. This process is continued through the same number of levels as in the decomposition process to obtain the original signal [9]-[12].

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III. IMPLEMENTATION OF WAVELET BASED DENOISING OF VAG SIGNALS

The noise present in the signal can be removed by applying the wavelet shrinkage denoising method while preserving the signal characteristics, regardless of its frequency content. The algorithm for denoising of signals using wavelet shrinkage method is given below.

This algorithm is applied to denoising a noisy signal. Assume that the received signal y(n) is given as follows.

$$y[n] = x[n] + d[n] \quad (7)$$

where x(n) will denote an unknown signal to be detected, and d(n) is a white Gaussian noise. The original signal may also have high frequency features. High frequency characteristics of original signal with wavelet transform is preserved. Therefore, the wavelet transform is an effective method for denoising the noisy signal. Standard wavelet thresholding techniques, consists of hard thresholding and soft thresholding functions [13]. Wavelet Transformation, threshold selection is very important. The signal if the threshold value is too large or too small cannot be estimated accurately [14]-[16].

Hard Thresholding (h): In hard thresholding, those wavelet coefficients with absolute values below or at the threshold level (λ) are affected only and they are replaced by zero value whereas others are kept unchanged.

$$\hat{Y}_{j,k}^{hard} = Y_{j,k} for |Y_{j,k}| > \lambda \quad (8)$$

$$= 0 \; for |Y_{j,k}| \leq \lambda \quad (9)$$

Soft Thresholding (s): In soft thresholding, coefficients above threshold level (λ) are also modified; they are reduced by particular value of the threshold.

$$\hat{Y}_{j,k}^{soft} = Y_{j,k} - \lambda for Y_{j,k} \geq \lambda \quad (10)$$

$$= 0 \; for |Y_{j,k}| < \lambda \quad (11)$$

$$= Y_{j,k} + \lambda \, for Y_{j,k} \leq -\lambda \tag{12}$$

The steps of the algorithm using soft and hard thresholding are as listed below [17].

1. Firstly, the received signal levels are separated by wavelet transform. Then, the received signal wavelet coefficients are calculated up to the desired level.
2. The variance (σ^2) of the noise is calculated using the wavelet coefficients.

$$\hat{\sigma} = \frac{med(|W_{j,k}|)}{0.6745}$$

where *med(.)* denotes the median.

3. The threshold value is calculated using the variance.

$$T = \sigma \sqrt{2.\log{(n)}}$$

where T is the threshold value and n is the length of signal.

4. Thresholding is performed using soft thresholding equation after the calculation of the threshold value.
5. The original signal is reconstructed using the inverse wavelet transform and retained coefficients.

IV. RESULTS OF DENOISING OF VAG SIGNALS

The acquired VAG signals are saved in a *wav format of the personal computer for subsequent processing. An example of acquired VAG signal is shown in figure.

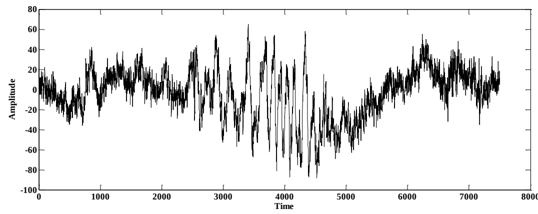

Fig.3. Waveform of a original VAG Signal (Noisy)

The acquired VAG signals were normalized to the maximum amplitude. This normalized signal is then decomposed into time-frequency representations using DWT. The major advantage of the DWT is that it provides good time resolution. Because of its great time and frequency localization ability, the DWT can reveal the local characteristics of the input signal.

In this work a fifth level discrete wavelet decomposition of the fourth order Coiflects is selected to obtain coefficients of all the components (i.e. details and approximation). The selection of wavelet is based on the fact that smoothness of the Coiflects wavelet increases as the order of filter increases. The choice of level of the decomposition is based on a desired low-pass cutoff frequency. The waveforms of all the coefficients of decomposition are shown in figure 4.

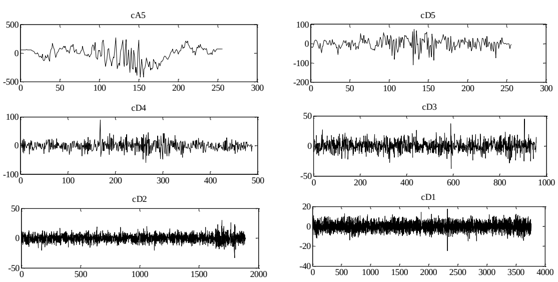

Fig.4. Coefficients of the Wavelet Decomposition

After the wavelet decomposition of the recorded signals, the noise can be further removed by wavelet de-noising technique. This process retains the noise containing decomposition coefficients and removes those associated with the noise. The calculation of threshold is done by universal thresholding algorithm with soft threshold [18]. This algorithm shows the best performance for the non-stationary VAG signals when using the fourth order Coiflets wavelet with three decomposition levels.

Reconstruction is the reverse process of decomposition. The signal is then reconstructed using de-noised coefficients of the wavelet decomposition. The details and approximation coefficients of the reconstructed signal are obtained. The waveforms of these coefficients of reconstruction and the reconstructed signal are shown in figure 5 & 6.

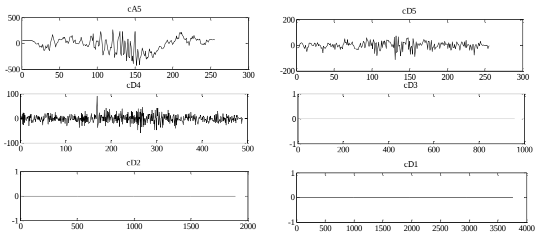

Fig.5. Thresholded Coefficients

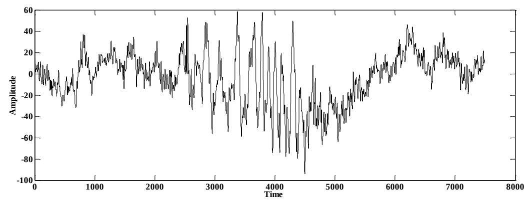

Fig.6. Waveform of a Reconstructed Signal (Denoised)

V. CONCLUSION

Vibroarthrographic signals are a suitable tool for assessments of knee joint related diseases, mostly due to its passive nature. The main benefit of this technique lies in its long-term measurement ability, which is important because of the longest joint of human body. The vibroarthrographic signals were de-noised using DWT. The applied wavelet based signal processing technique produces a de-noised knee joint sound signal which is more suitable for further diagnostic analysis. The results of this study are very promising and clearly indicate that the technique is accurate, robust, simple to implement and is very useful for the knee joint monitoring applications.

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S. H. Rahangdale

is working as Associate Professor in the department of Electronics Engineering in Manoharbhai Patel Institute of Engineering & Technology, Gondia, India. He is Graduate in Electronics Engineering from RTM Nagpur University, Nagpur. He is pursuing his Master of Engineering (By Research) from RTM Nagpur University, Nagpur. S. H. Rahangdale has more than 24 years experience in the field of academics and has about 03 research publications in various national and international conferences and journals. His area of research is Biomedical instrumentation, Biomedical signal processing and soft computing..

A. K. Mittra

is working as Head & Professor in the department of Electronics Engineering in Manoharbhai Patel Institute of Engineering & Technology, Gondia, India. He is Graduate in Electrical Engineering from GGD University Bilaspur, Post Graduated in Electronics and Control Engineering from BITS Pilani and PhD from Nagpur University. A. K. Mittra has vast experience in academic field and he has more than 30 research publications in various national and international conferences and journals. His area of research is Biomedical instrumentation, Biomedical signal processing and soft computing.