DECOMPOSITION AND CLASSIFICATION OF EARTHQUAKE SIGNALS USING DISCRETE WAVELET TRANSFORM AND FUZZY LOGIC CONTROL

Thesis Submitted in

Partial Fulfilment of the

Degree of Master of Philosophy (M.Phil)

By

SANGEETHA J

(19MPMAF004)

Department of Mathematics

Avinashilingam Institute for Home Science and Higher Education for Women

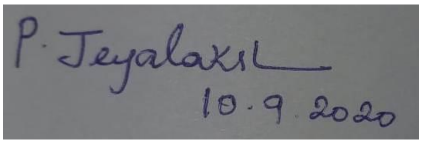
Coimbatore- 641043

September 2020

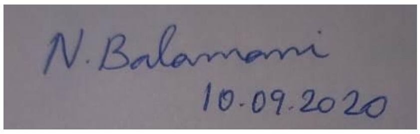
CERTIFICATE

CERTIFICATE

This is to certify that the dissertation entitled **Decomposition and Classification of Earthquake Signals using Discrete Wavelet Transform and Fuzzy Logic Control** submitted for the degree of Master of Philosophy (M.Phil) by **SANGEETHA J.** is the record of research work carried out by her during the period from July 2019 to September 2020 under my guidance and supervision, and that this work has not formed the basis for the award of any Degree, Diploma, Associateship, Fellowship, Titles in this University or any other similar institution of Higher Learning.



Signature of the Head of the Department

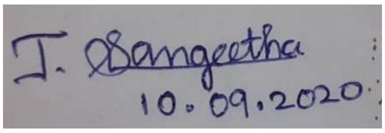


Signature of the Supervisor

DECLARATION

DECLARATION

I declare that the dissertation entitled **Decomposition and Classification of Earthquake Signals using Discrete Wavelet Transform and Fuzzy Logic Control** submitted by me for the degree of Master of Philosophy (M.Phil) is the record of work carried out by me during the period from July 2019 to September 2020 under the guidance of **Dr. N. Balamani,** Assistant Professor (SS), Department of Mathematics, Avinashilingam Institute for Home Science and Higher Education for Women, Coimbatore, and has not formed the basis for the award of any Degree, Diploma, Associateship, Fellowship, Titles in this University or any University or other similar institution of Higher Learning.



Signature of the Candidate

ACKNOWLEDGEMENT

ACKNOWLEDEMENT

Every work on its backdrop has the blessing of **LORD ALMIGHTY**. Therefore I submit my reverential gratitude at the feet of Lord Almighty.

I am grateful to **Dr. P. R. KRISHNAKUMAR**, chancellor, Avinashilingam Institute for Home Science and Higher Education for Women, Coimbatore for providing all facilities necessary for the study.

My special debt of gratitude to **Dr. PREMAVATHY VIJAYAN**, Vice Chancellor, Avinashilingam Institute for Home Science and Higher Education for Women, Coimbatore for providing the opportunity and exposure to the world of knowledge.

My special thanks to **Dr. S. KOWSALYA**, Registrar, Avinashilingam Institute for Home Science and Higher Education for Women, Coimbatore for administrative support and for providing adequate help required to carry out the work.

I express my deep sense of gratitude to **Dr. G. P. JEYANTHI**, Director (Research and Consultancy), Avinashilingam Institute for Home Science and Higher Education for Women, Coimbatore for her commendable advice and guidance in each and every process involved in doing the research work in a successful manner.

My sincere thanks to **Dr. K. UDAYA CHANDRIKA**, Professor, Department of Mathematics, Dean, School of Physical Sciences and Computational Sciences, Avinashilingam Institute for Home Science and Higher Education for Women, Coimbatore for her guidance and affectionate support, export suggestions throughout the project.

I express my heartfelt thanks to **Dr. P. JEYALAKSHMI**, Professor and Head, Department of Mathematics, Avinashilingam Institute for Home Science and Higher Education for Women, Coimbatore, for her support and guidance during the course of the investigation.

I express my heart-felt thanks and sincere gratitude to my guide **Dr. N. BALAMANI**, Assistant Professor (SS), Department of Mathematics, Avinashilingam Institute for Home Science and Higher Education for Women, Coimbatore, for her guidance, lively discussion, her patience and sacrifice for the successful completion of my thesis, enthusiastic support given throughout my research period. I render my indebtedness and great deal of heartfelt appreciation to my beloved guide for her keen interest, benevolent concern and untiring efforts without which this work would not have been shaped up and completed at all.

I am thankful to all the **Staff Members of the Department of Mathematics** who rendered their help whenever required.

I owe my special thanks to my **Beloved Parents, Friends and Well-Wishers**, who helped me by providing full strength, support and encouragement to complete my project successfully.

CONTENT

CONTENT

CHAPTER 1

CHAPTER 1

INTRODUCTION

SECTION 1.1

DIGITAL SIGNAL PROCESSING

Digital signal processing is one of the most powerful and upgrading technology which makes science and engineering as well-rich. The twenty-first century becomes revolutionary era for digital signal processing. It is well developing in various ranges of fields such as communications, radar and sonar, high fidelity of music reproduction, medical imaging etc. Each of these fields has developed a deep knowledge of DSP technology with its own algorithms, mathematics and specialized techniques (Steven W. Smith, 1999).

Digital signal processing and analog signal processing are subfields of signal processing. Over the analog processing, digital signal processing has many advantages such as approximation, time efficient, cost efficient, reliable and easily replicated. In order to digitalizing the analysis structure and manipulating an analog signal, analog- digital converter (ADC) converts into digital-analog converter (DAC) and vice versa. Signal processing has been computed using signal sampling. Sampling has been done in two stages: dicretization and quantization. Dicretization means signals divides into equal intervals of time with single measurement of amplitude. Quantization means each value is approximated by a value from finite set.

In DSP, digital signals are studied under one of the following domains:

Time and Space Domain: Time domain refers the analysis of signals with respect to time whereas space domain refers analysis of signal with respect to position. Most common approach which enhancement the input signals through a method called filtering. Digital filtering consists of some linear transformation of a number of surrounding samples around the current sample of the input or output signal. Various filters are linear and nonlinear filters, causal and non causal filters, time invariant filters, stable filters, finite impulse response and infinite impulse response filters.

Frequency Domain: The signals are converted from time or space domain to frequency domain by Fourier transform. Fourier transform converts the time domain into magnitude and phase component of each frequency. Frequency domain analysis also called as spectral analysis

Wavelet Domain: Signals are in the form of wave-like oscillation with amplitude that begins at zero, increases and then decreases back to zero. It seems like the seismographic or heart beat monitoring signals. Generally, wavelets are developed to know some specific properties where other domains fail to works. Wavelets can combine with known portions of damaged signals to extract information from the unknown portions.

In this thesis, we analyse the wavelet transformation over the signal processing.

SECTION 1.2

TYPES OF SIGNALS

In signals and systems, the classification of the signals has been done in various criteria. It depends on the different feature of values, determinacy of the signals and strength of the signals.

Analog signals: An Analog signal is a continuous signals in which the time varying feature of the signals are represented on some other time varying quantity, i.e. analogous to another varying signals. For instance, an analog audio signal, the instantaneous voltage varies continuously with sound pressure.

Digital signals: A digital signal is the signal which is constructed from a discrete set of waveforms of physical quantity. So it is used to represent as the sequence of discrete values. A logic signal is a digital signal with only two possible values and describe in bit stream. These signals can also be representing as three-valued logic or higher valued logics. Digital signals are present in the form of digital electronics especially computing equipment and data transmission.

Deterministic signals: Deterministic signals are the values at any time are predictable and can be calculated in the form of mathematical equation.

Random signals: Random signals are the signals that take a random value at any given time instant and tend to be modelled as stochastically.

Energy signals: The energy signals are equal to a positive value, but their average powers are zero.

$$0 < E = \int_{-\infty}^{\infty} s^2(t)dt < \infty$$

Power signals: Power signals are the signals whose average power are equal to the finite positive value, but their energy are infinite.

$$P = \lim_{T \to \infty} \frac{1}{T} \int_{-T/2}^{T/2} s^2(t)dt$$

SECTION 1.3

WAVELET IN SIGNAL PROCESSING

Wavelet theory provides a unified approach for the number of techniques that had been developed independently for various signals processing application. For instance, multi-resolution signal processing, used in computer vision: sub-band coding developed for speech and image compression and wavelet series expansions, developed in the applied mathematics and has been recently recognized as different views of a single theory (Amara Graps, 1995 and Ananthi Arun et al., 2019).

From digital signal processing to computer vision, wavelet transforms have been used widely to analyse and transformed the discrete types of data. The rapid growth of wavelet was developed in 1980’s which brings the new discoveries like multi-resolution analysis and orthonormal compactly supported wavelets. These advances tend to develop this field in new dimension of technologies (David and Patrick, 2009 and Kai, 2010)

Moreover, wavelet theory covers quite large area in signal processing. It treats both the continuous signal and discrete signal very well. It provides very general technique that can be applied to many tasks in signal processing. Therefore, it has numerous potential applications. In particular, the wavelet transforms is used for the analysis of non-stationary signals, because it provides an alternative approach to the classical short-time Fourier transform (STFT).

The basic difference is, in the short time Fourier transform which uses a single analysis window, whereas the wavelet transform uses short windows at high frequencies and long windows at low frequencies. For some applications it is desirable to see the wavelet transform as signal decomposition onto to the set of basis functions. In fact, basis function called wavelets always underlies the wavelet analysis.

Wavelets are obtained for a single valued function by dilations and contractions (scaling) as well as shifts. The wavelet function can be thought as band-pass filters. There are different types of wavelet transforms and depending on the application, one can prefer to the others. For a continuous input signal, the time and scale parameters can be continuous leading to continuous wavelet transforms. They are also in discrete wavelet transform.

SECTION 1.4

EFFECTS OF SEISMIC SIGNALS

Seismic signals are usually transient waveforms that radiated fro localized natural and manmade sources. They can be used to locate the source, to analyse source processes and to study the structure of the medium of propagation. The terms “seismic noise” refers to the undesirable ground motion which affects the conceptual model of the signal under investigation. Seismic noise depends on the available data, method of approach and analysis of the data (Fatemi et al., 2012, Peter et al., 2013 and Qi et al., 2016).

Seismic prospecting for oil and gas has undergone a digital revolution during past decade. The analysis of seismic signals are affected by the acquisition of data, the reduction of the data, the designing of digital filters to detect primary echoes from buried interfaces and the geometrical structure of earth sub surfaces (Carlos et al., 2000 and Yue Li et al., 2019).

Seismic signals processing are used most to study earthquake seismology, nuclear blast detection, earth crystal studies and architectural engineering. There are various seismological studies in various fields as follows:

- Ambient vibration due to natural resources (like ocean microseisms, winds, etc.)
- Man-made vibrations (from industry, traffic, etc.)
- Secondary signals resulting from wave propagation in an inhomogeneous medium (scattering)
- Effects of gravity (Newtonian attraction of atmosphere, horizontal acceleration due to surface tilt)
- Signals resulting from the sensitivity of seismometers to ambient conditions(temperature, air pressure, magnetic field)
- Signals due to technical imperfections or deterioration of the sensors(corrosion, leakage currents, defective semiconductors)
- Intrinsic self-noise of the seismograph(like Brownian noise, electronic and quantization noise)
- Artefacts from data processing

The study of earthquakes or analysis of the earth with seismic wave arrivals requires their detection above background noise in seismic records levels of natural ambient noise may vary by 60 dB (a factor of 1000 in amplitude) depending on the location, season, time of day and weather condition. (Albert et al., 2009, Liu Shucong and Xun Chen, 2014, Xuelong et al., 2016 and Xiang Li et al., 2020)

Here we have used the earthquake signal data which were occurred in Kobe, Japan on Jan 17th, 1995 for our study.

SECTION 1.5

RECONSTRUCTION OF THE SIGNALS

In order to analyse the signal, we can modify those signals which are suitable for our study. In signal processing, reconstruction refers to the determination of an original continuous signal from sequences of equally spaced samples. Reconstruction is also known as interpolation method i.e., it attempts to perform an opposite process that produces a continuous time signal coincide with the point of discrete time signal. Because the sampling process for general sets of signals is not invertible, there is numerous possible reconstructions from a given discrete time signal, each of which would sample to that signal at the appropriate sampling rate. (Almenar and Albiol, 1999, Morten Nielson, 2001 and Al-Shrouf et al., 2003)

Reconstruction process of the signals can be done by using suitable filters such as

Low pass filters (LPF): It allows only a frequency which is lower that a selected cut-off frequency and attenuates the signals with frequencies higher that than cut-off frequency.

High pass filters (HPF): It allows only a frequency which is higher than a selected cut-off frequency and attenuates the signals with frequencies lower than the cut-off frequency.

Band pass filters (BPF): It allows only a certain range of frequencies and attenuates the signals which are out of the range frequency.

Wavelet filters: It consists of many types of filters depending on the nature of signals, choosing the mother wavelet which filters the signals. Wavelet filters are most efficient because it is able to produce more detail feature of the signals

For perfect reconstruction, if the certain additional cases about the original signals and sampling rate are computed, then the original signal can be recovered exactly from its samples using a suitable filter.

SECTION 1.6

STATISTICAL VIEWS OF SIGNALS

In the study of extraction of the signal or parameter there is wide variety of applications for degraded measurements. To establish this, it is useful to employ finely-grained statistical model, diverse sensors which acquire extra spatial, temporal or multidimensional signal representations for instance, time-frequency.

When applied in combination of these approaches can be use to develop the highly sensitive signal estimation, detection or tracking algorithms which can be exploit small but persistent differences between signals, inferences and noise. Conversely these approaches will be able to improve the algorithms to identify the channel or system that producing a signal in additive noise and interference, even when the channel input is unknown but has known statistical properties. (Alfred O. Hero, 2016)

Statistical signal processing has root in probability theory, mathematical statistics, system theory and communication theory. This method involves following steps:

- Description of a mathematical and statistical model for measured data.
- Careful statistical analysis of the fundamental limitations of the data including deriving benchmarks on performance
- Development of mathematically optimal or suboptimal estimation/ detection algorithms
- Asymptotic analysis of error performance establishing that the proposed algorithm comes close to reaching a benchmark derived
- Simulations or experiments which compare algorithm performance to the lower bound and to other computing algorithm.

SECTION 1.8

FUZZY CLASSIFICATION

Fuzzy is probabilistic in nature, an uncertainty and imprecise. Mathematical concepts are very simple in fuzzy reasoning logic system. Fuzzy logic is convenient way to map an input space to an output space. It is flexible, tolerant of imprecise data and is based on natural language and human communication (George J. Klir and Bo Yuan, 1995)

Fuzzy inference system (FIS) is a system used to solve the new problems. FIS maps an input features to output classes using fuzzy logic. FIS can be created by graphical tools or command line functions or automatically generated using either clustering or adaptive neuro-fuzzy techniques. Fuzzy logic is easiest way to modify by including or excluding rules, there is no need to start a new fuzzy inference system from the beginning.

The fuzzy set provide with an intuitively pleasing method of representing one form of uncertainty. FIS is used to solve “decision problem” and act according to it. The fuzzy logic is helpful in artificial intelligence. By the principle of fuzzy structure it can able to deal with whether forecasting, medical support, identifying psychological aspects, information technology, pattern recognition and clustering (Arshdeep Kaur and Amrit Kaur, 2012 and Deepak et al., 2007)

FIS consists of four modules namely fuzzification module, knowledge base module, inference engine module and defuzzification module. Fuzzy inference methods are classified into direct and indirect method. In direct method Mamdani's and Sugeno's method are used. Mamdani's method is most commonly used fuzzy inference module. Mamdani model is a knowledge driven from predictive model and it works with inputs in the form of crisp data and also with intervals and linguistic terms. The major advantage of this model is to provide a measure of confidence for predicting future value when actual value is unknown. (Jerry, 2000, Károly Nagy and Márta Takács, 2008 and Timothy J. Ross, 2010)

The uncertainty plays a vital role in seismic signals. In weaker crust areas the ground motions were high where as in stronger crust area there will be moderate ground motion. In case of construction building or some other architectural work we need to understand the ground motion of the area. So FIS are easy to predict and analyse the seismic signals.

SECTION 1.9

PROFILE OF PRESENT WORK

The main objectives of the dissertation are:

- To analyse and reconstruct the signals with effective discrete wavelet transform which undergone for decomposition.
- To extract the selected feature from the decomposed signal.
- To classify the features of the signal using fuzzy inference system.

This thesis contributes decomposition and classification of earthquake signals. Particularly, it explains about the feature extraction of the denoised signal using suitable discrete wavelet transform (FK) by comparing the signal to noise ratio (SNR) values and percentage root means square (PRD) values. The features are extracted by log-energy entropy and peak-peak value where the effective results are obtained. Finally we use fuzzy inference system which helps us to view a better classification for the features. From this classification, we can able to find the effective results for uncertainty values.

The concepts of the thesis is presented in six chapters

Chapter 1 gives introduction about the proposed research work and the techniques which are used for the study.

In chapter 2 review of literature related to various signal analysis and fuzzy classification are presented

Chapter 3 deals with the basic concepts of wavelet and its applications

From the reconstruction of the signal, the efficient wavelet is obtained by comparing the signal-noise ratio value and a percentage root mean difference value is presented in Chapter 4.

In Chapter 5, the features are extracted using log-energy entropy and peak-peak value from the denoised signals.

In the final Chapter the features are classified using fuzzy inference system to obtain the favourable result.

CHAPTER 2

CHAPTER 2

REVIEW OF LITERATURE

The decomposition and classification of the signals are studied under various conditions. In order to study the ground nature and the coal mining processes, the seismological signals play a vital role. While the earth crust was not arranged in well formed manner, the signals from the earth made by either manmade or nature the strong part of the earth curst filter the high frequency better than the weaker part. By this improper arrangement of earth structure we couldn't get appropriate signals from the earth source. Moreover, it also gets distracted over other external factors through travelling.

To get the better signals and to reduce the noise contamination of the seismic signals we prefer to use discrete wavelet transform than the Fourier transform. Fourier transform has many disadvantages over choosing a basis function. In that case, we prefer wavelet transforms which provide more basis function. In this research work, we made a comparison result of Daubechies wavelet and Fejèr Korovkin wavelet and found that the Fejèr-Korovkin filter gets efficient result.

Furthermore, we extract the features from the reconstructed signals and the classifications carried over through fuzzy inference system under Mamdani method. Using fuzzy logic system it becomes easier to classify the signal in the range of hazardous, dangerous, high, moderate and low.

This chapter gives brief review about various methods of decomposing the signal under wavelet transform, different types of extracting the features and classifying the signals using fuzzy inference system. Section 2.1 deliberates the different approaches of discrete wavelet transform over various types of signals. Section 2.2 gives brief review on wavelet analysis based under seismology. Section 2.3 elaborates the statistical view about decomposition and reconstruction of seismic signals. The literature surveys on various kinds of feature extraction are briefly described in section 2.4. Final section gives review about the classification of the signals under fuzzy inference system

SECTION 2.1

WAVELET ANALYSIS IN SIGNAL PROCESSING

Oliver Rioul and Martin Vetterli (1991) presented the signal processing using wavelet transform over Fourier transform that can focused on the discontinuities and the orthonormal bases of the studied signals.

Amara graps (1995) introduced wavelets as mathematical functions that segmented the frequency and each component of frequency was matched with resolution after that the computation are made over it. She also presented the various concepts on wavelets decomposition compared with Fourier transform.

Steven W. Smith (1999) investigated the digital signal processing under various circumstances and proposed the different types of transformation to reconstruct the signal module, noise reduction, synthesizing signals using average filter, band pass filter, low pass filters, high pass filters and chebyshev filters.

Carlos I Huerta-lopez et al.(2000) introduced manifestation of earthquake records as non-stationary characteristics and wide frequency content. This article describes the frequency dependent dispersive effect i.e., it involves the studies of time variation of the intensity of ground motion which grows rapidly in short span and vanishes.

Arthur Asuncion (2002) studied the wavelet feature in digital signal processing and made a comparative result over Fourier transform. The set of wavelet coefficients in both time and frequency representation and also java implementation of wavelet based effects processor was investigated under several applications.

David K. Ruch and Patrick J. Van Fleet (2009) proposed the wavelet theory as an application oriented method. They also studied the biorthogonality conditions , wavelet packet structures and spaces where it perform, multiresolution analysis, B-splines and Daubechies scaling function to reconstruction of the signals.

Stèphane Mallat (2009) studied the wavelet analysis over many aspects as block thresholding for denoising, sparse approximations in redundant dictionaries with pursuit algorithm, noise reduction with model selection in redundant process, multichannel signal representation and processing.

Kai Schneider and Oleg V. Vasilyev (2010) reviewed the adaptive and multi-resolution wavelet methodology for modelling and simulation of turbulent flow with various aspects. This method involves the Navier-Stokes equation to emphasis the result of adaptive wavelet transform and the decomposition of wavelet structure are carried out into different level.

Fatemi et al. (2012) proposed parametrical model of strong ground motion to design basis earthquake records. A parameter value describes the power spectrum of high frequency and the low frequency contents and the time modulating function are determined. In particular, the hazardous levels of specific geographical region were studied by them statistically.

Rogelio Ramos et al. (2017) investigated the external noise removal in electrical Scanning Vibrating Electrode Technique (SVET) by localizing the corrosion process of aluminium alloy. By using the discrete wavelet transform, signal to noise ratio are computed and threshold method makes an effective result to localize the corrosion process.

Ananthi Arun et al. (2019) analysed various signals in the form of Fourier analysis and Fast Fourier Transform to resolve the signal into its frequency components into its spectral components in sine and cosine form.

SECTION 2.2

WAVELET ANALYSIS IN SEISMOLOGY

Albert C. To et al. (2009) presented the comparison between Fourier transform and discrete wavelet transform and denoising technique is applied on synthetic data and experimental geophysical data. Finally they obtained wavelet based technique gives better result.

Jiajun Han and Mirko Van der Baan, (2015) studied a ensemble empirical mode decomposition using discrete wavelet transform combined with adaptive thresholding in micro-seismic and seismic data to reduce the noise in non-structured portion.

Chengwu Li et al. (2015) investigated micro seismic characteristic among different materials as coal, cement and glass materials. By using wavelet packet transform under local mean decomposition (WPT-LMD), denoising and analysing the micro seismicity (MS) events carried out in frequency domain to get the better efficiency to make coal mining safety.

Xuelong Li et al. (2016) studied the coal and rock dynamic disasters using micro seismicity technology by characterising three aspects such as signal spectra, wavelet packet energy and fractal features.

Juan Li et al. (2018) proposed a new denoised approach on novel down-hole micro seismic data on empirical wavelet transform along with the adaptive thresholding. They computed spectrum segmentation strategy and characteristics of frequency of the signals in different modes and obtained the potential result under empirical mode decomposition, wavelet transform and synchrosqueezed wavelet transform.

Yue Li et al. (2019) introduced the two dimensional compact variational mode of decomposition algorithm for desert region seismic signal processing. This algorithm perform better result by evaluating the denoising the signal using f-x predictive filtering, wavelet denoising using Fejèr-Korovkin filter both in experimental result and synthetic data.

Jingsong yang et al. (2019) proposed the simulation experiment carried over on Ricker signals and noise reduction by wavelet comprehensive threshold to inherit and develop the advantages of hard threshold and soft threshold denoised method. The simulation results were compared by mean square error (MSE) and signal to noise ratio (SNR).

SECTION 2.3

DECOMPOSITION OF THE SIGNAL

Stephane Mallat and Sifen Zhong (1992) analysed the mutiscale edge detection is equivalent to finding the local maxima of the wavelet transform. They derived the numerical aspects of one dimensional and two dimensional signals from the multi scale edge detection and compress the data in desired format.

David L. Dohono (1995) presented a new threshold method called after her name Dohono’s threshold. She investigated the reconstruction of the signals using the soft threshold by decomposing the noisy signals in wavelet domain. Moreover, this research computed over independent and identically distributed standard Gaussian random variables.

Almenar and Albiol (1998) analysed the ECG recording of different kinds of interferences which included several noises. By cancelling these noises they consulted various method and found the adaptive method shown a good performance. Moreover, this technique provides simpler form than other techniques.

Al-Shrouf et al. (2003) proposed a new algorithm for electrocardiogram (ECG) compression to reduce the beat rate by clinically permissible level to reconstruct the signals using discrete wavelet transform. This compression is based on the linear residual that used in wavelet detail coefficient structure by evaluating percentage root means square difference (PRD).

Manuel Blanco-Velasco et al. (2005) presented the quality measurement of the reconstructed signal in an electrocardiogram (ECG) compression by evaluating the percentage root means square difference (PRD) and compression ratio (CR) in various level of decomposition using discrete wavelet transform and wavelet packets.

Mikhled Alfaouri and Khaled Daqrouq (2008) proposed a new approach for finding the threshold value of Electrocardiography signals using wavelet transform coefficients. ECG signals can exploit the important features in different manner. While comparing to Dohono's relation, his approach gives a better result.

Liu Shucong and Chen Xun (2014) presented a new method to improve the signal to noise ratio (SNR) value and resolution of the seismic signals by using a wavelet packet to use new threshold method and adaptive threshold to denoise the seismic signals without any loss of important detail features.

Qi-Sheng Zhang et al. (2016) studied the wavelet thresholding to reduce the random noise in simulation results, synthetic data and real data. Comparing the values of the soft threshold, hard threshold and modified threshold. They evaluate the signal to noise ratio (SNR) and mean square error (MSE) in different threshold method by using Matlab.

Nibaldo Rodriguez and Lida Barba (2017) proposed a multi input and multi output auto regressive model to improve monthly fish catches using two types of wavelet functions (i.e.) Fejèr- Korovkin wavelet filter and Daubechies wavelet filter and comparing those two filter by evaluating root means square error and finally Fejèr wavelet filter perform better approach than Daubechies filter.

Yong Lu et al. (2018) investigated the earthquake signals using discrete wavelet transform and fast Fourier transform, analysing the spectrum of signal each layer and reconstruct the signal by computed threshold values. They concluded that analog approach and Matlab approach gives efficient result.

Xiang Li et al. (2020) investigated the micro seismic signal denoising by applying the features as empirical mode decomposition, compressed sensing, soft thresholding and combined EMD_CS_ST using discrete wavelet transform under 10 different noise level. They obtained better results by comparing signal to noise ratio, signal standard deviation, correlation coefficient, waveform diagram and spectrogram before and after denoising.

SECTION 2.4

FEATURE EXTRACTION OF THE SIGNAL

Shannon (1948) presented a new approach to develop the concepts of information theory for communication in mathematical methods. He introduced an entropy concept to reduce the noise over signal and construct the procedure to approach the feature of randomness of signal. This entropy named after him, Shannon entropy. The various kinds of entropy were developed from it.

Ronald R. Coifman and Mladen Victor Wickerhauser (1992) studied the method of selecting best basis function for wavelet transform and the geometric interpretation of Shannon entropy.

Deon Garrett et al. (2003) proposed a new extraction of linear and non linear method from Brain Computer Interfaces (BCI) based EEG signals as complex spatial and temporal pattern from noisy multidimensional time series. They analysed the nonlinear method as neural network and vector machines which has higher dimensional and noisy nature of EEG signals.

Dean Cvetkovic et al. (2008) studied the effects of pulsed electromagnetic field at extremely low frequency at various signals such as photoplethysmographic (PPG), electrocardiographic (ECG), electroencephalographic (EEG) signals. Wavelet transformations are used to extract the features and classify the signals in neural networks with statistical approach which provides the feasible method for feature extraction.

Serap Aydin et al. (2009) proposed the electroencephalography series with various healthy patients and classifying the signals using multilayer neural networks architecture by computing the log energy entropy, Shannon entropy and Sample entropy. While comparing those entropies, the log energy entropy gives the better result. Log energy values are considered as better signal feature that characterize the degree of EEG complexity.

Beenamol et al. (2012) studied the different entropy features like Shannon entropy and Tsallis entropy in seismic signal using wavelet transform. By applying suitable threshold value in denoising technique, the signal to ratio noise value is analysed.

Tianyi Wang and Subrat Nanda (2012) investigated the feature extraction of the system i.e. when to extract the features of the signals and how to manipulate the features.

Nandish et al. (2012) presented a feature extraction and classification of EEG signals using neural network based technique. They extracted the features like auto regression, energy spectrum density, energy entropy and linear complexity and computed the average and max & min method of given set of features.

Meyer-baese and Schmid (2014) described feature extract and selecting pattern recognition method by using the mathematical methods for reducing the dimensionality of pattern representation. It measures the accuracy, time, number of samples and cost efficient to classify the features.

Raghu et al. (2015) proposed the behaviour of EEG signals extracting the features using time-domain frequency and log-energy entropy using wavelet packet by decomposing into 2 to 5 levels using different wavelet transforms. They proved that the features are efficient in log-energy entropy as compared to Shannon entropy.

Alfred O. Hero (2016) explained the detail extraction and classification of signals features using different statistical method. Using a suitable statistical algorithm, parameters of the features are efficiently analyzed.

Hüseyin Göksu (2018) proposed the feature analysis of log-energy entropy using wavelet packet of brain computer interfacing oriented electroencephalographic signals and obtained the efficient result than the traditional Fourier time or frequency domain signal processing techniques classifying under multilayer perceptron (MLP).

Debasis Kundu provided information about the signals from different physical observation. Due to random natural disturbances, unstable behaviour of system, assessment of modal performances and some other unwanted disturbances can be reduced or eliminated by using appropriate statistical approaches.

SECTION 2.5

FUZZY CLASSIFICATION OF SIGNALS

Jarkko niittymaki et al. (1979) investigated fuzzy logic system in two methods as fuzzy control method and fuzzy inference method in the study of traffic control system by using the Mamdani model which can easily classify the peak hour and make the adjustment of signal through this model.

George J. Klir and Bo Yuan (1995) introduced the basic structure and theoretical approach of fuzzy system and analysed the concepts of measure theory and uncertainty principle. They introduced fuzzy classification in neural network, artificial intelligence, medical diagnosis, whether prediction and physiological behaviour concepts in theoretical model.

Jerry M. Mendel (2000) proposed a research work on model based statistical signal process using fuzzy logic control. He reviewed singleton and non-singleton fuzzy system and explained the type-2 fuzzy system reduced to type 1 fuzzy system using a new method called type reduction. He produced the example, Glass chaotic time series signal having corrupted additive noise and equalization of non-linear time varying channel to reduce type 2 set to type 1 set.

Deepak R. Keshwani et al. (2007) developed a prediction of permeability of molecular compound through human skin and computed two Mamdani type rule based fuzzy models for permeability and temperature of human skin and obtained the result with less value of entropy.

Károly Nagy and Márta Takács (2008) proposed a work in type 2 fuzzy logic system applications of SAAD that involved in signal processing problems. Due to uncertainty nature of the signals they handled the type 2 fuzzy logic systems of stochastic error measurements using stochastic adding A/D conversion which do the parallel measurements.

Timothy J. Ross (2010) proposed the concepts of fuzzy application in various engineering field. The uncertainty structure involved in randomness of the signals has been evaluated by using fuzzy inference system by choosing suitable aggregation method.

Priti Srinivas Sajja and Rajendra Akerkar (2010) studied about the knowledge-based system for development in various sectors. They explained the development of physical, economical, educational and gross national product using the collected data which improves the work of artificial intelligence.

Melek Acar Boyacioglu and Derya Avci (2010) investigated an adaptive network – based fuzzy inference system for stock market price analysis which is able to determine the accuracy of the stock market returns.

Arshdeep Kaur and Amrit Kaur (2012) developed a new approach fuzzy logic control system in air conditioning system as Mamdani model and neuro fuzzy model and analysed the control of compressor speed by temperature and humidity with the help of respective sensors, comparison made over through Matlab toolbox.

Sandya et al. (2013) proposed the classification of continuous time series signal by extracting features like minimum, maximum, mean, standard deviation and variance values using fuzzy logic control under Mamdani method.

Alavi (2013) analysed the decision making technique using Mamdani based fuzzy inference system for grading the production of dates with desired quality and the grading reached the experimental result approximately with human expert team.

Taiseer Mohamed siddig and Mohamed Ahmed Mohmmed (2014) analysed the study classification of ECG signal with the extracted features like log-energy entropy and energy components using wavelet transform by fuzzy inference system. They obtained accurate values for the specificity, sensitivity, and total classification accuracy for normal, rare, abnormal signals by using fuzzy classification.

CHAPTER 3

CHAPTER 3

PRELIMINARIES

SECTION 3.1

INTRODUCTION TO WAVELET

3.1.1 Wavelet Definition

The term “wavelet” generally used to refer an oscillatory vanishing wave which has ability to describing the time-frequency plane with different time support. Basically, wavelets are created to have a specific property that makes them useful for signal processing. In case of analysing the non-stationary or transient phenomena, wavelet are best supportive tool to analyse it.

3.1.2 Characteristic of Wavelet

Wavelet is a mathematical tool that can be used to extract the features or information for the study purpose. We can extract features for audio signals, communication signals and images. Computationally, the wavelet ψ, is a function of zero average, having the energy concentrated in time.

$$\int_{-\infty}^{\infty} \psi(t)dt = 0$$

Here, we can extract many features with time and frequency. For that, a family of wavelets can be constructed for a function $\psi(t)$, generally known as ‘mother wavelet’, which can be confined in a finite interval and then by using translation with the factor u and dilation with a scale parameter s, are termed as ‘Daughter wavelet’ $\psi_{u,s}(t)$.

$$\psi_{u,s}(t) = \frac{1}{\sqrt{s}}\psi\left(\frac{t-u}{s}\right)$$

3.1.3 Wavelet Analysis

The wavelet analysis is computed by projecting the input signal which are analysed on the wavelet function. It implies the multiplication and integration as

$$\langle x(t), \psi_{u,s}(t)\rangle = \int x(t)\psi_{u,s}(t)dt$$

Depending on the signal characteristic that we want to analyse, purposefully we can use different scales and translations of mother wavelet. Advantages over wavelet are this allows us to change freely the size of analysing function (window), to make it suitable for favourable resolution, either in the time or frequency domain. In order to deal with higher resolution in time domain analysis, we want to study all the rapid changes which appearing in the signal. This can be computed by using a contracted version of mother wavelet. Conversely, for high resolution in frequency domain, we want to use dilated version of same function.

3.1.4 Multi Resolution Analysis

The time-frequency resolution problem is raised by Heinsberg uncertainty principle still the problem exists, regardless of the used analysis technique. In the Short Time Fourier transform (STFT), a fixed time frequency resolution is used. In multi resolution approach (MRA), it is possible to analyse a signal at different frequencies with different resolution. The schematic diagram represents the change in resolution.

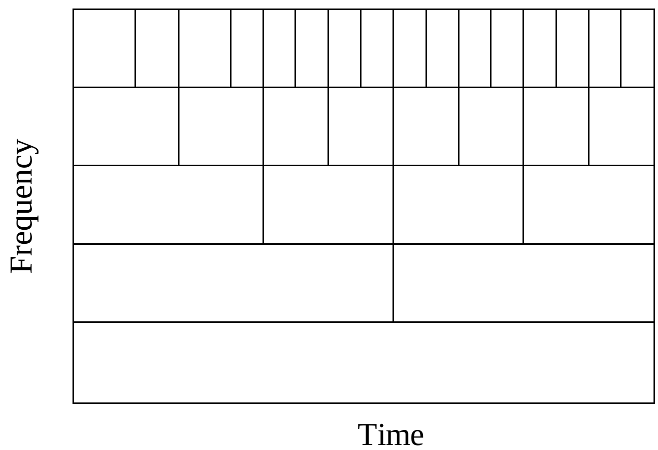


Figure 3.1 Multi-resolution time frequency plane

The resolution of the figure 3.1, it is assumed that low frequency last for long duration of the signal, whereas high frequency appears from time to time as short burst.

The wavelet analysis calculates the correlation between wavelet function $\psi(t)$ and the signal under consideration. The similarity between wavelet function and the signal is computed separately for different time intervals, and results subject into dimensional representation. The analysing function $\psi(t)$ is nothing but a mother wavelet.

3.1.5 Construction of Wavelet

In comparison with Fourier transform, analyzing the wavelet function of the wavelet transform can be chosen with more freedom, without the need of using sine-forms. For continuous wavelet transform (CWT), several kind of wavelet function are developed with all have specific properties. A mother wavelet $\psi(t)$ is classified as a wavelet, if following mathematical criteria satisfied,

1. A wavelet must have finite energy

$$E = \int_{-\infty}^{\infty} |\psi(t)|^2 \, dt < \infty$$

   The energy E equals to the integrated squared magnitude of the mother wavelet $\psi(t)$ and must be less than infinity.

2. If the $\psi(f)$ is the fourier transform of the wavelet $\psi(t)$, the following condition must hold,

$$C_\psi = \int_{0}^{\infty} \frac{(\hat{\psi}(f))^2}{f} \, df < \infty$$

   The condition implies that wavelet has no zero frequency components ($\psi(0) = 0$) i.e. the mean value of the wavelet $\psi(t)$ must be equal to zero. This condition is known as the admissible constant. The value of C_ψ depends on the chosen wavelet.

3. In the complex region, the wavelets has the Fourier transform $\psi(f)$ must be both real and vanishes for negative frequencies.

SECTION 3.2

CLASSIFICATION OF WAVELET TRANSFORM

The wavelet analysis on signals processing performs a greater result while compared to the traditional Fourier transform. The wavelet are mainly classified into two types depending on their frequency range, namely

- Continuous wavelet transforms.
- Discrete wavelet transforms.

3.2.1 Continuous Wavelet Transform

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 parameters United States of America. And the scale parameter s, ψ is denoted as mother wavelet and * denoted as complex conjugate is used in case f complex wavelet. The signal energy is normalized as every scale by dividing the wavelet co-efficient by $\frac{1}{\sqrt{|s|}}$. This ensures that wavelet have the same energy at every scale.

By changing the scale parameter *s*, the mother wavelet can be contracted and dilated. The translation parameter *u*, specifies the location of wavelet in time. The elements of $\phi_{WT}(u,s)$ are called as wavelet co-efficient is associated to a scale (frequency) and a point in a time domain.

3.2.2 Inverse Continuous Wavelet Transform

So far we studied in Fourier transform, the inverse function also exist in the wavelet transform. The inverse continuous transform is defined by,

$$x(t) = \frac{1}{C_{\psi}^{2}} \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} \phi_{WT}(u,s)\ \frac{1}{s^{2}} \psi\left(\frac{t-u}{s}\right) du\ ds$$

Here C_ψ is admissible constant must satisfies the second wavelet condition. The scale parameter is inversely proportional to frequency parameter. A large scale corresponds to a low frequency, which gives the global information. Moreover, the small scale corresponds to a higher frequency, which gives detail information about signal.

3.2.3 Discrete Wavelet Transform

The continuous wavelet transform (CWT) performs multi resolution analysis using contraction and dilation of the wavelet functions. The discrete wavelet transform (DWT) uses filter banks for reconstruction of the multi resolution analysis in the time-frequency plane. Multi resolution filter banks and special wavelet filters are used in DWT for the analysis and reconstruction of signals. The working principles of DWT are as follows

Filter bank

A filter bank consists of the filters which separate the input signal into various frequency bands. A discrete time signal x(t) enters into the analysis band and filtered by two filters L(z) and H(z) where L(z) and H(z) denotes the low-pass and high-pass filter bank. Both the filters separate the frequency content of the input signals in frequency bands of equal width.

The output of the filters each contains half of the frequency content, but an equal amount of the samples as the input signal. The two outputs together contain the same frequency content as in the input signal; however the amount of the data is doubled. Therefore, down sampling by a factor two ($\downarrow 2$), is applied to the output of the filter in the analysis bank.

The original signal are reconstructed using synthesis filters bank, in the synthesis filter bank, the signals are undergone to the up sample ($\uparrow 2$) and then passed through the H'(z) and L'(z), where H'(z) and L'(z) denoted the inverse of high-pass filters and low-pass filters. The filters in synthesis bank are based on the filters in the analysis bank. The outputs of the filters in the synthesis bank are summed and leads to reconstructed single y(t).

The different output signal analysis filter banks are called sub-bands and the filter bank technique is also called as sub-band coding.

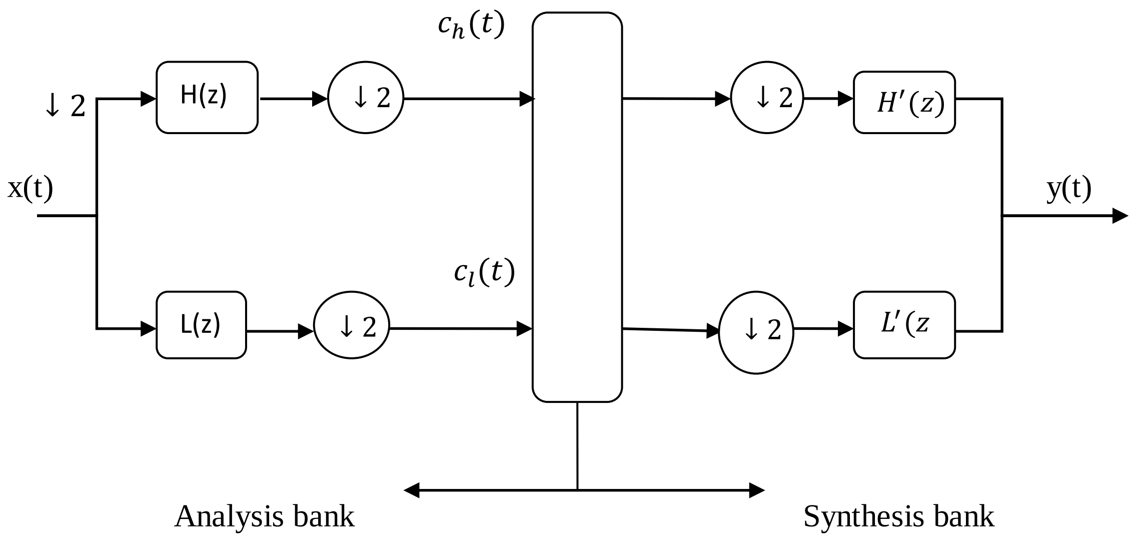


Figure 3.2 Two channel filter bank

Down and up sampling

The low and high pass filters L (z) and H (z) splits the signal content to the frequency into half. To avoid the redundancy, it performs logically a down sampling with a factor two. If the half of the samples of filtered signals $C_l(t)$ and $C_h(t)$ are reduced, it is possible to reconstruct the signal x(t). The down sampling operation ↓ 2 saves only the even numbered component of the filter output, here it is not invertible. In the frequency domain, the affect of discarding the information is called aliasing. If the Shannon sampling theorem is met, no loss of information occurs.

The sampling theorem of Shannon states that down sampling a sampled signal by a factor M produced a signal whose spectrum can be calculated by partitioning the original spectrum into M equal bands and summing these bands. In the synthesis bank, the signals are first up sampled before filtering. The up sampling by a factor two ↑ 2 is performed by adding zeros in between the scales of the original signals. The transpose of ↓ 2 is ↑ 2. $\downarrow 2 * \uparrow 2 = I$, since ↑ 2 is right inverse of ↓ 2. This shows that the original signal obtain again with up and down sampling. By inserting zeros and then removing them, the original signals are obtained again.

Perfect reconstruction

If the filter bank in bi orthogonal, then it is possible for perfect reconstruction. Furthermore, some design criteria for both the analysis and synthesis filters should be met to prevent aliasing and distortion and to guarantee a perfect reconstruction. In the two filter bank, the filters L(z) and H(z) split the signal into two frequency band filters are respectively a low-pass filter and high-pass filters. If the filters are perfect brick wall filters the down sampling would not lead to loss of information. In practical, the ideal filters need not be realized, so a transitions band exists. Besides aliasing, this leads to an amplitude and phase distortion in each of the channels of the filter bands.

For the two channel filter bank, aliasing can be prevented by designing. The filters of the synthesis filters bank as,

$$L'(z) = H(-z) \quad (1)$$

$$H'(z) = -L'(-z) \quad (2)$$

To eliminate distortion, a product filters $P_0(z) = L'(z)\,L(z)$ is defined. Distortion can be avoid if

$$P_0(z) - P_0(-z) = 2z^{-N} \quad (3)$$

Where N is overall delay in the filter bank. Generally N^{th} order filters produces a delay of N samples. The perfect reconstruction filter bank can be designed in two steps.

1. Design a low-pass filters P_0 satisfying (3)
2. Factor P_0 into L'(z)L(z) and using (1) and (2) to calculate H(z) and H'(z).

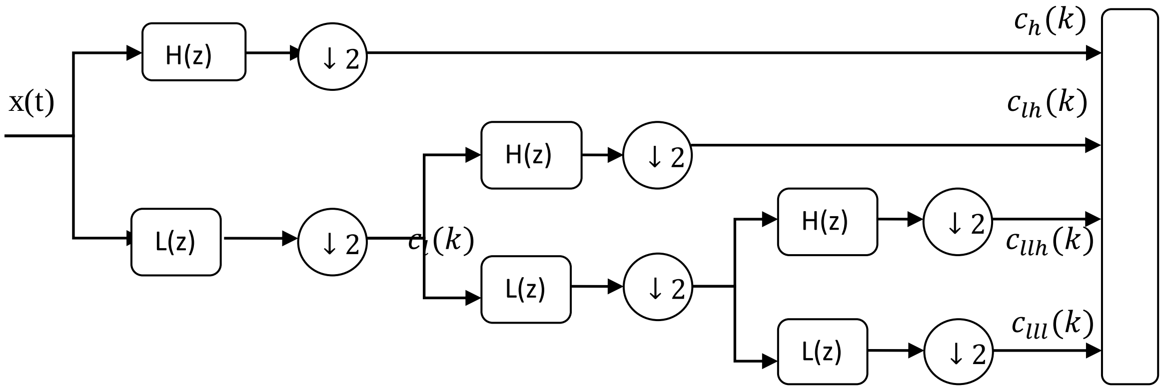
The design of the product filter P_0 of the first step and the factorization of the second step can be done in several ways.

Multiresolution Filter Banks

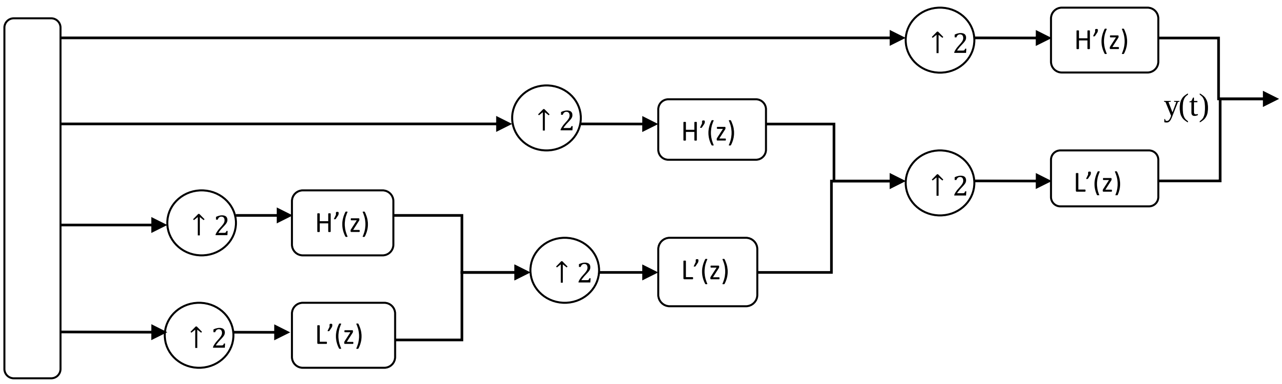
For higher frequencies (low scales), which lasts for a short period of time, a good time resolution is desired. For low frequencies (high scales) detailed resolution is more important. DWT uses filter banks for multi resolution analysis in order to analyze the signals at different frequencies with different resolution.

The approximation and details of the signals x(t) can be retrieve by the low-pass and high-pass filtering branches of the filter bank respectively. A three level filter bank is shown in fig 3.3. The filter bank can be expanded to an arbitrary level, depending on the desired resolution.

In the second level, the output of L(z) and H(z) double the time resolution and decrease the frequency content, i.e. the width of the window is increased. After each level, high-pass filter represents the highest half of the frequency content of the low-pass filter of the previous level, this leads to a pass-band. Set of filters L (z) and H (z) of following structure are called wavelet filters.



(a) Analysis bank



(b) Synthesis bank

Figure 3.3 Three level filter bank

Wavelet filters

The filter bank is shown in fig 3.4 is increasing in the down-sampling rate leads to a larger time grid for lower frequencies (higher scales). The filters can be interrupted as a wavelet function at different scales. However they are not exact scaled versions of each other, if the number of levels is increased and the impulse responses of the equivalent filters converge to a stable waveform, the filters L(z) and H(z) are wavelet filters.

The wavelet filters can be classified into two classes, orthogonal and biorthogonal wavelets. Several wavelet families, designed for the DWT.

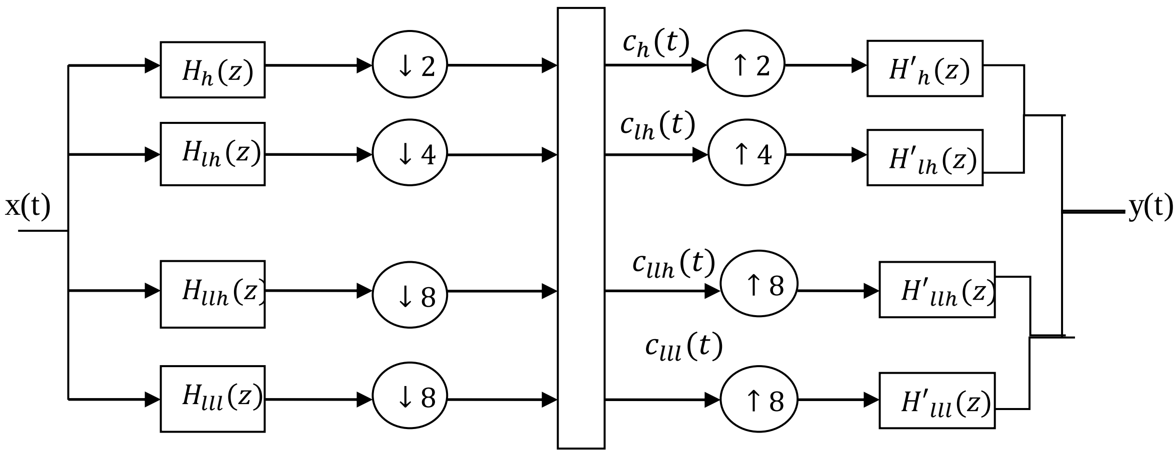


Figure 3.4 Combined three level filter bank

The limit wavelet functions i.e. the stable waveforms, can be constructed the easiest from the synthesis bank. For lower branch, consisting of only low-pass filter and up-sampling, the impulse response converges to final function *l(n)* for which the following difference equation holds.

$$\phi(t) = \sum_{n=0}^{N} l(n)\phi(2t - n)$$

This function is known as the scaling function of the wavelet. For the band-pass sequences the impulse responses converge holding the find difference equation which can be obtained as

$$\psi(t) = \sum_{n=0}^{N} h(n)\psi(2t - n)$$

The final equation of the band-pass sequences *h(n)* is the wavelet function $\psi(t)$.

The sub band with wavelet coefficient is called the approximation sub band cA and contains the lowest frequencies. The other sub band is called detail sub bands cD and gives the detail information of the signal. The wavelet coefficient represents the signal content in the various frequency bands.

The wavelet coefficients in the different frequency bands of the DWT can be processed in several ways. By adjusting the wavelet coefficients the reconstructed signal of the synthesis filter bank can be changed in comparison to the original signal. This gives the DWT some attractive properties over linear filtering. Compared to the CWT, the DWT is easier to compute and the wavelet coefficients are easier to interpret since no conversion from scale to frequency has to be made.

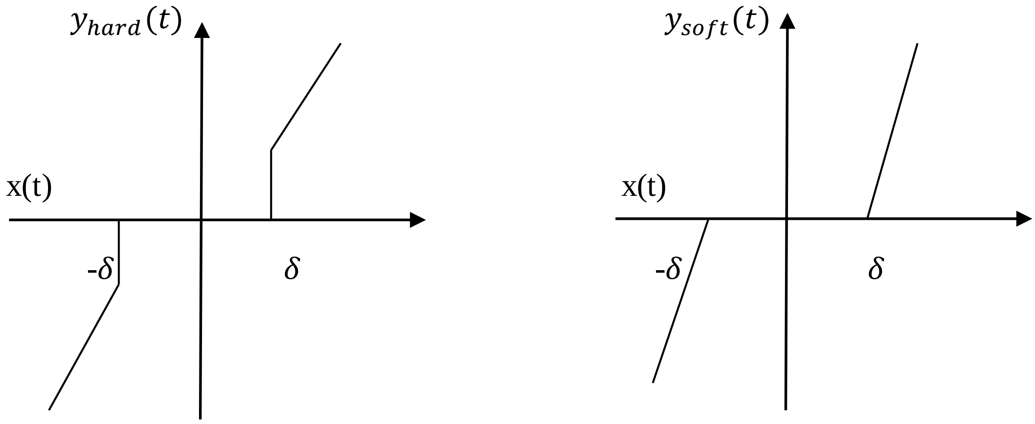
SECTION 3.3

WAVELET PERFORMANCE OVER SIGNAL ANALYSIS

Signals are input for the wavelet analysis. The resulting wavelet coefficient can be manipulated in many ways to achieve certain result; these include denoising, compression, feature detection, etc.

Denoising

The denoising and feature detection of the signals using the wavelet transforms is done by representing the signal by a small number of coefficients. This wavelet shrinkage as based on the thresholding, as developed by Dohono and Johnstone. The signal is composed into L levels before thresholding is applied.



(a) Hard (b) soft

Figure 3.5 Thresholding

There are two types of thresholding namely hard and soft thresholding with threshold δ. Hard thresholding zeros out of small coefficients, resulting in the efficient representation. Soft thresholding softens the coefficients exceeding the threshold by lowering them by the threshold value. When thresholding is applied, no perfect reconstruction of the original signal is possible. Soft thresholding gives better compression performance.

The output of the soft and hard thresholding can be written as

$$y_{hard} = \begin{cases} x(t), & |x(t)| > \delta \\ 0, & |x(t)| \le \delta \end{cases}$$

$$y_{soft} = \begin{cases} sign\big(x(t)\big)(|x(t)| - \delta), & |x(t)| > \delta \\ 0, & |x(t)| \le \delta \end{cases}$$

Only the large coefficients are used for the reconstruction of the image. The denoising is not limited to a special kind of noise; different kinds of disturbances can be filtered out of the images.

Thresholding generally gives low-pass version of the original signal. An appropriate threshold δ can be suppressing noise present in a signal. For denoising applications, generally soft thresholding is used. It is assumed that the noise power is smaller than the signal power.

Signal Structure Decomposition

The signal can be considered to be composed of three parts namely a harmonic (tonal), a transient and a stochastic part (noise).

$$s(t) = s_{tonal}(t) + s_{transient}(t) + s_{noise}(t)$$

There are three parts can be separated by an algorithm since they are not orthogonal to each other. The noise is assumed to be a Gaussian random colour noise. For the analysis the noise spectral properties are estimated.

Noise Model

A model of the noise can be obtained by estimating the parameters of the noisy random process. For the Gaussian noise, the process is entirely determined by its power spectrum. Random noises are averaged over critical bands. The summation of the variances $\sigma_k$of these critical bands gives

$$s_{noise}(t) = \sum_{k=1}^{n} \sigma_k W_k(t).$$

where W_k is a Gaussian random generator which contains frequencies in the sub-band of the interest. The variances are assumed constant over a sub-band.

Denoising algorithm

The denoising algorithm proposed as based on a wavelet packets decomposition which frequency resolution closely matches the critical sub-bands. Within the arise of sub-bands hard thresholding is performed according to

$$T_{t_k}(x) = \begin{cases} 0 & if\ |x| < t_k \\ x & if\ \ |x| \geq t_k \end{cases}$$

The threshold of t_k is chosen adaptively. The processes of denoising are as follows

i) Separation

The three different parts of the signal can be estimated successfully. Before estimating the tonal part a preliminary noise filtering is performed in order to reduce biases. The tonal part is estimated using a lapped cosine transform. The overlap reduces the influence of the discontinuities. The harmonic components are selected by thresholding.

After estimation of the tonal part another noise filtering is performed. The transient part is separated using a standard dyadic DWT. For the separation, again thresholding relative to the maximum coefficient is applied.

Finally, the noise is estimated by a critical band based wavelet packets analysis. In an wavelet packets analysis not only the approximations, but also the details are split to lower levels. The variances of the noises in the various sub-bands are estimated from the sample variances of the wavelet coefficients.

ii) Signal denoising

Noise reduction is based on the removing the interrupted noises presented in the signal. The level of soft, high-frequency passages is raised to make the signal sharper than the noise, where as the loud passages is not changed.

The multi resolution properties of wavelet analysis reflect the frequency resolution of the signal. The wavelet transformation is adapted to analyse the local variations in signals. Noise is distinguished into properties in the time and frequency domain. White noise is present in all frequencies Gaussian noise, generated by almost all natural phenomena, and is normally distributed. Uniform noise has a constant probability density in the time domain.

White noise is most difficult to detect and to remove. The harmonic signal content is closely correlated, resulting in the larger coefficients than the uncorrelated noise. The noise can be removed by discarding all coefficients.

White noise can be handled either by hard or soft thresholding. Hard thresholding sets all the wavelet coefficients below a given threshold value to zero and exhibits artefacts, soft threshold soothes the signals by reducing the wavelet coefficients by a quantity equal to the threshold value, note that soft thresholding modifies the signal energy.

Methodology used for denoising process

In order to optimize the parameters, the cross-validation method is used to select the optimal wavelet function and its decomposition level. The denoising of a signal is done in three steps

1. Decomposition of the signal by the DWT
2. Thresholding of the wavelet co-efficient
3. Reconstruction of the signal

For a good denoising result, a good thresholding level has to be estimated. The wavelet function and the decomposition level also pay an important role in the quality of the denoised signal. The optimal threshold value is estimated using a soft thresholding approach. The goal of cross-validation is to minimize the error between the denoised signal and the ideal signal. The cross-validation procedure of a signal with the length N=2^p consists of the following steps.

1. Two functions, one for odd points (f_0) and other for even points (f_e) are derived by dividing the original signal and re-indexing the data points.
2. The even function is estimated by interpolation of the odd function

$$f_e^* = \frac{(f_0(i) + f_0(i+1))}{2}, i = 1, \ldots, 2^{p-1},$$

3. The DWT is applied to the estimated signal
4. Thresholding is applied to the transformed signal

5. The filtered signal is reconstructed ($\overline{f_e}$) using IDWT

6. The signal to noise ratio (SNR) and Percentage root mean square value (PRD) is calculated and the reconstructed functions are estimated.

CHAPTER 4

CHAPTER 4

COMPARATIVE STUDY OF EFFECTIVE WAVELET BY DENOISING

SECTION 4.1

RECONSTRUCTION OF SIGNAL

The Kobe earthquake data is taken for our study and presented in the graphical form using MATLAB and it is shown in the figure 4.1. In this study, the two basis functions of wavelet transform namely Daubechies(db) and Fejèr-Korovkin(fk) wavelet are considered. Both the filters decompose the signals into four levels and denoted by fk4 and db4.

Steps to reconstructing the signals

The processes of comparing the two wavelets, by decomposing the signal are undergone through five steps [10][14][15][16][24].

Step 1 Generating noise signal and adding to original signal.

Step 2 Decomposing the noisy signal using corresponding wavelet.

Step 3 Applying the corresponding threshold values.

Step 4 Reconstructing the signal using inverse wavelet transform.

Step 5 Calculating the signal-noise ratio and percentage root mean square difference value for corresponding wavelet.

Step 1: Generating Noise Signal and Adding to Original Signal

In the signal processing, the most common problem occurs as noise disturbances. The noise signal happens in many ways. It is classified majorly as technical noises and non-technical noises. In technical issues, the error can be easily identified and rectified by replacing the equipments. In non-technical issues, such as human error, experimental error cannot be rectified easily. In this case, we add some noisy signal which can be decomposed using wavelet filters. Generating noise means adding random noise to original signal. The above concept is described mathematically as follows,

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

Where, Y (n) - original signal free from noise.

X (n) - random noisy signal

N(n) - noisy earthquake signal

The noisy earthquake signals are shown in figure 4.2. 1000 samples are extracted from noisy signal N(n) and presented in figure 4.3

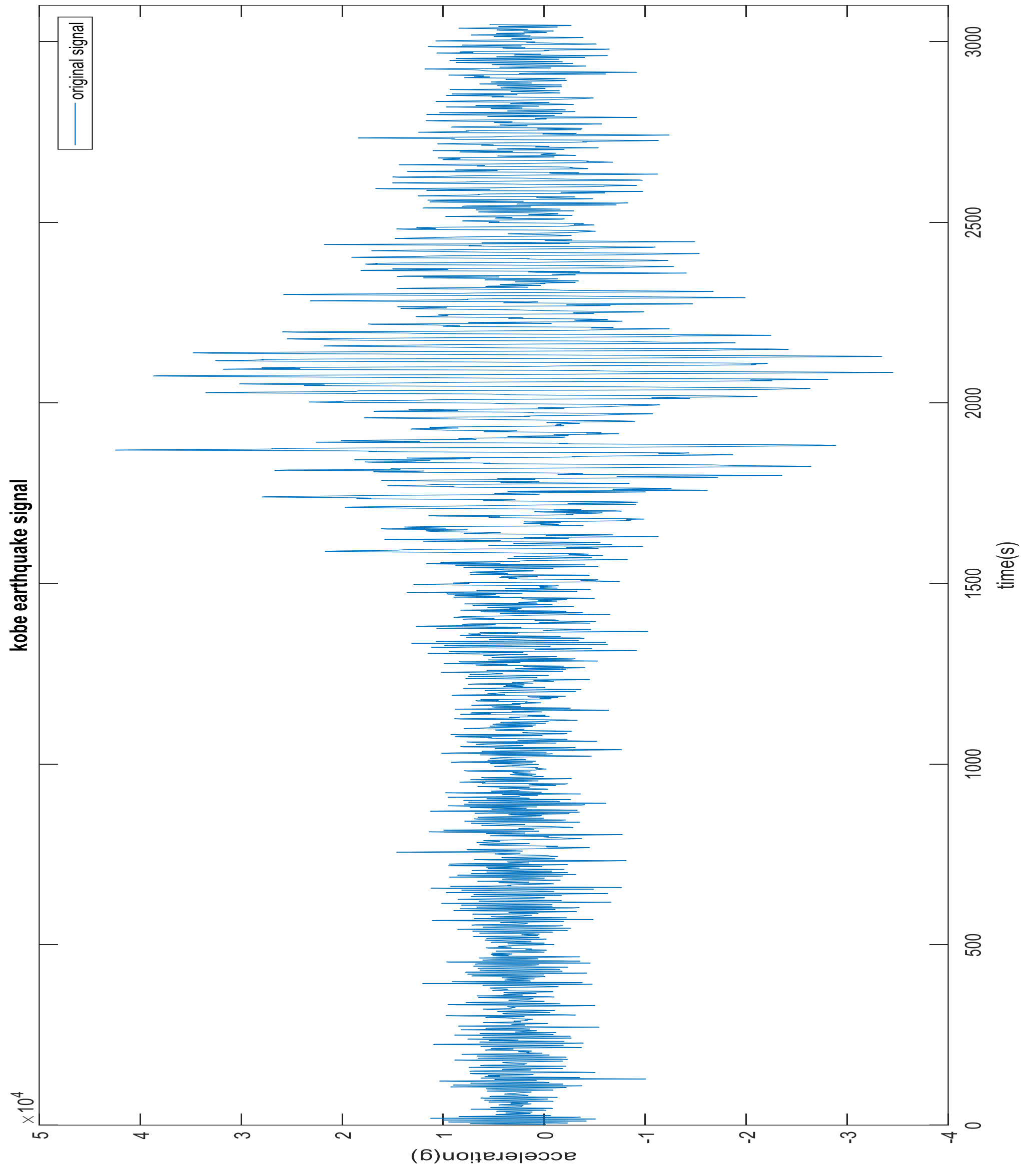


Figure 4.1 The Kobe earthquake signal

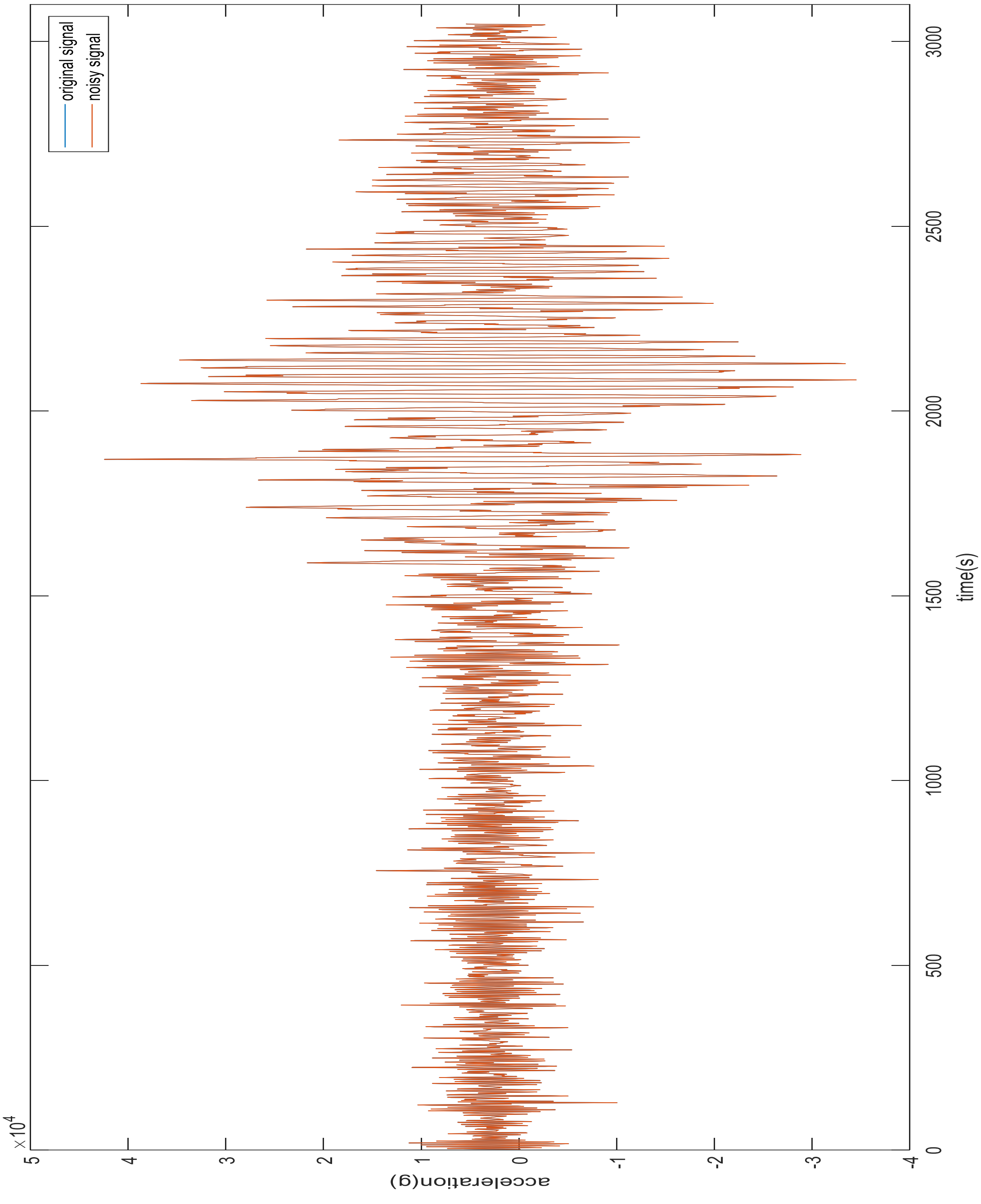


Figure 4.2 Noisy Signal

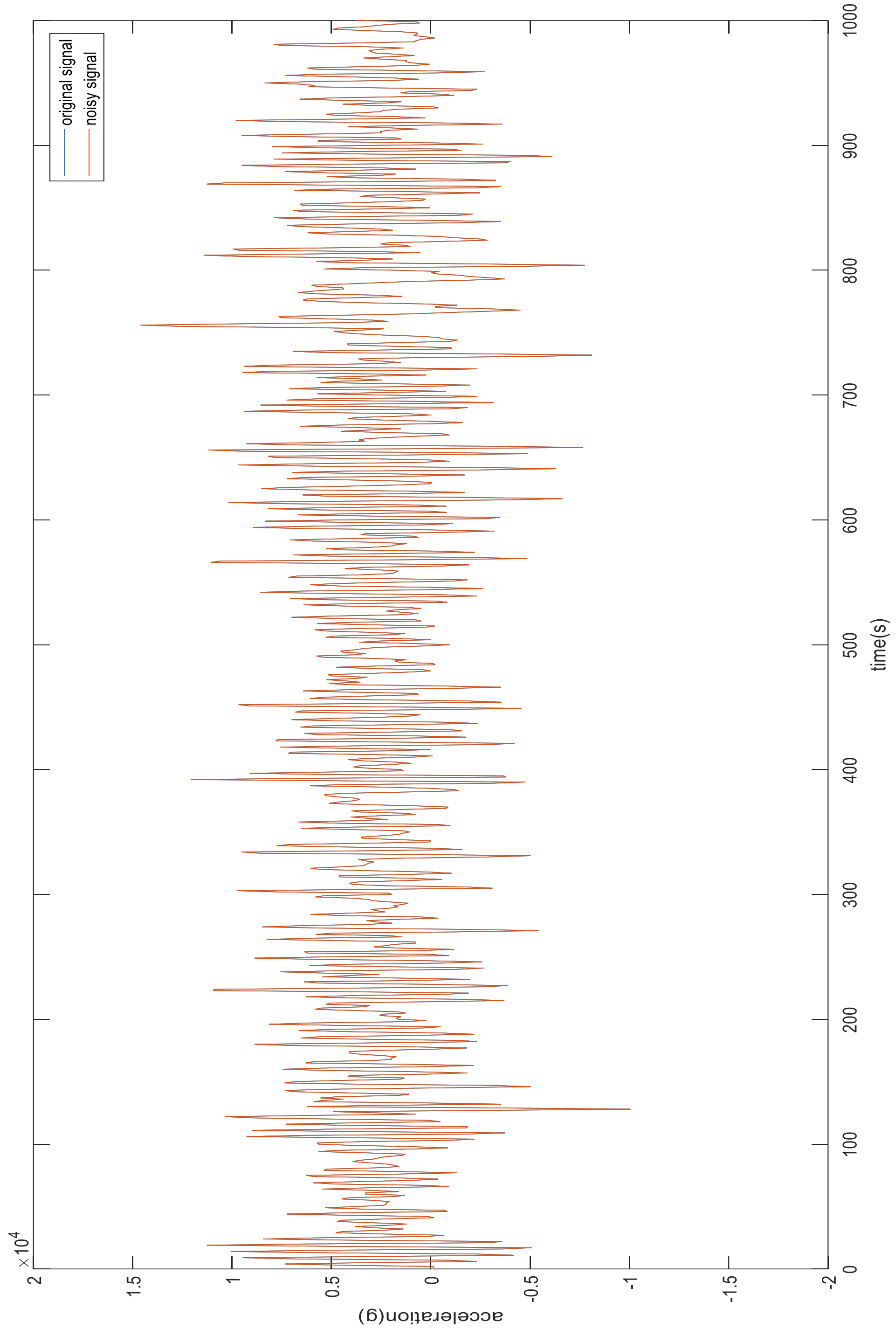


Figure 4.3 Sample Noisy Signal

Step 2: Decomposing the noisy signal using Wavelets

The noisy earthquake signal is decomposed into four levels using Daubechies wavelet (db4) and Fejèr-Korovkin wavelet (fk4) in discrete wavelet transform. For each level, there exists an approximation coefficient and detail coefficient respectively. Here, $a_j(n)$ represents the set of approximation coefficients and $d_j(n)$ represents the set of detail coefficients.

Using MATLAB, we obtained the pictorial form of approximation coefficients and detailed coefficients for Daubechies and Fejèr-Korovkin wavelet and shown in figure 4.4, figure 4.5, figure 4.6 and figure 4.7. In this case, the approximation coefficients are not taken into account because it contains more level of energy and low level of frequency.

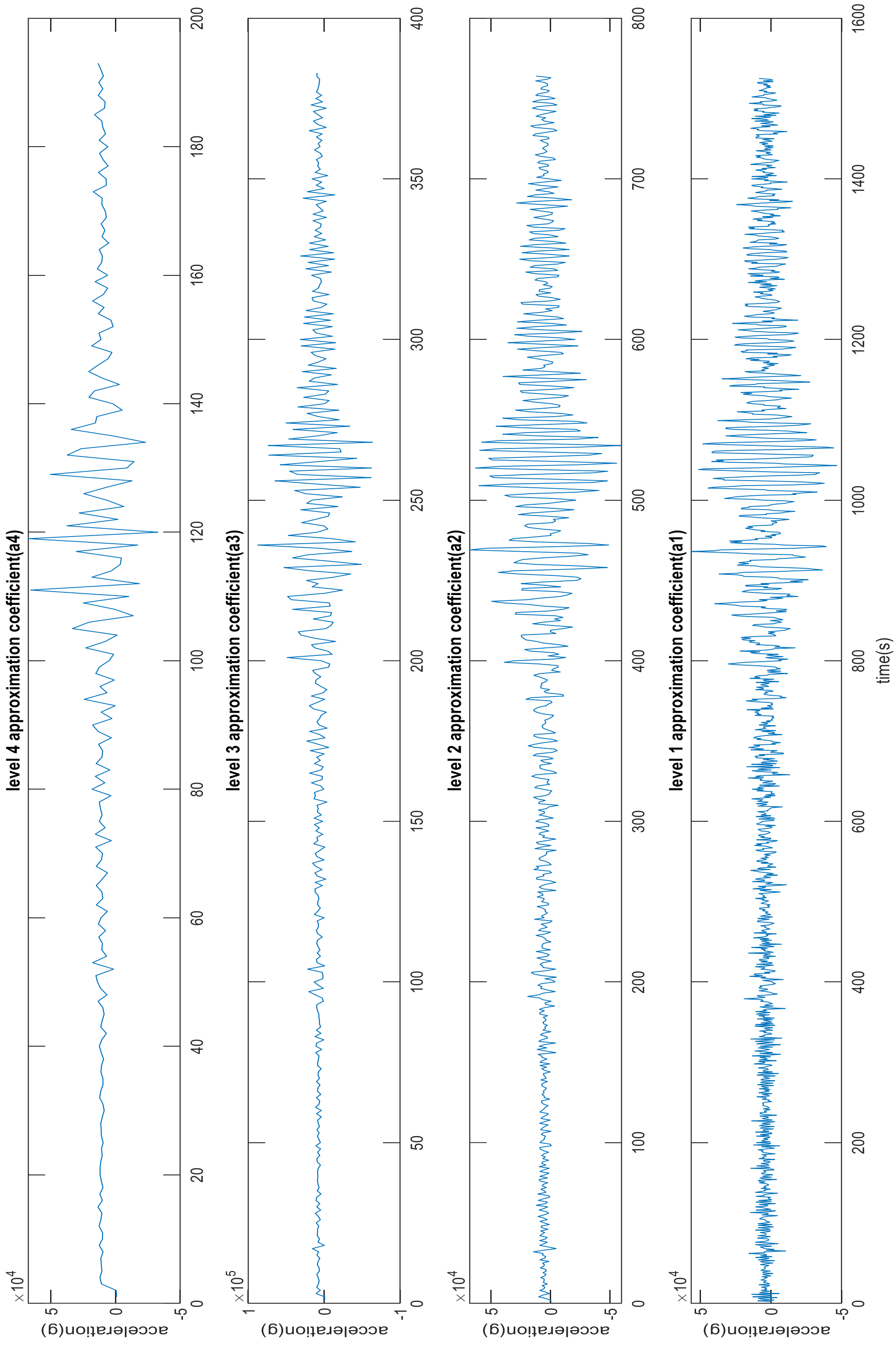


Figure 4.4 Fk wavelet approximation coefficients

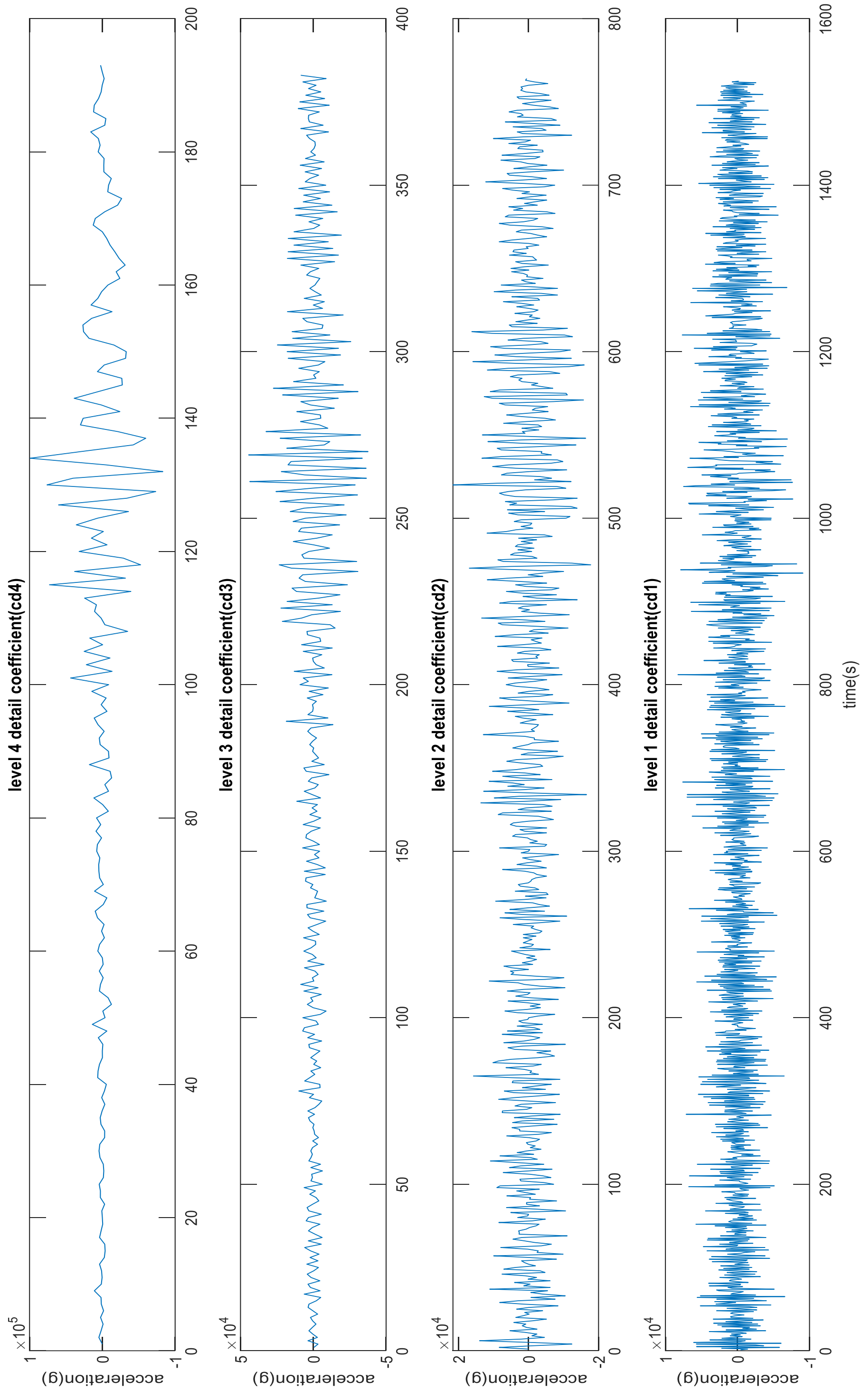


Figure 4.5 Fk wavelet detail coefficients

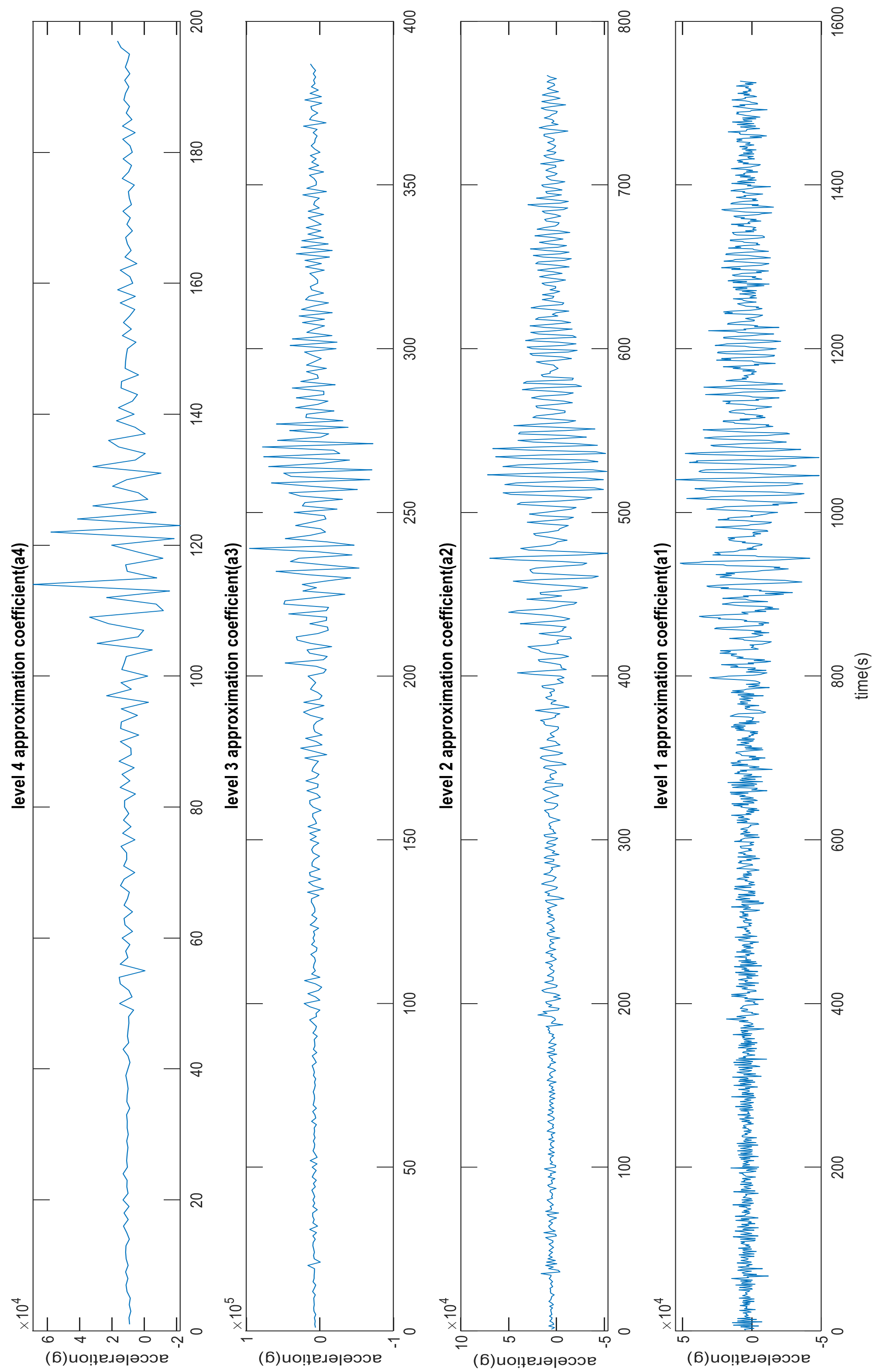


Figure 4.6 DB wavelet approximation coefficients

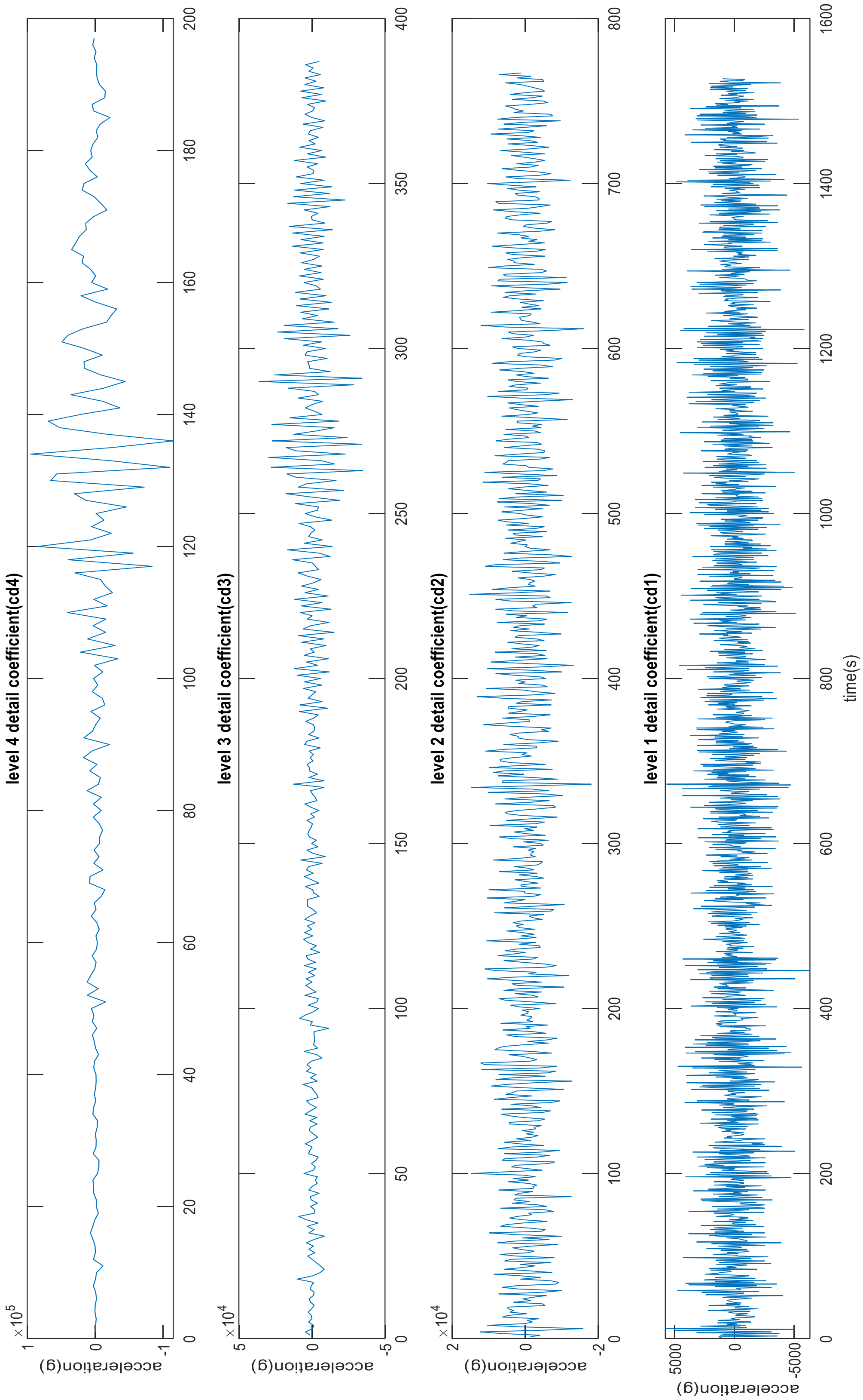


Figure 4.7 DB wavelet detail coefficients

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,

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

where, T - Threshold value

C - Constant value

$\sigma(N(n))$ - Standard deviation of noisy signal

$\sigma(d_j(n))$ - Standard deviation of detail coefficient of j levels, (j =1, 2, 3, 4)

n - Number of samples

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

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

Where $C_{j,k}$ - Detail wavelet coefficient transform.

$D\,(C_{j,k})$ - Output of coefficient after threshold is applied.

T - Chosen threshold value

The optimal threshold value is computed using MATLAB for db4 and fk4 wavelet and presented in the table 4.1 and table 4.2 respectively.

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

Step 4: Reconstructing the Signal using Inverse Wavelet Transform

After applying the threshold value, we need to reconstruct the signal as we done in other transforms. Wavelet transform also consist the inverse function. From this reconstruction we can get decomposed signal in original domain. The main reason for using the inverse method is, in some problems cannot be solved in original domain or it consumes more time to solve in original domain. For that case, we converting from original domain to another domain and solving the problem then inverse the function back to its original domain.

For this conversion, threshold plays an important role. Without loss of originality, we need to choose the threshold value and then reconstruct the noisy signal. The threshold only applied to the detail coefficient where it contains detailed feature that does not exists in approximation coefficient.

The inverse wavelet transform functions of both the filters are presented graphically in figure 4.8 and 4.9.

The figure 4.10 exhibits the reconstructed combined form of both wavelets. Samples are extracted from reconstructed combined form of both wavelet and presented in figure 4.11.

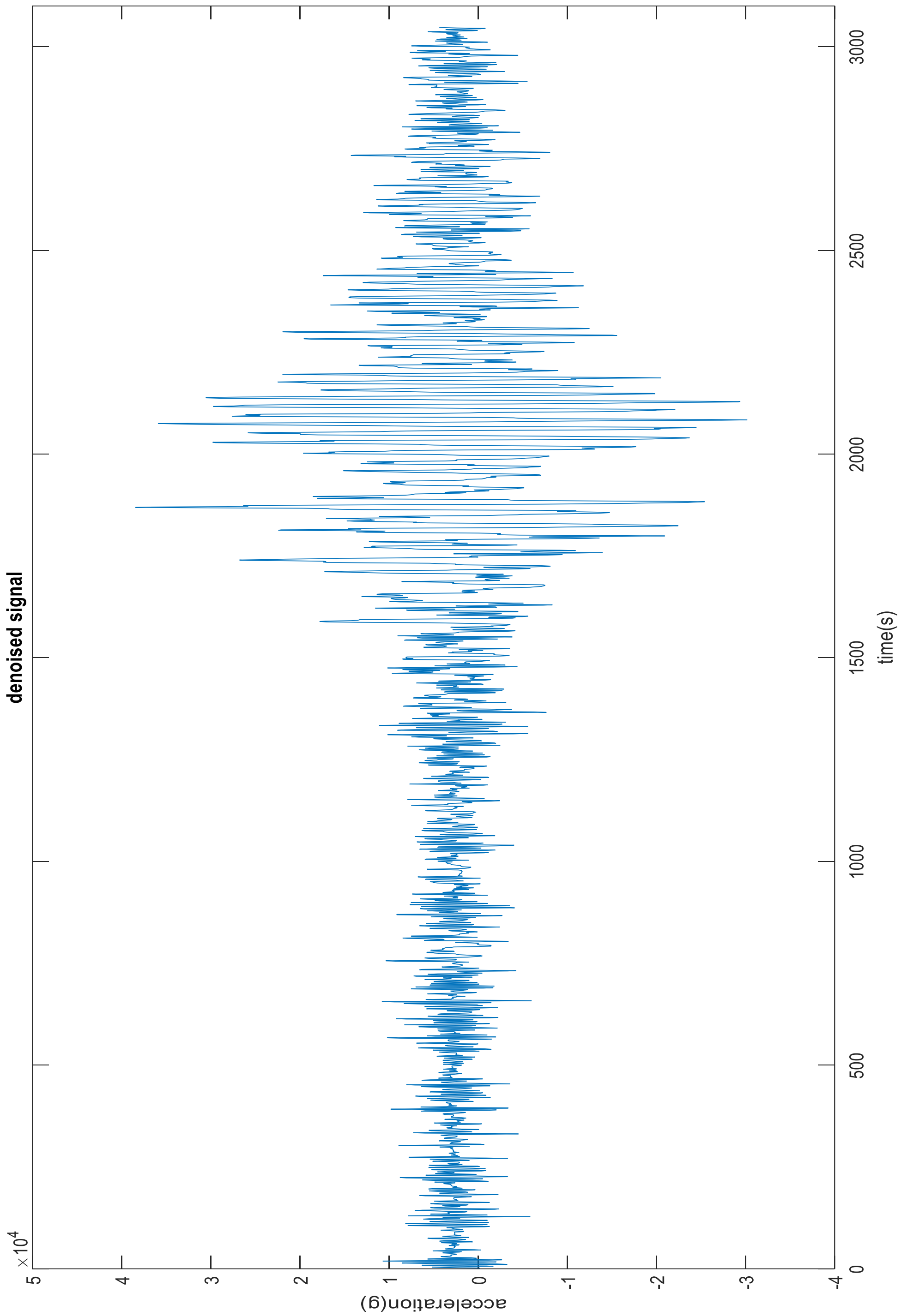


Figure 4.8 Denoised signal (using FK wavelet)

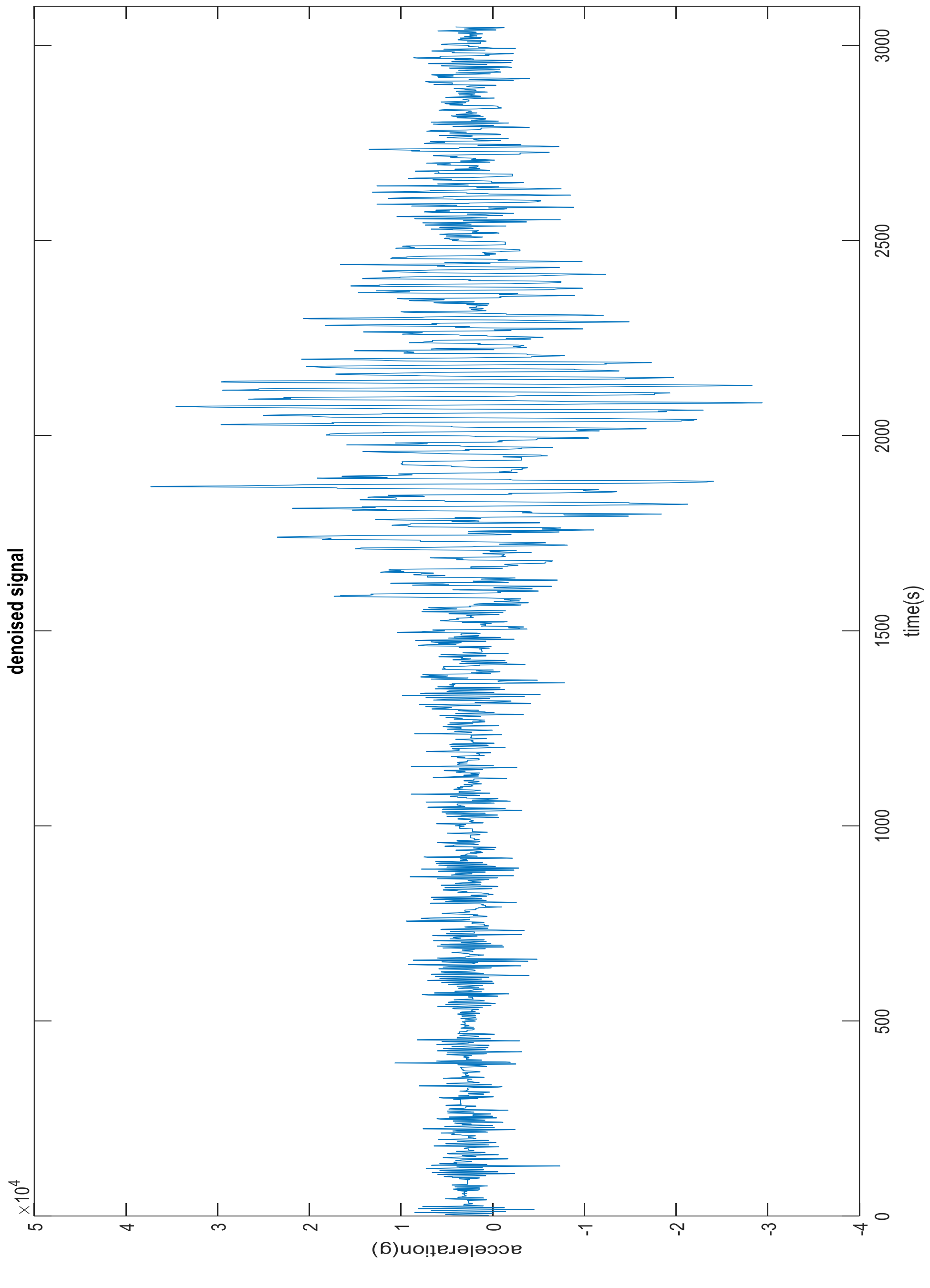


Figure 4.9 Denoised signal (using DB wavelet)

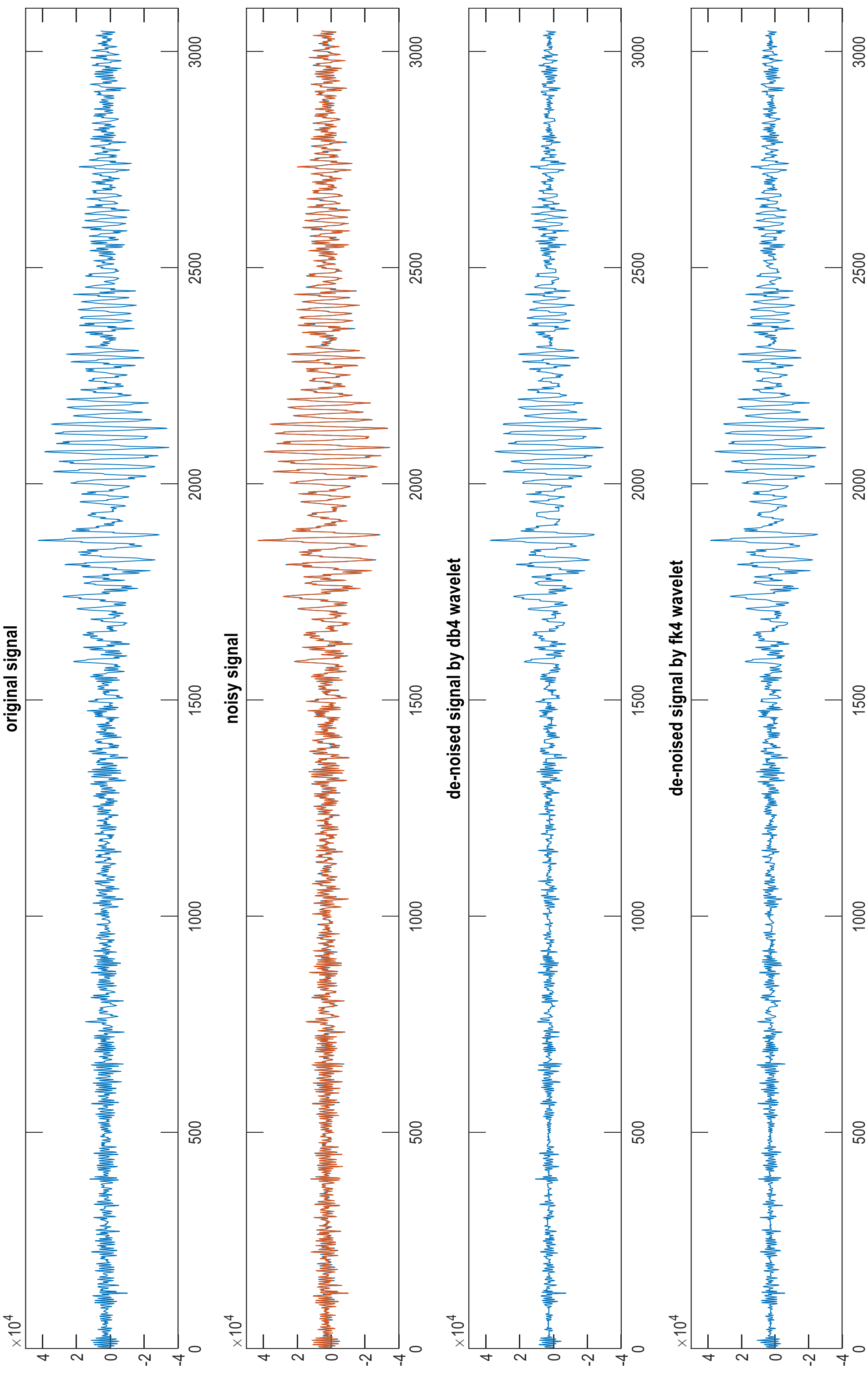


Figure 4.10 combined form db and fk wavelet

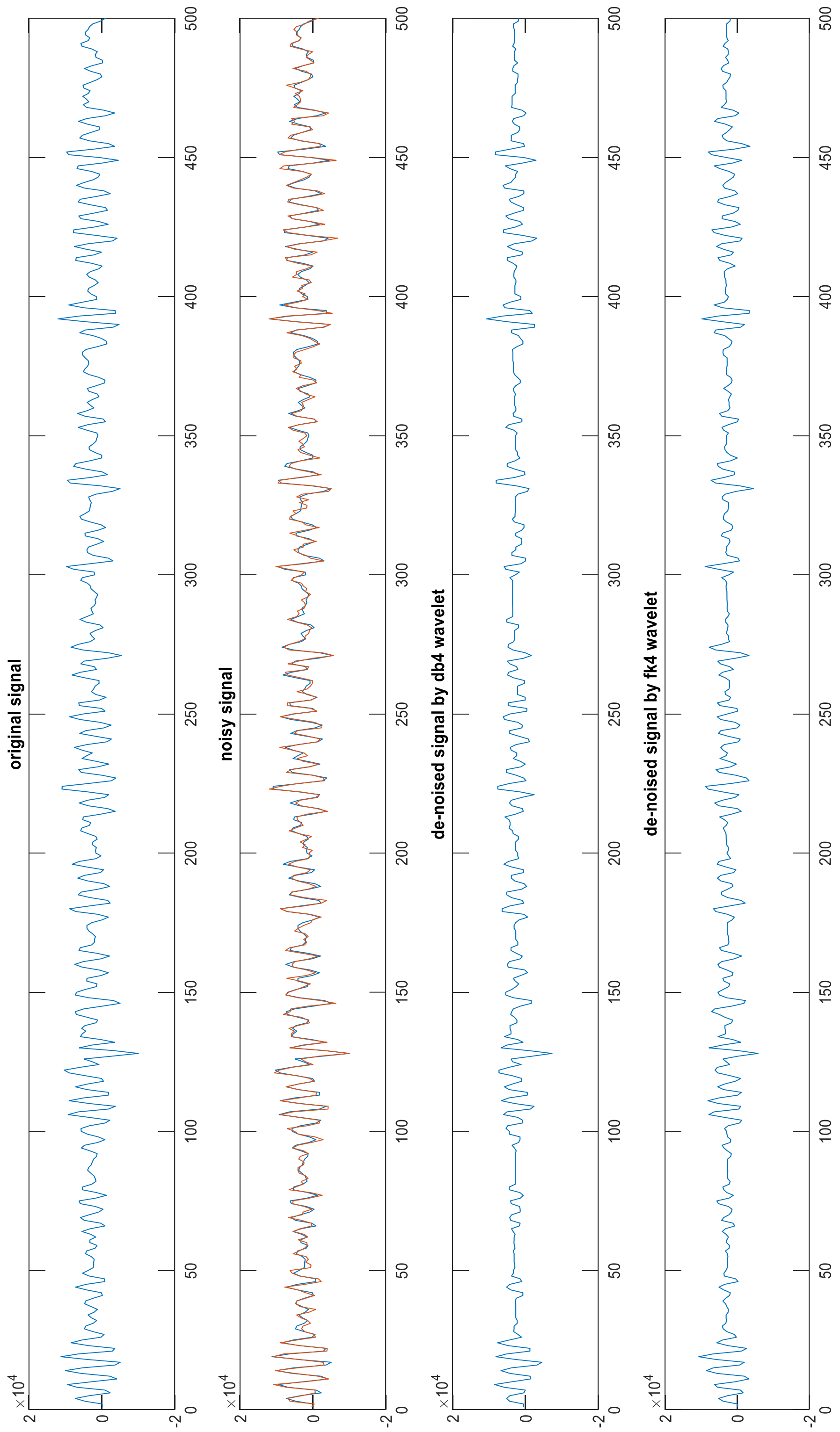


Figure 4.11 Combined form of extracted wavelet

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

$$\text{PRD} = \sqrt{\frac{\sum(Y(n)-Y_R(n))^2}{\sum(Y(n))^2}} \times 100$$

$$\text{SNR} = Log_{10}\frac{\sum(Y(n))^2}{\sum(N_R(n))^2}$$

where Y(n) - Original earthquake signal

$Y_R(n)$ - Reconstructed earthquake signal

$N_R(n)$ - Noisy signal

Using denoised signal, PRD and SNR values are computed by MATLAB and exhibited in the following table 4.3.

Table 4.3 PRD and SNR values

Wavelet	PRD	SNR
Db4	26.9201	2.3537
Fk4	23.2596	2.6105

From the above table, 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.

CHAPTER 5

CHAPTER 5

FEATURE SELECTION AND EXTRACTION

SECTION 5.1

FEATURE EXTRACTION

5.1.1 Feature Extraction

Feature extraction is the process of reducing the dimensionality of raw data which is considered as initial set of data. In large set of data, such as signal processing which are non-stationary and the characteristic of each wave cannot be calculated simultaneously. For this case, we reduce its dimension and calculated the signal in the extraction process. [32][33][35][38][53]

Feature extraction is the method to selected or combine variables into features. Reducing the amount of data set efficiently that undergoing process, which are accurately and completely describing the original set of data.

The process of feature extraction is useful when we need to reduce the number of resources needed for processing without losing important or relevant information. It can also reduce the amount of redundant data for given analysis. Also the reduction of data and the machines effort in building variable features which appreciate the speed of learning and generalization steps in the machine learning process.

Feature extractions are based on finding the mathematical methods for reducing the dimensionality. In most of the cases, the statistical methods are involving for the extraction the commonly using statistical methods for extracting features are mean, median, mode, variance, standard deviation. Apart from the statistical methods, there are another methods such as energy, entropy, peak- amplitude, peak-peak value, root means square value and signal to noise ratio.

Feature extraction plays a vital role to determine the separating properties of pattern classes. The choice of feature attributes or measurements has important influences on the following four classes, such as

- Accuracy of the classification
- Time needed for classification
- Number of examples needed for classification
- Cost of performing classification

SECTION 5.2

FEATURE SELECTION

In chapter 4, we proved that the Fejèr-Korovkin (fk) wavelet is more efficient than Daubechies (db) wavelet. 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 [42][44],

- Entropy
- Peak-peak value

Entropy

The entropy is the expected value of the self information which was introduced by Shannon. The self information quantifies the level of information which are associated with one particular outcome or event of a random variable, whereas the entropy quantifies how "informative" the entire random variable in averaged on all its possible outcome [48].

Shannon Characterization of Entropy

1) The measurement of signal should be continuous i.e. which changing the value of one of the probabilities by a very small amount should only change the entropy by small amount.

2) If all the outcomes obtained are equally likely, then the entropy is maximal. In this cases, the entropy increases with the number of outcomes.

3) If the outcomes are certainty, then the entropy should be zero. Because entropy only deals with uncertainty.

4) The amount of entropy should be same independently of how the regarded as being divided into parts.

There are many types of entropy. The most commonly used entropy are Shannon entropy and log-energy entropy.

i) Shannon Entropy

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

ii) Log-Energy Entropy

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

where i = Number of samples

n = Sample size

W= Wavelet decomposition co-efficient

Peak-Peak value(P-p value)

Peak-peak is the difference between the maximum positive to the maximum negative amplitudes of the waveform. The peak of the waveform can be easily identified and measured by oscilloscope. Here we measure the peak-peak amplitude as,

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

where $M_i =$ Maximum positive

$m_i =$ Maximum negative

i = Number of samples

n = Sample size

Log- energy entropy value and peak-peak value are calculated for 61 samples using MATLAB and presented in the following table 5.1.

Table 5.1 Calculated values of Log-Energy Entropy and Peak-peak values

Signal value	Log-Energy Entropy	Peak-peak values
7513	775.4733	13912
4042	783.8817	5004
8551	782.0017	13944
7650	782.1127	8803
5295	766.8218	12055
8349	780.6001	11060
7421	774.9717	13417
9055	785.6737	13157
4973	767.9313	8394
9840	791.3530	11572
5664	769.9459	8158
5716	768.0561	12339
4514	729.4666	11401
8650	782.7223	16719
4514	750.1443	11426
4514	739.3232	11799
5767	768.2162	11822
9217	786.8470	13199
5512	769.7643	8437
3753	776.8812	6984
8698	783.0797	10872
4024	763.2794	8936
4462	756.2824	9893
8276	788.8159	8962
6609	772.5871	7801
4527	765.0342	10337
11243	799.2449	16652
8608	782.4159	16011
7733	776.7310	10141
8813	783.9249	14538

8358	780.6570	11774
11420	802.3130	21916
11420	829.1693	21356
7309	774.3749	19763
31999	842.5362	34857
31999	861.4657	33733
31999	893.2527	44818
31999	943.3548	63840
10045	792.6735	17652
16760	835.1713	23078
31999	941.0642	53460
31999	945.9360	66038
31999	939.9584	59893
31999	907.8026	42936
12100	828.1566	22287
31999	849.7350	37470
28915	786.5460	30189
27475	814.7854	27800
30131	858.9146	29199
9107	786.0520	15084
7202	773.8379	13386
11420	808.5237	18732
11420	809.1272	18300
8492	781.5758	15471
12177	808.6636	22297
4513	753.0176	12504
4514	749.9934	11539
3376	750.1879	7865
8692	783.0320	13873
7275	774.1975	12086
3847	757.4325	8520

CHAPTER 6

CHAPTER 6

FUZZY CLASSIFICATION

SECTION 6.1

FUZZY INFERENCE SYSTEM

Zadeh (1973) provides the influential work on fuzzy algorithms that introduced the idea of computing the control algorithm by logical rules. A mapping of input space into output by using fuzzy logic is called fuzzy inference system. A fuzzy inference system tries to formalize the human language in the form of fuzzy logic. A fuzzy logic control consists of set of rules in the form of 'IF (the given condition satisfied), THEN (the result for the consequences obtained)'. [1][40][45][52]

Thereby, the antecedents and the consequents of these IF-THEN rules are associated with the fuzzy concepts i.e. the linguistic terms, there are often called as fuzzy conditional statements. In FLC/FIS terminology, a rule of fuzzy control is a fuzzy conditional statement, by which the antecedent is a condition in domain and the consequent is system control. The inputs of fuzzy rule based systems should be given in the form of fuzzy sets. So therefore we have to fuzzifying the crisp inputs. Furthermore, the outputs of the fuzzy system are in the form of fuzzy values, here we need to change into crisp value by the process of defuzzification.

FIS is also known as fuzzy models, fuzzy associated memory, fuzzy-rule based systems, fuzzy expert systems and fuzzy logic controller. Generally FIS consists of four modules.

(a) Fuzzification
(b) Knowledge base
(c) Inference engine
(d) Defuzzification

(a) Fuzzification

The first step of fuzzy inference system (FIS) is fuzzification. In fuzzification, the input value or crisp value changed into fuzzy values. The Fuzzification interface involves the function such as initially it measures the values of crisp values it is considered an input variables. After measuring the input variables it tends to perform some operations. By this operation it prefers to transfer the range of input variables into their corresponding universe of discourse or crisp values. Then the function of fuzzification converts the input data into suitable linguistic values, so that the fuzzy set can be labelled.

(b) **Knowledge Base**

It consists of IF-THEN rule that computes the fuzzified value. It comprises the database set and the linguistic values of rule based control. So that we get the program to be performed according to its rule. Moreover, rule or knowledge based is accessible by user and it is user defined. Therefore it can be easy to access. In this process the database is defining the linguistic control rules and manipulates the fuzzy data in fuzzy logic control.

(c) Inference Engine

Fuzzy inference engine is the kernel of fuzzy logic control system. It has the capability to stimulate the human reasoning process by making fuzzy inference of the inputs and if- then rules. After the fuzzy knowledge base step, a fuzzy inference steps in invoked for each of the relevant rules to produce a conclusion based on their knowledge-base degree. There are two types of methods namely clipping method and scaling method to produce the conclusion. Both the methods generate an inferred conclusion by suppressing the membership function of the consequent, the extent to which they suppress the membership function depends on the degree to which the rule is matched.

(d) **Defuzzification**

Transforms the fuzzy values obtained by inference engine into crisp value. It is inverse process of fuzzification method. The values obtained from this step are tends to mapping the suitable scale values. This converts the range of output variables into corresponding universe of discourse/ crisp value. Moreover, from the inference fuzzy control, the defuzzification yields the non fuzzy control action to obtain the crisp values. The Defuzzification consists of many methods such as Centroid of area, bisection of area, mean of max, smallest of max, largest of max. We used Centroid of area method for defuzzification.

Centroid of area

$z_{COA} = \frac{\int_z \mu_A(z)\, z\, dz}{\int_z \mu_A(z)\, dz}$, where μ_A is aggregated output of membership function.

SECTION 6.2

METHODS OF FUZZY INFERENCE SYSTEM

FIS mainly classified into two methods namely Mamdani and T-Sugeno method which are commonly used in all type of fuzzy classification.

6.2.1 Mamdani Method

The most commonly used fuzzy inference system technique is so-called Mamdani method which was proposed by Mamdani and Assilian. It was initially applied to control a system engine and boiler combination by synthesizing a set of linguistic control rules obtained from human operators [30]. In Mamdani model, the fuzzy implication is modelled by Mamdani's minimum operator, the conjunction operator is "min", the t-norm from compositions rule is "min" and the aggregation of rules is "max". In order to explain the working model of fuzzy logic control we considered two inputs and one output problem that includes the rules which examined as follows:

- If x is A OR y is B, then z is C
- If x is A AND y is B, then z is C
- If x is A, then z is C

where A and B are input values whereas C is an output value.

6.2.2 Takagi-Sugeno Method

The Takagi-Sugeno Kang (TSK) model was introduced by Takagi and Sugeno(1985). This model was reduced the number of rules determined by Mamdani model, especially for complex and high dimensional problems. To achieve this goal, the TSK model replaced the fuzzy sets in the consequent part (then-part) of the Mamdani rule with a linear equation of the input variables, for examples two input and one output TSK model consist of the rules in the following form.

If x is A and y is B, then z=ax+by+c, where a, b, c are numerical constants.

SECTION 6.3

PROPOSED METHOD FOR CLASSIFICATION

6.3.1 Fuzzy Rules

From the knowledge based condition, fuzzy rules are constructed by the linguistic terms with variable constraints. In this proposed method fuzzy rule consists of two input variables and one output variable using IF-THEN condition is defined as follows

1. If entropy is weak and peak-peak value is low, then fuzzy classified signal as low.
2. If entropy is medium and peak-peak value is low, then fuzzy classified signal as moderate.
3. If entropy is strong and peak-peak value is low, then fuzzy classified signal as affected.
4. If entropy is weak and peak-peak value is medium, then fuzzy classified signal as moderate.
5. If entropy is medium and peak-peak value is medium, then fuzzy classified signal as affected.
6. If entropy is strong and peak-peak value is medium, then fuzzy classified signal as dangerous.
7. If entropy is weak and peak-peak value is high, then fuzzy classified signal as dangerous.
8. If entropy is medium and peak-peak value is high, then fuzzy classified signal as hazardous.
9. If entropy is strong and peak-peak value is high, then fuzzy classified signal as hazardous.

The number of fuzzy rules depends upon the number of input variables and their membership functions. In this fuzzy rule based selection model has two input variables and three memberships function i.e. $3^2 = 9$ rules. Figure 6.1 describes fuzzy rule design for two input variables, one output variable and three membership function.

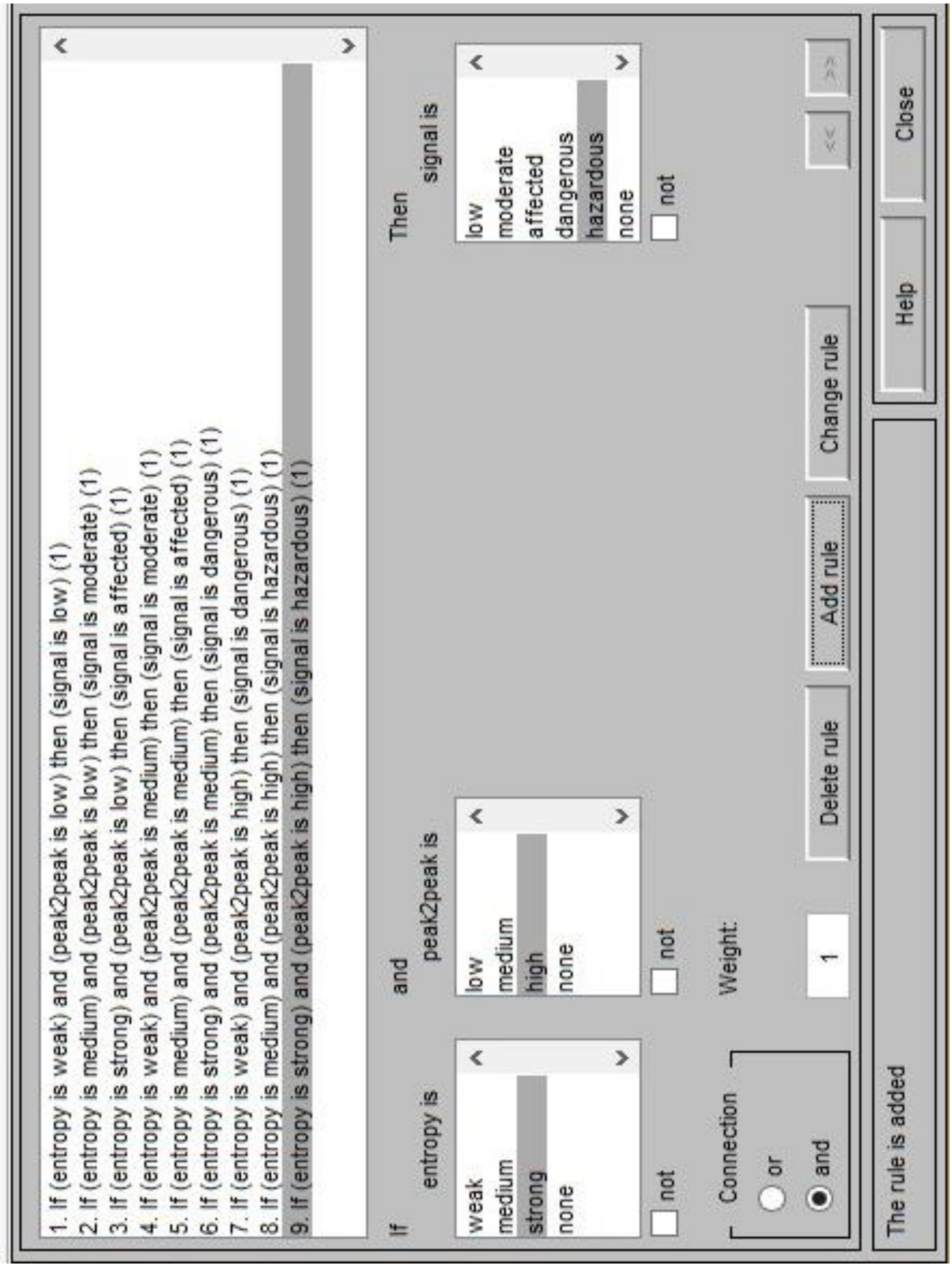


Figure 6.1 Fuzzy Rules Design

6.3.2 Fuzzy Constraints

Constructing constraints in fuzzy system is most significant step because the constraints provide a limiting factor that prevents a system from moving closer to achieving its goal. When the system is continuously improves, it leads to improve everything at once. But it occasionally leads to give sustainable improvement in overall performance. This is because not all improvements are created equally. In that case, we use constraints in certain weakest part of the system to make whole system strong. Thus, constraints are resistance point to make for more significant improvement with less effort in a relatively short time. Without the constraints, the performance of the system becomes infinite or unlimited. We must apply the constraints in order to control the system to get a desired value. In case of fuzziness of the system, we need to restrict or control over the values which improves better result.

In this study, we considered the following constraints for fuzzification process.

Input variables = 2(entropy and peak-peak)

Output variables=1 (signal)

Membership function=3 (weak, medium, strong)

Connection= 'AND'

Defuzzification= 'Centroid'

Aggregation= 'sum'

Applying Mamdani's method to the above constraints the following fuzzy rule based model is obtained and shown in Figure 6.2.

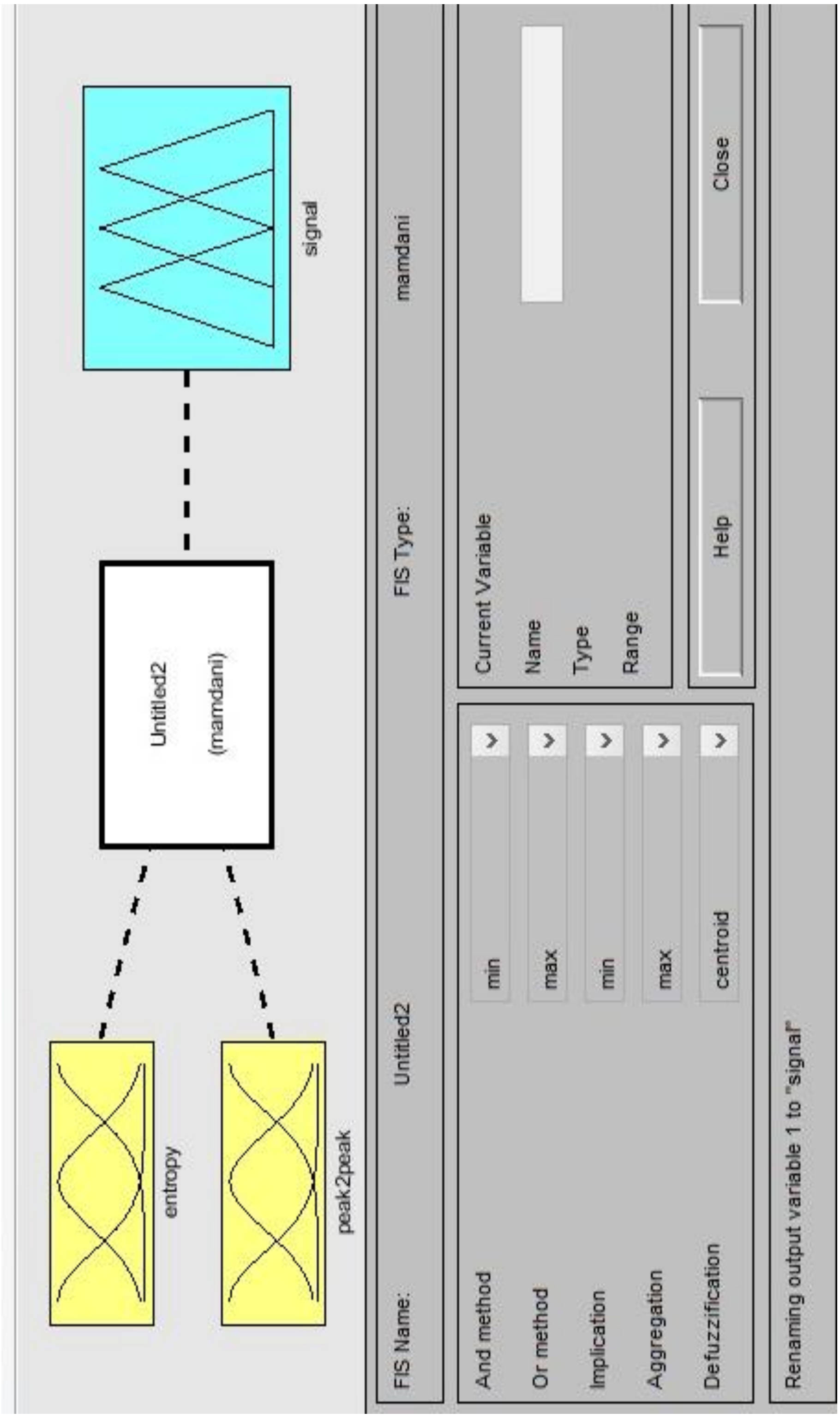


Figure 6.2 Fuzzy rule based model

6.3.3 Membership Function

Membership function maps elements of a given universal set X, i.e. crisp set into real number in [0, 1]. If the membership functions of the fuzzy set A is denoted by μ_A, and it is defined as $\mu_A : X \longrightarrow [0, 1]$

Being a fuzzy set, each set is defined completely and uniquely by one particular membership function. The symbols of membership functions may also use as labels of an associated fuzzy set. There are different types of membership function such as triangular membership function, trapezoidal membership function, Gaussian membership function, Gaussian bell membership function, etc. In this study, we used trapezoidal membership function for input variable and triangular membership function for output variable.

Figure 6.3, 6.4 and 6.5 represent membership function plots for the two input variables and one output variable respectively.

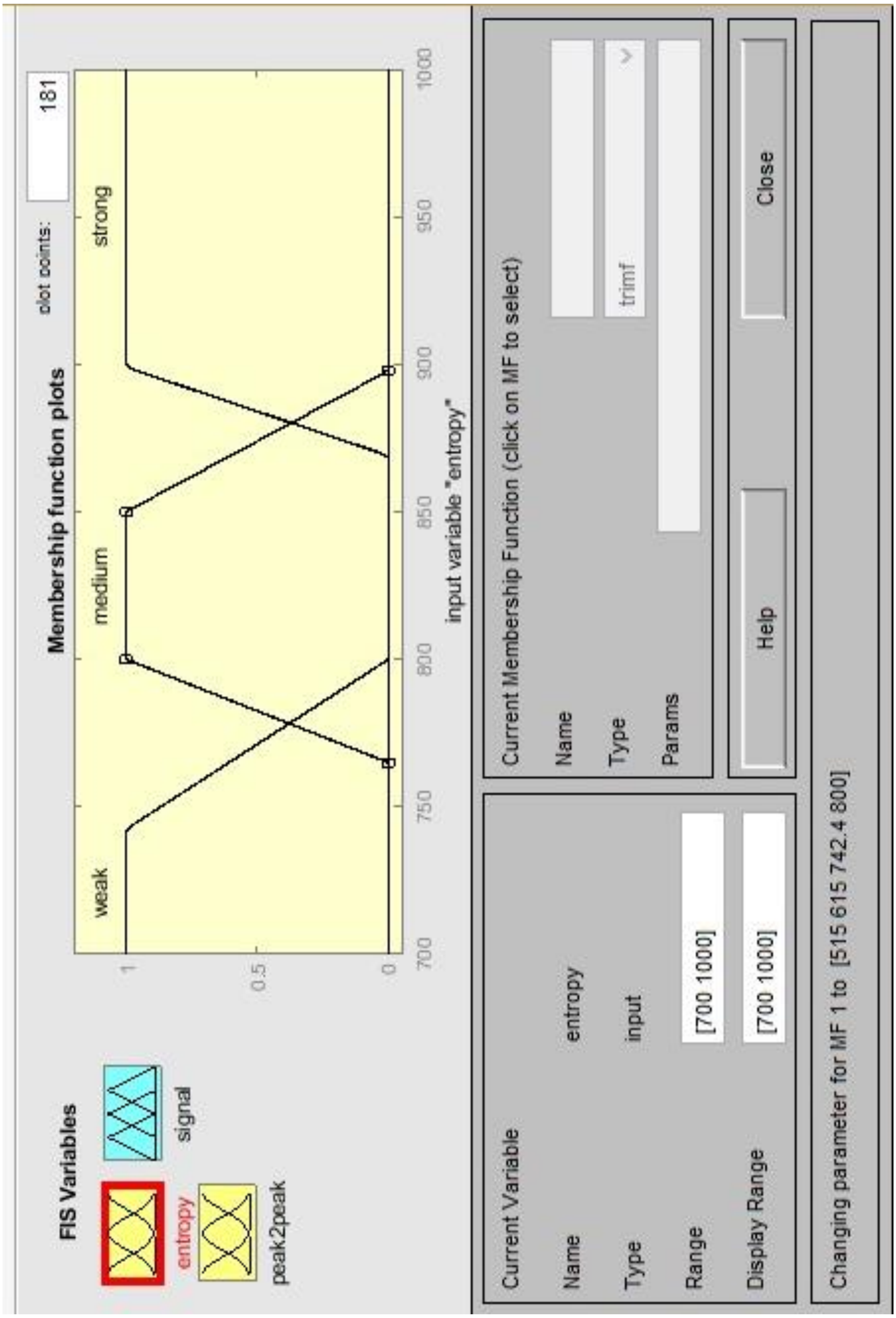


Figure 6.3 Membership Functions (log-energy entropy)

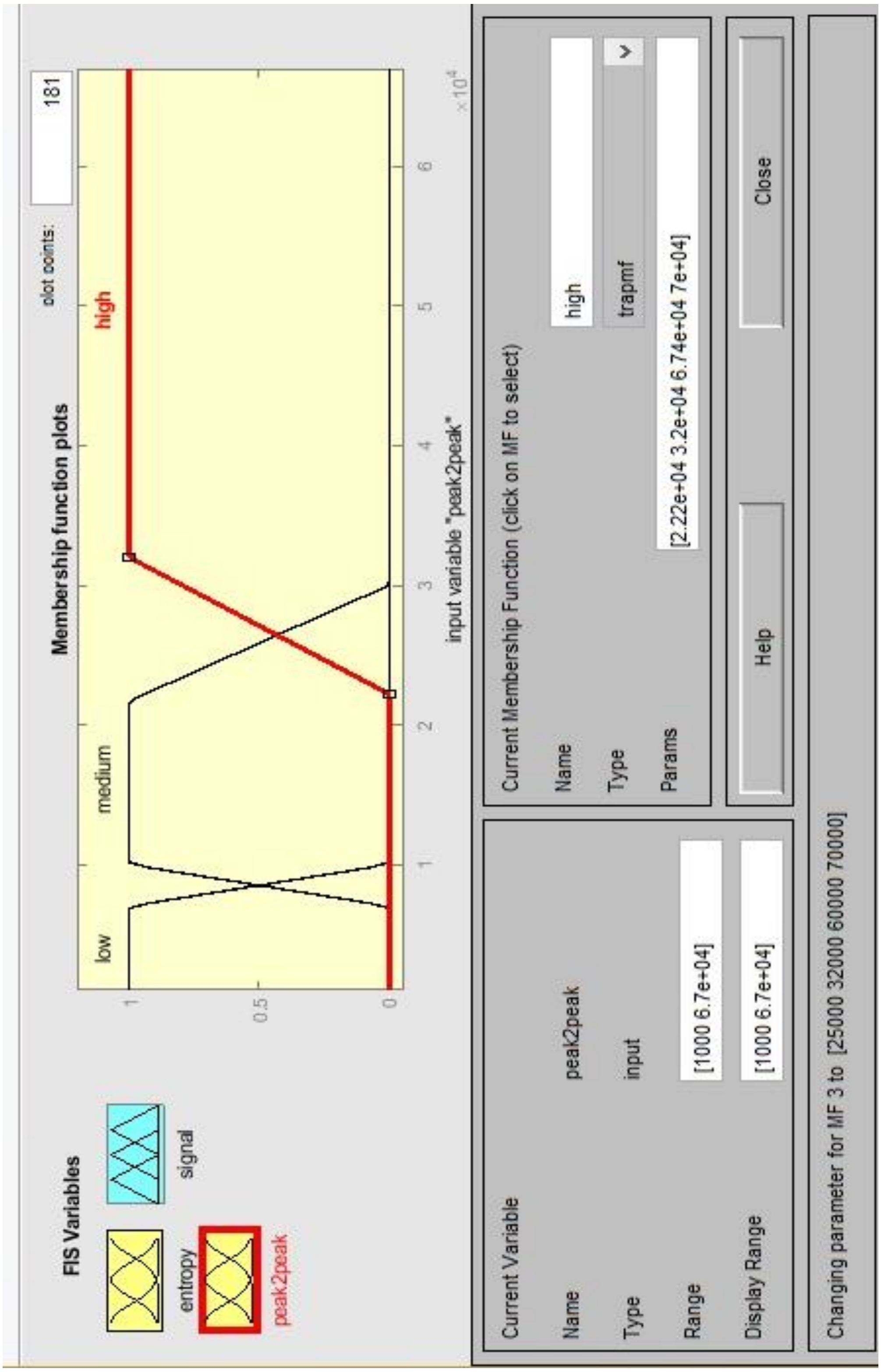


Figure 6.4 Membership Function (peak-peak)

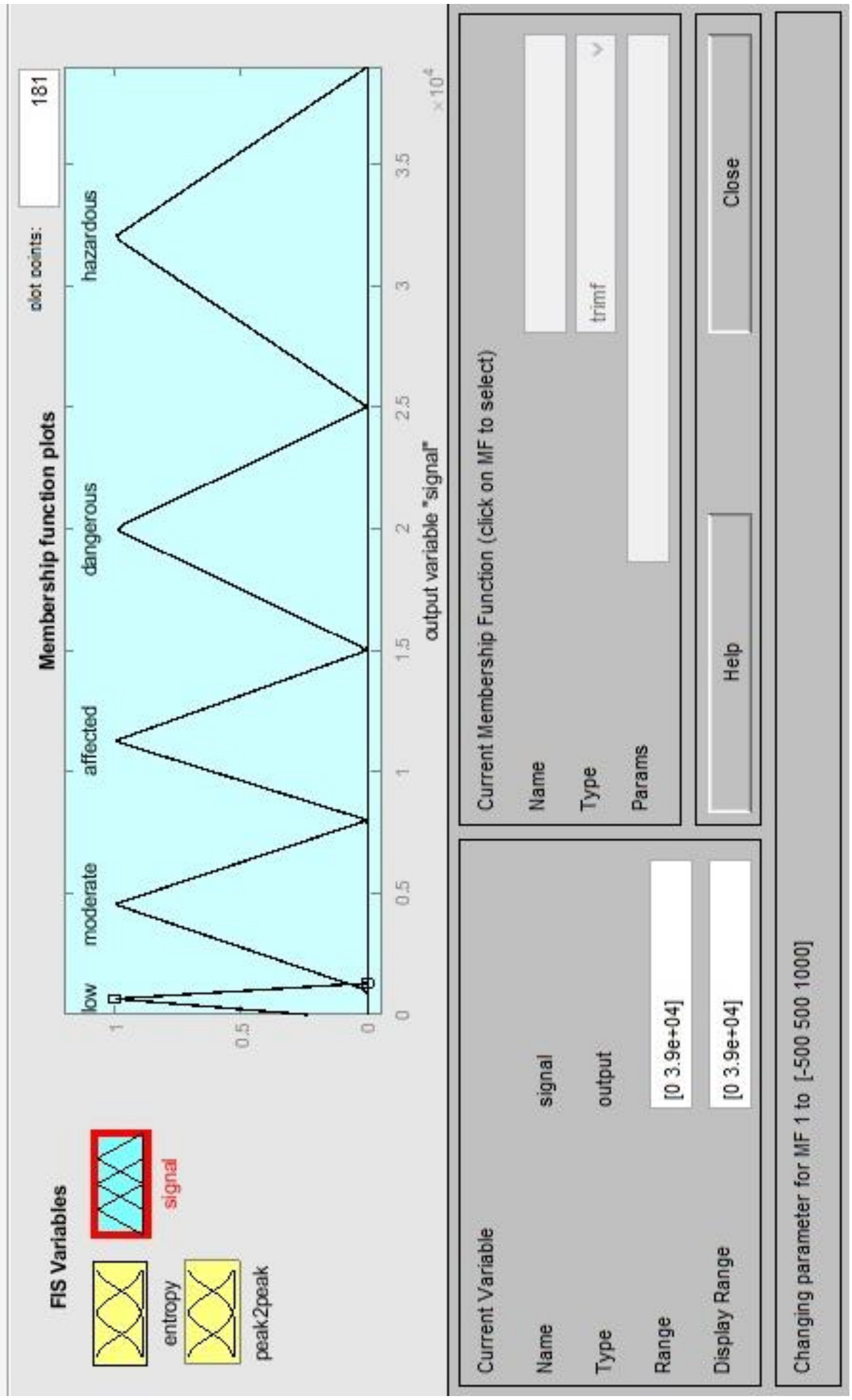


Figure 6.5 Membership Function (signal)

6.3.4 Fuzzy Score

Fuzzy scores allow us to identify non-exact matches of the target object, it is basic for the any search engine frameworks and one of the main reason is to get a relevant data for a given conditions. For the given individual input score, the fuzzy inference system generates the corresponding output fuzzy score. Fuzzy scores are calculated by the FIS system using all fuzzy constraints and membership functions. Fuzzy scores depend on the given fuzzy rules.

Fuzzy score are in between interval [0,1]. Therefore it becomes very easy to score the value using defined algorithm. Moreover, given fuzzy variables as linguistic terms it can quickly modulates the function. Instead of probability measures, this helps us to find the affected, non-affected, desirable or undesirable part under construction can be easily predicted and reconstructed. The computed fuzzy score for fuzzy variables are shown in Figure 6.6.

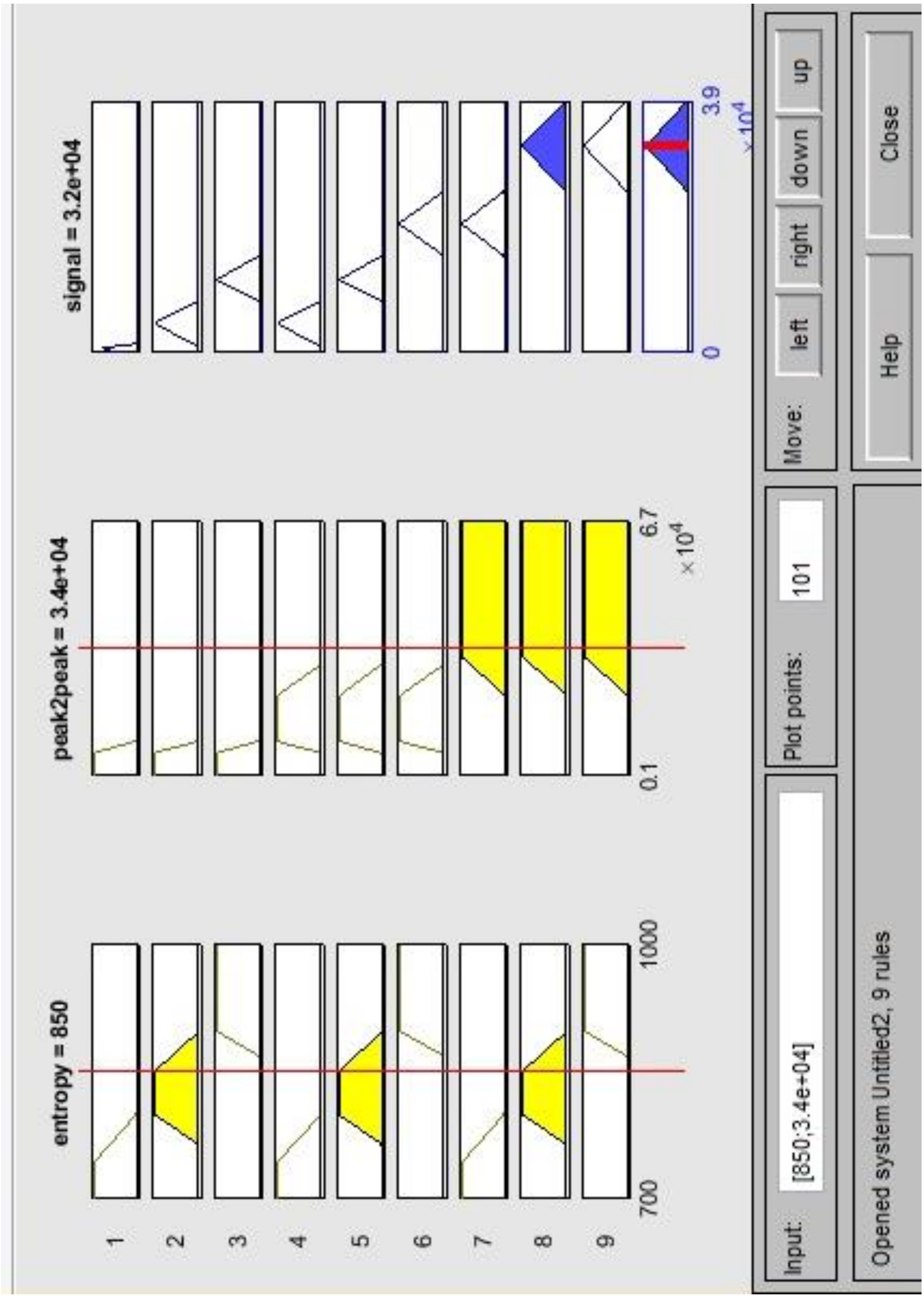


Figure 6.6 Fuzzy Score

6.3.5 Fuzzy classification

A classifier is an algorithm that assigns a class label to an object, based on the object description. It predicts the class label. The object description are in the form of vector containing value of the features (attributes) deemed to be relevant for the classification task. Moreover, the classifiers learn to predict the label for the objects using pre-defined algorithm and a training data set. When pre-defined data sets are not given then the classifier can be designed from prior knowledge and expertise. Once a module is pre-defined then the classifier is ready for operation on the unknown function.

Using MATLAB, selected 61 samples from Kobe earthquake data signals are analysed by fixing the range 0-1000 as low, 1000-5000 as moderate, 5000-10000 as affected, 10000-20000 as dangerous and 20000-35000 as hazardous. The computed result is shown in table 6.1. The above computation is also presented pictorially in figure 6.7.

Table 6.1 Feature Classification Using Fuzzy Logic Control

Signal value	Log-Energy Entropy	Peak-peak value	Classification
7513	775.473	13912	affected
4042	783.882	5004	moderate
8551	782.002	13944	affected
7650	782.113	8803	affected
5295	766.822	12055	affected
8349	780.600	11060	affected
7421	774.972	13417	affected
9055	785.674	13157	affected
4973	767.931	8394	moderate
9840	791.353	11572	affected
5664	769.946	8158	affected
5716	768.056	12339	affected
4514	729.467	11401	moderate
8650	782.722	16719	affected
4514	750.144	11426	moderate
4514	739.323	11799	moderate

5767	768.216	11822	affected
9217	786.847	13199	affected
5512	769.764	8437	affected
3753	776.881	6984	moderate
8698	783.080	10872	affected
4024	763.279	8936	moderate
4462	756.282	9893	moderate
8276	788.816	8962	affected
6609	772.587	7801	affected
4527	765.034	10337	moderate
11243	799.245	16652	dangerous
8608	782.416	16011	moderate
7733	776.731	10141	moderate
8813	783.925	14538	moderate
8358	780.657	11774	moderate
11420	802.313	21916	dangerous
11420	829.169	21356	dangerous
7309	774.375	19763	affected
31999	842.536	34857	hazardous
31999	861.466	33733	hazardous
31999	893.253	44818	hazardous
31999	943.355	63840	hazardous
10045	792.674	17652	dangerous
16760	835.171	23078	dangerous
31999	941.064	53460	hazardous
31999	945.936	66038	hazardous
31999	939.958	59893	hazardous
31999	907.803	42936	hazardous
12100	828.157	22287	dangerous
31999	849.735	37470	hazardous
28915	786.546	30189	hazardous
27475	814.785	27800	hazardous

30131	858.915	29199	hazardous
9107	786.052	15084	affected
7202	773.838	13386	affected
11420	808.524	18732	dangerous
11420	809.127	18300	dangerous
8492	781.576	15471	affected
12177	808.664	22297	dangerous
4513	753.018	12504	moderate
4514	749.993	11539	moderate
3376	750.188	7865	moderate
8692	783.032	13873	affected
7275	774.198	12086	affected

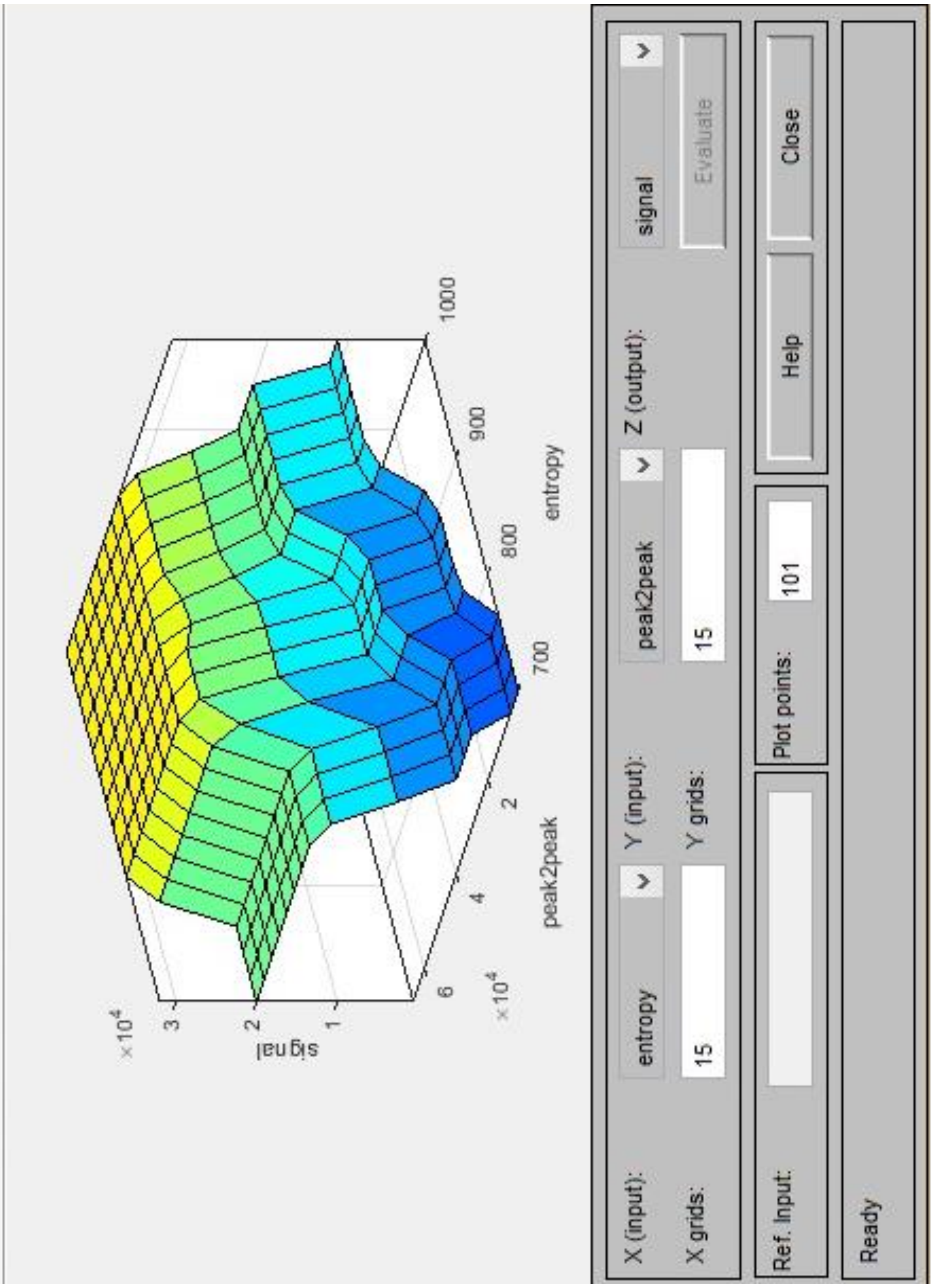


Figure 6.7 3D surface viewer

SUMMARY AND CONCLUSION

SUMMARY AND CONCLUSION

In this thesis, decomposition and classification of earthquake signals (Kobe) using discrete wavelet transform and fuzzy logic control are considered. Using MATLAB, we analysed earthquake data signal by decomposition, extraction of features and fuzzy classification.

In **chapter 1**, the theoretical concepts of seismic signal processing under wavelet transform are investigated.

Literature survey of various signal analysis and fuzzy classification are discussed in **chapter 2**.

In **chapter 3**, the preliminary definitions that are needed for the study are presented.

In **chapter 4,** the signal-noise ratio values and percentage root mean difference values for selected wavelets are computed.

Extracting the features like log-energy entropy and peak-peak value from denoised signal are calculated in **chapter 5**.

In **chapter 6**, the features are classified by using fuzzy inference system.

In this thesis, we analyzed the ground motion of KOBE (Japan) earthquake data by three-stage process: Decomposition, Feature Extraction and Classification. Using suitable wavelet transform, the signals are decomposed and features are extracted by Peak-peak value and Log-Energy Entropy. Fuzzifying the inputs and defuzzifying the output distribution using formulated fuzzy rules and Mamdani-based Fuzzy method by Fuzzy Inference System (FIS). Finally, we have done classification of the signals as low, moderate, affected, dangerous and hazardous as defined in fuzzy regulations. Using MATLAB, the above process is computed by Fuzzy Logic Control and 3D figure is presented for corresponding feature classification. This study will be helpful for the design of architectural structure with seismic excitation and sub layers of earth crust.

REFERENCES

REFERENCES

[1] **Alavi, N.** (2013), 'Quality Determination of Mozafacti Dates using Mamdani Fuzzy Inference System', Journal of the Saudi Society of Agricultural Sciences, 12, 137-142.

[2] **Albert C. To, Jeffrey R. Moore and Steven D. Glacer** (2009), 'Wavelet Denoising Techniques with Applications to Experimental Geophysical Data', Signal Processing, 89, 144-160.

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

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

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

[6] **Amara Graps** (1995), 'Introduction to Wavelets', IEEE computer society, 2(2), 1-18.

[7] **Ananthi Arun, S., Ananthanarayanan, Sivakannan S. and Prasanth, G.** (2019), 'Wavelet Transforms Applications and Interpretations based on the Signal Genesis', International Journal of Engineering and Advanced Technology, 9(1S), 30- 37.

[8] **Arshdeep Kaur and Amrit Kaur** (2012), 'Comparison of Mamdani Fuzzy Model and Neuro Fuzzy Model for Air Conditioning System', International Journal of Computer Science and Information Technologies, 3(2), 3593-3596.

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

[10] **Beenamol, M., Prabavathy, S. and Mohanalin, J.** (2012), 'Wavelet Based Seismic Signal De-Noised using Shannon and Tsallis Entropy', Computers and Mathematics with Applications, 64, 3580-3593.

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

[12] Chengwu Li, Xiaomeng Xu and Lihui Dong (2015), '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.

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

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

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

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

[17] Debasis Kundu, 'Statistical Signal Processing', Indian institute of technology, Kanpur, 1-5.

[18] Deepak R. Keshwani, David D. Jones, George E. Meyer and Rhinda M. Brand (2007), 'Rule Based Mamdani Type Fuzzy Modelling of Skin Permeability', Applied Soft Computing, 8, 285- 294.

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

[20] George J. Klir and Bo Yuan (1995), 'Fuzzy Sets and Fuzzy Logic: Theory and Application', Prentice Hall.

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

[22] Jarkko Niittymaki, Riku Nevala and Esko Turunen, 'Fuzzy Traffic Signal Control and a New Inference Method- Maximal Fuzzy Similarity', 716-728.

[23] Jerry M. Mendel (2000), ‘Uncertainty, Fuzzy Logic, and Signal Processing’, Signal Processing, 80, 913-933.

[24] Jiajun Han and Mirko Van der Baan (2015), ‘Microseismic and Seismic Denoising via Ensemble Empirical Mode Decomposition and Adaptive Thresholding’, Geophysics, 80(6), KS69-KS80

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

[26] Juan Li, Yuan Li, Yue Li and Zhihong Qian (2018), ‘Downhole microseismic signal denoising via Empirical Wavelet Transform and Adaptive Thresholding’, Journal of Geophysics and Engineering, 15, 2469- 2480.

[27] Kai Schneider and Oleg V. Vasilyev (2010), ‘Wavelet Methods in Computational Fluid Dynamics’, Annual Review of Fluid Mechanics, Annual Reviews, 42, 473-503.

[28] Károly Nagy and Márta Takács (2008), ‘Type-2 fuzzy sets and SSAD as a possible Application’, Acta Polytechnica Hungarica, 5(1).

[29] Liu Shucong and Xun Chen (2014), ‘Seismic Signals Wavelet Packet De-Noising Method based on improved Threshold Function and Adaptive Threshold’, Computer Modelling and New Technologies, 18(11), 1291-1296.

[30] Mamdani, E. H. and Assilian, S. (1975), ‘An experiment in linguistic synthesis with a fuzzy logic controller’, International Journal Man-machine Studies, 7, 1–13

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

[32] Melek Acar Boyacioglu and Derya Avci (2010), ‘An adaptive network- Based Fuzzy inference System (ANFIS) for the prediction of stock market return: The case of the Istanbul Stock Exchange’, Expert Systems with Applications, 37, 7908-7912.

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

[34] Morten Nielsen (2001), 'On the Construction and Frequency Localization of Finite Orthogonal Quadrature Filters', Journal of Approximation Theory, 108, 36-52.

[35] Nandish, M., Stanfford Michahial, Hemanth Kumar, P. and Faizan Ahmed (2012), 'Feature Extraction and Classification of EEG Signal using Neural Network Based Techniques', International Journal of Engineering and Innovative Technology, 2(4), 1-5.

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

[37] Olivier Rioul and Martin Vetterli (1991), 'Wavelets in Signal processing', IEEE SP MAGAZINE, 14-38.

[38] Meyer-baese, A. and Schmid, V. (2014), 'Pattern recognition and signals analysis in medical imaging', 22-69.

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

[40] Priti Srinivas Sajja and Rajendra Akerkar (2010), 'Knowledge- Based Systems for Development', Advanced Knowledge Based Systems: Model, Applications and Research, 1, 1-11.

[41] Qi-sheng Zhang, Ji-Juan Jiang, Jin-hai Zhai, Xin-yue Zhang, Yi-jun Yuan and Xin-wu Huang(2016), 'Seismic Random Noise Attenuation using Modified Wavelet Thresholding', Annuals of Geophysics, 59, S0647-S0657

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

[43] Rogelio Ramos, Benjamin Valdez-salas, Roumen Zlatev and Michael Schorr Wiener (2017), 'The Discrete Wavelet Transform and It Application for Noise

Removal in Localized Corrosion Measurements', Hindawi International Journal of Corrosion, 1-7.

[44] Ronald R. Coifman and Mladen Victor Wickerhauser (1992), 'Entropy-Based Algorithms for Best Basis selection', IEEE, 38(2), 713-718.

[45] Sandya H.B., Hemanth Kumar P., Himanshi Budiraja and Susha K. Rao, (2013), 'Fuzzy rule based feature extraction and classification of time series signals', International Journal of Soft Computing and Engineering, 3(2), 42-48.

[46] Serap Aydin, Hamdi melih saraoglu and Sadik kara (2009), 'Log Energy Entropy-based EEG Classification with Multilayer Neural Networks in Seizure', Annals of Biomedical Engineering, 37(12), 2009, 2626- 2630.

[47] Shannon C.E. (1949), 'A Mathematical Theory of Communication', University of Illinois Press, 1-54.

[48] Stephane Mallat and Sifen Zhong (1992), 'Characterization of signals from Mutiscale Edges', IEEE Transactions on Pattern Analysis and Machine Learning Intelligence, 14(7), 710- 732

[49] Stèphane Mallat (2009), 'A Wavelet Tour of Signal Processing: The Sparse Way', third edition, Academic Press of Elsevier, 1-30.

[50] Steven W. Smith (1999), 'Digital Signal Processing', second edition, California Technical publishing.

[51] Takagi, T. and Sugeno, M. (1985), 'Fuzzy identification of systems and its applications to modelling and control,' IEEE transactions on systems, man and cybernetics, 15(1), 116–132.

[52] Taiseer Mohammed Sidddig and Mohammed Ahmed Mohmmed (2014), 'A study of ECG signal Classification using Fuzzy Logic control', International Journal of Science and Research, 3(2), 374-380.

[53] Tianyi Wang and Subrat Nanda (2012), 'A Tutorial on Feature Extraction Methods', phm society..

[54] Timothy J. Ross (2010), 'Fuzzy logic with engineering applications', John Wiley & Sons, third edition.

[55] Tiwary, U. S., 'Fuzzy sets (Type-1 and Type- 2) and their applications', 1-59.

[56] Xiang Li, Linlu Dong, Yifan Lei and Nuwen Xu (2020), 'Micro Seismic Signal Decomposing via Empirical Mode Decomposition, Compressed Sensing and Soft Thresholding', Applied Sciences, 10, 1- 16.

[57] Xuelong Li, Zhonghui Li, Enyuan wang, Junjun Feng, Liang Chen, Nan Li and Quanle Zou (2016), 'Microseismic Signal Spectra, Energy Characteristics and Fractal Features prior to Rock Burst: A Case Study from the Qianqiu Coal Mine, China', Journal of Earthquake Engineering, 1-21.

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

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

[60] Zadeh, L. A. (1973), 'Outline approach to the analysis of complex systems and decision processed', IEEE Transactions on Systems, Man and Cybernetics, SMC-3, 28-44.

PUBLICATIONS

PUBLICATIONS

[1] Sangeetha, J. and Balamani, N. (2020), ‘Feature extraction and classification of earthquake signal using fuzzy logic control’, Aegaeum Journal, 8(9), 453-460.

[2] Sangeetha, J. and Balamani, N., ‘Decomposition and feature extraction of earthquake signal using discrete wavelet transform’, (submitted).