Advances and Applications in Mathematical Sciences
Volume 21, Issue 4, February 2022, Pages 1753-1762

DECOMPOSITION AND FEATURE EXTRACTION OF EARTHQUAKE SIGNAL USING DISCRETE WAVELET TRANSFORM

J. SANGEETHA and N. BALAMANI

M. Phil Scholar
Department of Mathematics
Avinashilingam Institute for Home
Science and Higher Education for Women
Coimbatore, Tamilnadu, India
E-mail: sangeethajagan009@gmail.com

Department of Mathematics
Avinashilingam Institute for Home
Science and Higher Education for Women
Coimbatore, Tamilnadu, India
E-mail: nbalamani77@gmail.com

Abstract

In recent years, the generation of earthquake ground motion is important for the design of engineering structures with seismic excitation. In this paper, we analyze the earthquake data's for ground motion by Decomposition and Feature Extraction. The signals are first decomposed by suitable wavelet transform and the features of those signals are extracted by peak-peak value and Log-Energy Entropy. Using MATLAB, the above process is computed and the results are presented in graphical and tabular form.

1. Introduction

Seismic signals are in transient waveforms that radiated for localized natural and manmade sources. One of the most dangerous seismic signals is earthquake signal. Earthquakes not only endanger the human life but also made enormous loss to mankind. Using earthquake waves we can able to locate the source, analyze the process and structure of propagating media.

2020 Mathematics Subject Classification: 05C78.
Keywords: wavelet transform, seismic signal data processing, denoise, feature extraction.
Received October 5, 2020; Accepted November 10, 2020

Apart from disasters, Seismic prospecting for oil and gas has undergone a digital revolution during past decade. Seismic signal processing is used to study earthquake seismology, nuclear blast detection, earth crystal studies and architectural engineering. Moreover, the uncertainty plays a vital role in seismic signals. In case of architectural work we need to understand the ground motion of the area. In this study, we decompose the earthquake signal using effective wavelet transform and extracting the features which are easy to analyze the seismic signals.

Monitoring seismic signals were performed under various transform by many authors. Carlos I Huerta-Lopez et al. [6] studied frequency analysis on earthquake records. The comparison between Fourier transforms and discrete wavelet transform using denoised method in synthetic data and experimental geophysics data were investigated by Albert et al. [1]. Fatemi et al. [12] presented the parametrical model of strong ground motion to design basis earthquake records. Peter Bormann et al. [18] studied about the Seismic signals and noise. Chengwu Li et al. [7] investigated Micro seismic characteristic among different materials studied on WPT-LMD and MS for mine safety. Denoising the seismic signal using WT and FFT and spectrum analysis was carried over through FFT by Yong Lu et al. [20]. The simulation experiment on Ricker signals and noise reduction carried over by wavelet compressive thresholds was studied by Jingsong Yang et al. [14]. Yue Li et al. [21] analyzed 2DCVM decomposition algorithm using Fk filter in desert region seismic signal processing.

The quality measurement on reconstructed ECG signal using PRD values were investigated by Al-Shrouf et al. [4], Manuel et al. [15] analyzed ECG signal using CR values and Milkhled et al. [16] studied ECG signals by applying different threshold values under WP and DWT. Nibaldo et al. [17] proposed the Effectiveness of Fejèr-korovkin filter in MIMO auto regression model.

A new adaptive scheme for ECG enhancement was investigated by Almenar et al. [3]. Comparison of linear, non linear and feature selection of BCI-EEG signal was presented by Deon Garrett et al. [11]. Effects of pulsed electromagnetic field at low frequency on PPG, ECG and EEG were studied by Dean Cvetkovic et al. [10]. Raghu et al. [19] investigated the effects of Log energy entropy of ECG signal using WP. Alfred O. Hero [2] studied statistical method for feature extraction and classification. Hüseyin Göksu [13] proposed feature analysis of log energy entropy using BCI-EEG by MPL.

This paper deals with comparative study of finding efficient wavelet using PRD and SNR values and the feature extraction of effective reconstructed signal.

2. Wavelet Transform Principle

The term "wavelet" refers to an oscillatory vanishing wave which has ability to describing the time-frequency plane with different time support. The wavelets are categorized as discrete and continuous [5] [8].

The continuous wavelet transform is defined as

$$\phi_{WT}(u, s) = \frac{1}{\sqrt{|s|}} \int_{-\infty}^{\infty} x(t) \psi^* \left(\frac{t - u}{s} \right) dt.$$

The transformed signal $\phi_{WT}(u, s)$ is a function of the translation (u) and the scale(s), mother wavelet (ψ) and $*$ as complex conjugate function. The signal energy is normalized as every scale by dividing the wavelet co-efficient by $\frac{1}{\sqrt{|s|}}$. In practical cases signals are in discrete form. In discrete wavelet transform the scaling(s) and translation (u) are considered as $s = s_0^j$, $u = ks_0^j b_0$, while $j \in Z$. The corresponding discrete wavelet functions are written in the following form:

$$\psi_{u,s}(t) = s_0^{-\frac{j}{2}} \psi \left(\frac{t - ks_0^j b_0}{s_0^j} \right) = s_0^{-\frac{j}{2}} \psi(s_0^{-j} t - kb_0).$$

And the discretized wavelet coefficients are written as

$$C_{u,s} = \int_{-\infty}^{\infty} x(t) \psi_{u,s}^*(t) dt.$$

3. Proposed Methodology

The required earthquake signal dataset are considered using MATLAB with varying frequency and regular interval of time. We used earthquake signal occurred in Kobe, Japan on Jan 17th, 1995 for our study. The given data set are consists of 3048 samples. The proposed methodology is presented in the figure 1.

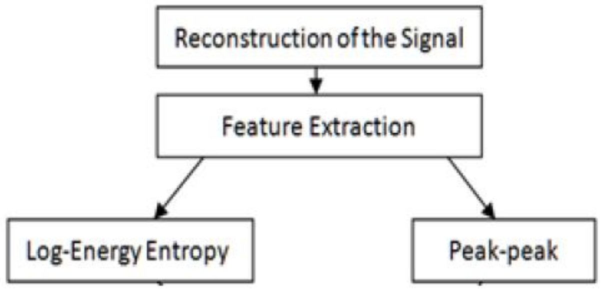

Figure 1. Proposed Methodology.

4. Reconstruction of the Signal

Comparing the Fejèr-korovkin wavelet [17] and Daubechies wavelet, both the wavelet has decomposed into four levels and denoted as fk4 and db4 [1]. The processes of comparing the two wavelets, by decomposing the signal are undergone through five steps.

Step 1. Generating Noise Signal and Adding to Original Signal.

Generating noise means adding some random noisy signal to original earthquake signal. It is expressed mathematically as follows [20] [21]

$$Y(n) + X(n) = N(n).$$

Where, $Y(n)$- original signal free from noise, $X(n)$- random noisy signal and $N(n)$- noisy signal.

Step 2. Decomposing the noisy signal using Wavelets.

The noisy signal is decomposed into four levels using Fejèr-Korovkin wavelet (fk4) and Daubechies wavelet (db4) in discrete wavelet transform and shown in figure 2 and figure 3 respectively.

Step 3. Applying the Corresponding Threshold Values.

The threshold values are applied to the detail coefficient of Daubechies wavelet and Fejèr-Korovkin wavelet. The optimum threshold value is formulated mathematically as follows, [9] [14] [16]

$$T = C \times \sqrt{\frac{\sigma(N(n))}{\sigma(d_j(n))} \times n}.$$

Where, T-Threshold value, C-Constant value, $\sigma(N(n))$- standard deviation of noisy signal and $\sigma(d_j(n))$- standard deviation of detail coefficient of j levels $(j = 1, 2, 3, 4)$.

The detail coefficient of noisy signal for each level is used to shrink by soft threshold type as

$$D(C_{j,k}) = \begin{cases} 1 & C_{j,k} \geq T \\ 0 & \text{otherwise}. \end{cases}$$

Where $C_{j,k}$- detail wavelet coefficient transform, $D(C_{j,k})$- output of detail coefficient after threshold is applied, T-Chosen threshold values and n-Number of samples. The optimal threshold values for db4 and fk4 wavelet are presented in the table 4.1 and table 4.2 respectively.

Step 4. Reconstructing the Signal using Inverse Wavelet Transform.

After applying the threshold value, the signals are reconstructed by inverse wavelet transform using MATLAB software. The reconstructed combined forms of both wavelets are shown in figure 4 and Samples are extracted from reconstructed combined form of both wavelet and presented in figure 5.

Step 5. Calculating Signal-Noise Ratio (SNR) and Percentage Root Means Square Difference Value (PRD).

$$PRD = \sqrt{\frac{\sum (Y(n) - Y_R(n))^2}{\sum (Y(n))^2}} \times 100 \quad SNR = Log_{10} \frac{\sum (Y(n))^2}{\sum (N_R(n))^2}.$$

Where $Y(n)$- Original signal, $Y_R(n)$- Reconstructed signal and $N_R(n)$- Noisy signal. Using denoised signals, PRD and SNR values are computed by MATLAB and exhibited in table 4.3.

Table 4.1. The formulated threshold values for Daubechies wavelet (db4).

Threshold value $(T)(\times 10^3)$	Number of samples (n)	$(\sigma(d_j(n))(\times 10^3)$	Sub signals
8.4497	1527	1.6464	D1
3.3401	767	5.2924	D2
1.8455	387	8.7466	D3
1.3167	197	2.3528	D4

Table 4.2. The formulated threshold values for Fejèr-Korovkin wavelet (fk4).

Threshold value $(T)(\times 10^3)$	Number of samples (n)	$(\sigma(d_j(n))(\times 10^3)$	Sub signals
6.9310	1525	2.4437	D1
3.2560	764	5.5474	D2
1.6683	383	10.594	D3
0.8497	193	20.577	D4

Table 4.3. PRD and SNR values.

Wavelet	PRD	SNR
Db4	26.9201	2.3537
Fk4	23.2596	2.6105

From table 4.3, we observed that the SNR values and PRD values are more efficient in Fejèr-Korovkin wavelet than the Daubechies wavelet. From this result, we concluded that Fejèr-Korovkin wavelet is more efficient in signal processing and the details are preserved while comparing to Daubechies in discrete wavelet transform.

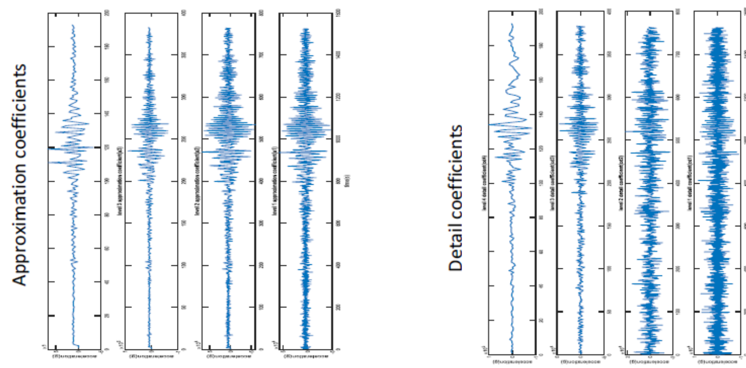

Figure 2. Fejèr-Korovkin wavelet.

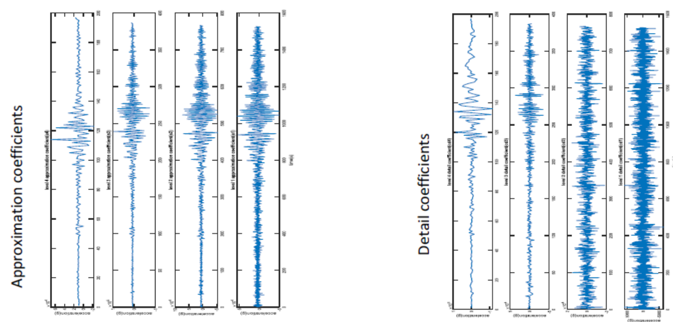

Figure 3. Daubechis wavelet.

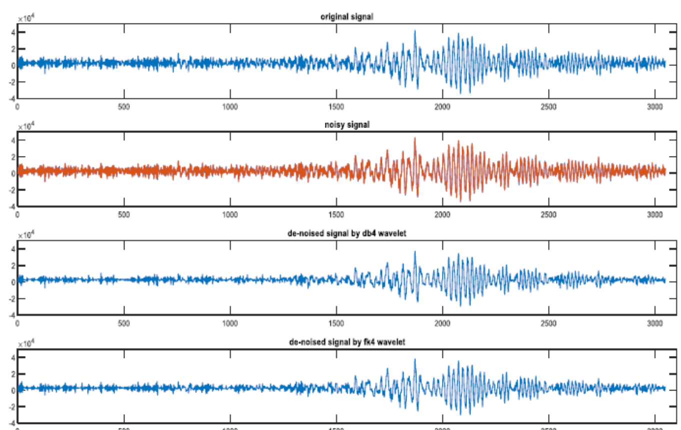

Figure 4. Combined form of db and fk wavelet.

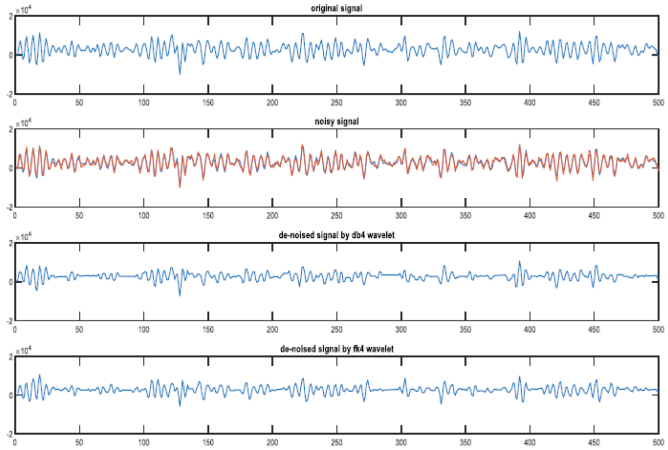

Figure 5. Combined form of extracted wavelet.

5. Feature Extractions

Feature extractions are based on finding the mathematical methods for reducing the dimensionality of raw data by combining variables into features [2][10][11]. By the result of denoised signal we extract the features and segmenting the data's into 61 samples. Here we calculate the following features namely log- energy entropy and peak-peak values.

(i) Log-energy entropy: For each samples the Log-Energy Entropy values are computed by, [4] [15]

$$E_{LE}(W) = \sum_{i=1}^{n} \log (x_i^2)$$

Where i = number of samples, n = sample size and W = wavelet decomposition co-efficient.

(ii) Peak-Peak value: Peak-peak is the difference between the maximum positive to the maximum negative amplitudes of the waveform. For each samples the peak-peak values are computed by,

$$P - P = \sum_{i=1}^{n} (M_i - m_i).$$

Where M_i = Maximum positive, m_i = maximum negative, i = number of samples and n = sample size. The results of feature extraction are presented in table 5.1

Table 5.1 Feature Extracted Data from Denoised Signal

Signal	Log-Energy Entropy	Peak-peak	Signal	Log-Energy Entropy	Peak-peak	Signal	Log-Energy Entropy	Peak-peak
7513	775.4733	13912	8698	783.0797	10872	31999	941.0642	53460
4042	783.8817	5004	4024	763.2794	8936	31999	945.936	66038
8551	782.0017	13944	4462	756.2824	9893	31999	939.9584	59893
7650	782.1127	8803	8276	788.8159	8962	31999	907.8026	42936
5295	766.8218	12055	6609	772.5871	7801	12100	828.1566	22287
8349	780.6001	11060	4527	765.0342	10337	31999	849.735	37470
7421	774.9717	13417	11243	799.2449	16652	28915	786.546	30189
9055	785.6737	13157	8608	782.4159	16011	27475	814.7854	27800
4973	767.9313	8394	7733	776.731	10141	30131	858.9146	29199
9840	791.353	11572	8813	783.9249	14538	9107	786.052	15084
5664	769.9459	8158	8358	780.657	11774	7202	773.8379	13386
5716	768.0561	12339	11420	802.313	21916	11420	808.5237	18732
4514	729.4666	11401	11420	829.1693	21356	11420	809.1272	18300
8650	782.7223	16719	7309	774.3749	19763	8492	781.5758	15471
4514	750.1443	11426	31999	842.5362	34857	12177	808.6636	22297
4514	739.3232	11799	31999	861.4657	33733	4513	753.0176	12504
5767	768.2162	11822	31999	893.2527	44818	4514	749.9934	11539
9217	786.847	13199	31999	943.3548	63840	3376	750.1879	7865
5512	769.7643	8437	10045	792.6735	17652	8692	783.032	13873
3753	776.8812	6984	16760	835.1713	23078	7275	774.1975	12086
						3847	757.4325	8520

6. Conclusion and Future work

Seismic signals are more non-stationary in nature. For architectural purpose, the seismic signals should be in control. Here we analysed one of the seismic signals such as earthquake data signal (Kobe), which is more noise disturbances in nature. Using suitable wavelet transform, the signals are decomposed and features are extracted by Peak-peak value and Log-Energy Entropy. This study will be helpful for the design of architectural structure with seismic excitation and sub layers of earth crust. This study can be extended to classifying the extracted features using fuzzy logic control in future.

References

[1] C. T. Albert, R. Jeffrey Moore and Steven D. Glacer, Wavelet Denoising Techniques with Applications to Experimental Geophysical Data', Signal Processing 89 (2009), 144-160.

[2] Alfred O. Hero, Statistical Methods for Signal Processing, (2016), 1-22.

[3] V. Almenar and A. Albiol, A New Adaptive Scheme for ECG Enhancement, Signal Processing 75(3) (1999), 253-263.

[4] A. Al-Shrouf, M. Abo-Zahhad and Sabah M. Ahmed, A Novel Compression Algorithm for Electrocardiogram Signals based on the Linear Prediction of the Wavelet Coefficients, Digital Signal Processing 13 (2003), 604-622.

[5] Arthur Asuncion, Signal Processing Applications of Wavelets 1-5.

[6] Carlos I. Huerta-lopez, YongJune Shin, Edward J. Powers and Jose M. Roesset, Time Frequency Analysis of Earthquake Records, 12WCEE2000 1724 (2000), 1-8.

[7] Chengwu Li, Xiaomeng Xu and Lihui Dong, A Study on the Characteristics of Micro Seismic Signal during Deformation and Failure of different Materials under Uniaxial compression, Hindawi Publishing Corporation Shock and Vibration 2016, 2015, 1-12.

[8] David K. Ruch and Patrick J. van Fleet, Wavelet Theory: An elementary approach with applications', John Wiley and Sons, Inc., (2009).

[9] David L. Dohono, De-noising by Soft-Thresholding', IEEE Transaction on Information Theory 41(3) (1995), 613- 627.

[10] Dean Cvetkovic, Elif Derya übeyli and Irena Cosic, Wavelet Transform feature extraction from human PPG, ECG and EEG signal responses to ELF PEMF exposures: A pilot study, Digital Signal Processing 18 (2008), 861-874.

[11] Deon Garrett, David A. Peteron, Charles W. Anderson and Michel H. Thaut, Comparision of Linear, Nonlinear and Feature Selection for EEG signal Classification, IEEE Transactions on Neural Systems and Rehabilitation Engineering 11(2) (2003), 141-144.

[12] A. A. Fatemi, A. Bagheri, G. Shodrati Amiri and Z. Tabrizian, Generation of Design Basis Earthquake Accelerograms, 15 WCEE LISBOA (2012), 1-6.

[13] Hüseyin Göksu, BCI oriented EEG analysis using Log Energy Entropy of Wavelet Packets, Biomedical Signal Processing and Control 44 (2018), 101-109.

[14] Jingsong Yang, Jie Li and Han Wang, A Seismic signal denoising method based on Wavelet Comprehensive Threshold, ITM Web of Conferences 25(01014) (2019), 1-3.

[15] Manuel Blanco-Velasco, J. Fernando Cruz-Roldan, Ignacio Godino-Llorente, Joaquin Blanco-Velasco, Carlos Armiens-Aparicio and Francisco Lopez-Ferreras, On the use of PRD and CR parameters for ECG compression', Medical Engineering and Physics 27 (2005), 798-802.

[16] Mikhled Alfaouri and Khaled Daqrouq, ECG signal Denoising by Wavelet Transform Thresholding', American Journal of Applied Sciences 5(3) (2008), 276-281.

[17] Nibaldo Rodriguez and Lida Barba, Fejer-korovkin Wavelet based MIMO model for Multi-step ahead Forecasting of Monthly Fishes Catches', POLIBITS 56 (2017), 71-76.

[18] Peter Bormann and Erhard Wielandt, Seismic signals and noise (2013), 2-62.

[19] S. Raghu, N. Sriram and G. Pradeep Kumar, Effect of Wavelet Packet Log Energy Entropy on Electroencephalogram (ECG) Signals International Journal of Biomedical and Clinical Engineering 4(1) (2015), 32-43.

[20] Yong Lu, Yongming Huang, Wei Xue and Guobao Zhang, Seismic Data Processing Method Based on Wavelet Transform for Denoising, Cluster Computing (2018), 1-12.

[21] Yue Li, Linlin and Chao Zhang, Desert Seismic Signal Denoising by 2D Compact Variational Mode Decomposition, Journal of Geophysics and Engineering 16 (2019), 1048-1060.