sEMG FEATURE EXTRACTION USING HYBRID TECHNIQUES FOR POWER X.A

By

GOH AI LING

FINAL PROJECT REPORT

Submitted to the Department of Electrical & Electronic Engineering
in Partial Fulfillment of the Requirements
for the Degree
Bachelor of Engineering (Hons)
(Electrical & Electronic Engineering)

Universiti Teknologi PETRONAS
Bandar Seri Iskandar
31750 Tronoh
Perak Darul Ridzuan

CERTIFICATION OF APPROVAL

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Approved:

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Assoc. Prof. Dr. Irraivan Elamvazuthi
Project Supervisor

UNIVERSITI TEKNOLOGI PETRONAS
TRONOH, PERAK

May 2012

CERTIFICATION OF ORIGINALITY

This is to certify that I am responsible for the work submitted in this project, that the original work is my own except as specified in the references and acknowledgements, and that the original work contained herein have not been undertaken or done by unspecified sources or persons.

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Goh Ai Ling

ABSTRACT

This research is about the surface Electromyography (sEMG) feature extraction using hybrid method for Powered Exoskeleton Arm (Power X.A) application. The main objective of this research is to investigate the feature extraction techniques for EMG signal processing. This report is divided into 5 chapters. The first chapter is about the introduction, the second chapter is on the literature review and theory of this research, the third chapter is on the methodology used in this project, the fourth chapter is the discussion of the results and the final chapter is the conclusion and recommendation of this research. EMG is the biomedical signal and widely in used in clinical applications. This research can be divided into 3 parts where the 1st part is on the design on the experimental procedure, the 2nd part is on the signal acquisition and the 3rd part is on the feature extraction based on hybrid techniques. The raw EMG signal was collected from different test subjects and further processed in MATLAB to obtain the clean EMG signal. The most powerful EMG feature extraction which is wavelet techniques and mean absolute value was used for this research. The result shows that Daubechies wavelet order 7 in level 1 and 2 gives the best performance in EMG feature extraction.

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LIST OF ABBREVIATIONS

CWT	-	Continuous Wavelet Transform
DWT	-	Discrete Wavelet Transform
EMG	-	Electromyography
MAV	-	Mean Absolute Value
MUAP	-	Muscle Action Unit Potential
NN	-	Neural Network
RMS	-	Root Mean Square
SC	-	Slope Sign Change
sEMG	-	Surface EMG
WL	-	Waveform Length
ZC	-	Zero Crossing

CHAPTER 1
INTRODUCTION

1.1 Background Study

In this new era, biomedical area has been improved with new technology to increase the quality of human lives. With the help of current technologies, we can be able to investigate the diseases or weaknesses which have been found in the human body. Electrical signal which is obtained from any organ of human body exhibits the physical variable of the activity is known as biomedical signal.

Electromyography (EMG) signal which is a type biomedical signal derived from neuromuscular activities of skeletal muscle [1]. EMG signal measures electrical currents generated in the muscle fibers and can be observes at the surface of the skin. Technology to collect the EMG signal from human body has been widely developed and used for clinical and engineering purpose. Research has been carried out on EMG signal due to the importance of EMG in physiological area.

1.2 Problem Statement

EMG signal are often used as an input for rehabilitation and diagnostics purpose in clinical applications. EMG signal also act as control signal for the powered exoskeleton devices for upper limbs and lower limbs. Exoskeleton is an external structure mechanism with joints and links corresponding to human body. This application has been widely developed using EMG signal for the people who has loss their muscle strength. Deterioration of skeletal muscle is changing with age. The decline in muscle strength may have important functional consequences. The powered exoskeleton device is crucial for human with loss of muscle strength. Figure 1 shows the graph with muscle strength loss with age.

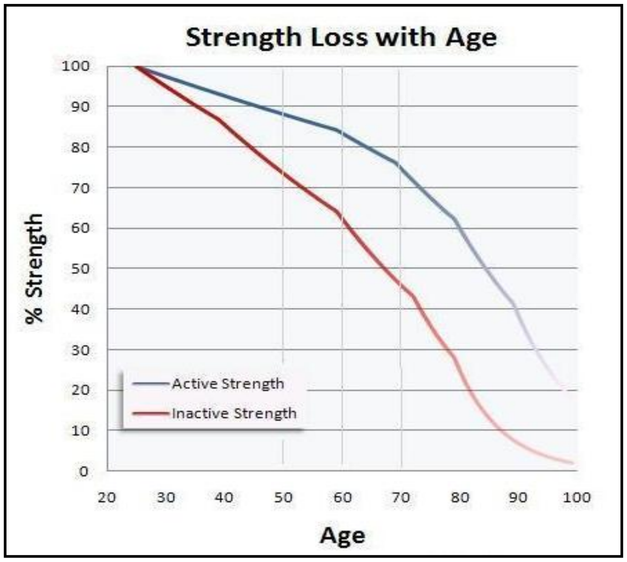


Figure 1: Graph for Strength Loss with Age.

Adapted from StrongAge (n.d.)

There are many people in this world who are losing their arm's muscle strength. Due to this, many researchers are developing algorithms for the powered exoskeleton application to improve the disable people life. In this project, the main focuses are on the upper limb of human body for the powered exoskeleton arm application. The powered exoskeleton arm model is shown as Figure 2 below.

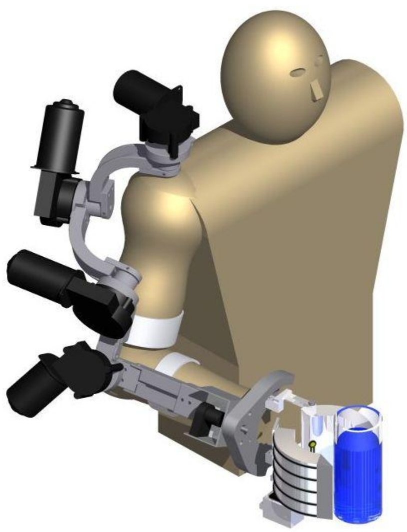


Figure 2: The powered exoskeleton arm. Adapted from

University of Kwazulu-Natal (2009) MR2G Bio-Engineering Unit.

Due to the non-stationary and subject dependency characteristic of the EMG signal, we can say that EMG is a complicated signal. Since the EMG signals are subject dependent, the selection of the feature extraction to be able to classify different motions become a difficult task. In past decades, vast research and efforts has been made in establish more suitable algorithms, improving current methodologies, and improvise tracking techniques which can attain more accurate EMG signals [4].

1.3 Objectives

There are three objectives in this research which are:

i. To investigate and understand the techniques and application for EMG
ii. To design the appropriate experimental procedure for signal acquisition
iii. To highlight the useful information from the EMG signal using hybrid techniques which is the combination of frequency domain and time domain techniques.

1.4 Scope

The scope of this research can be divided into two parts. The first part is to conduct the experiment and collect the raw EMG signals from the test subjects and the second part is to process the EMG signal offline.

1.5 Equipment Required

The equipment required to carry out this research are as below:

i. Delsys Trigno Wireless Sensors – equipment to acquire EMG signals
ii. Delsys TrignoWorks 4.0 – Software for signal acquisition
iii. Alcohol – to remove the skin sites from test subjects

iv. MATLAB 2009a (student version) – to process and analysis the EMG signals

CHAPTER 2
LITERATURE REVIEW

2.1 Measuring and Collecting EMG signal

EMG is known as a complex signal where it is based on the physiological properties of human muscle. These physiological properties of EMG signal are controlled by human body nervous system. Noise will be acquired while EMG signal travelling through different tissues. Muscle action potential is developed from the muscle tissue which conducts electrical current. Technique to record the information in muscle action potential is known as surface EMG (sEMG). The surface EMG is the summation of the entire muscle action unit potential (MUAP) underneath the sensors that placed on the skin surface [5]. The electrical signal generated during muscle activation which is the EMG signal can be measured by placing the EMG sensors on the surface of the skin at the desired muscle. Placing the sensor at the correct place can give a better EMG signal. We can obtain a good EMG signal by finding a good and stable skin surface. From the skin surface the EMG sensor can be arranged parallel to the desired muscle. The superposition with the MUAP with surface EMG is shown in Figure 3.

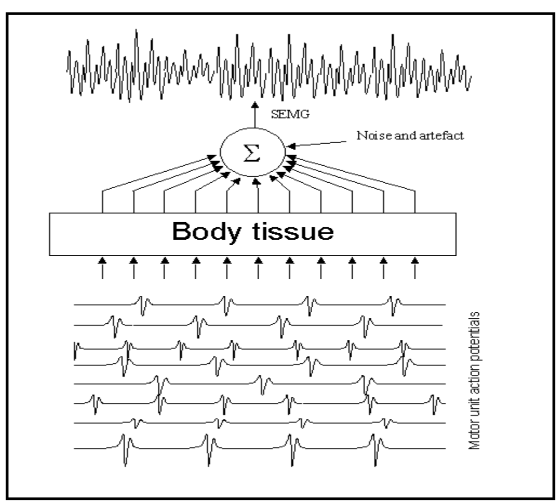


Figure 3: sEMG as superposition with the MUAP.

In signal acquisition, determine the choice of the suitable muscle to collect the sEMG signal are critical in order to discriminate between movement of the powered exoskeleton arm and the choice of the sensors to apply. The correct procedure and types of movement needed to be taken into examination in order to achieve a better result.

Since we are considering the application for the control of exoskeleton arm, we will be looking at the muscles focusing on human hand. Human hands are capable of 4 types of basic motion. These are flexion, extension, pronation and supination. Figure 4 shows the human hand basic motion and Figure 5 shows the human forearm muscle.

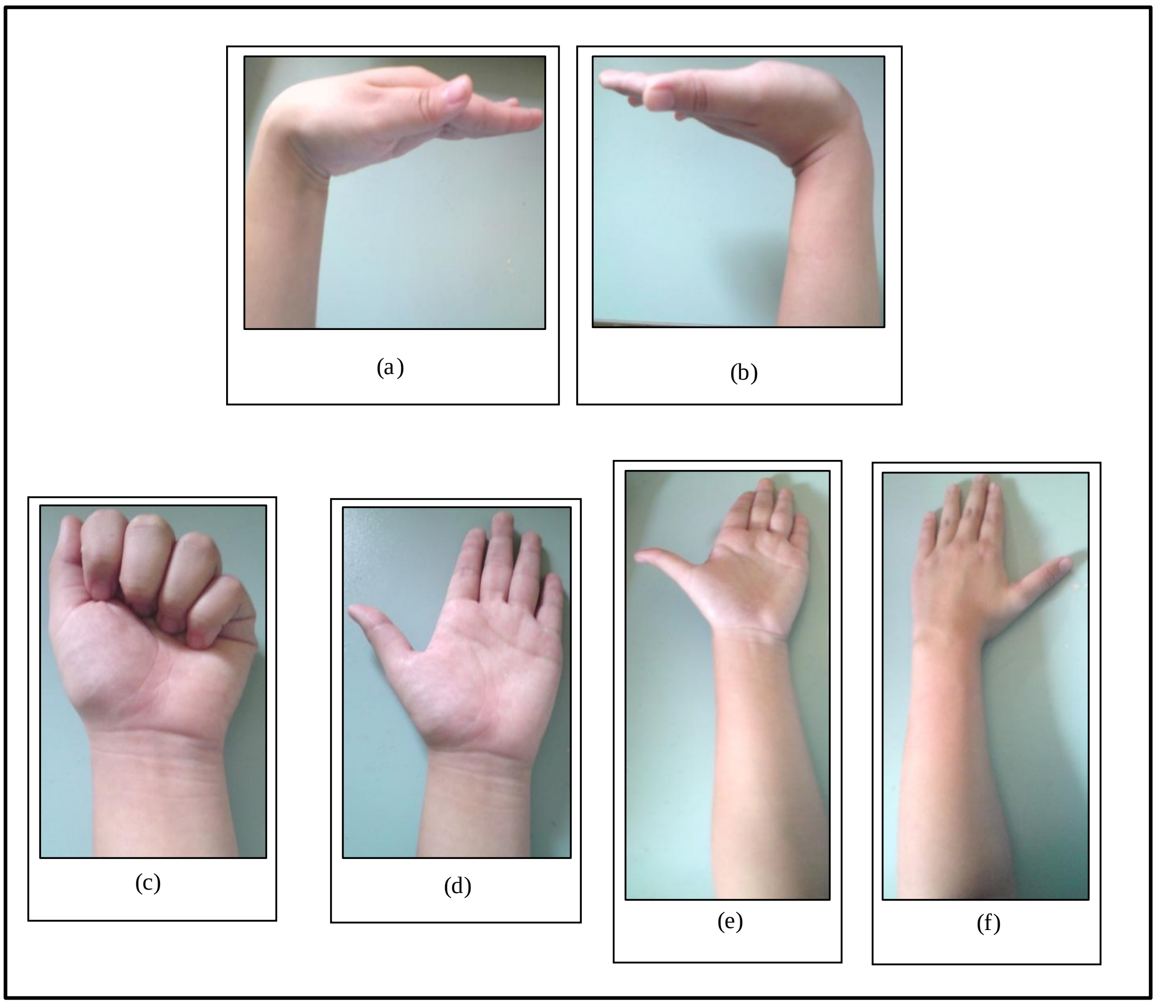


Figure 4: Hand Basic Movement (a) Wrist flexion (b) Wrist extension (c) Hand close

(d) Hand open (e) Forearm Supination (f) Forearm Pronation

The lists of important muscle are show in Table 1 below.

Table 1: List of movements and muscles involve

Body Part	Movement	Muscle
Wrist	Extension	Extensor Capri radialis, Extensor carpi ulnaris
	Flexion	Flexor Capri radialis, Flexor carpi ulnaris
Hand	Open	Palmaris Longus
	Close	
Forearm	Pronation	Pronator teres
	Supination	

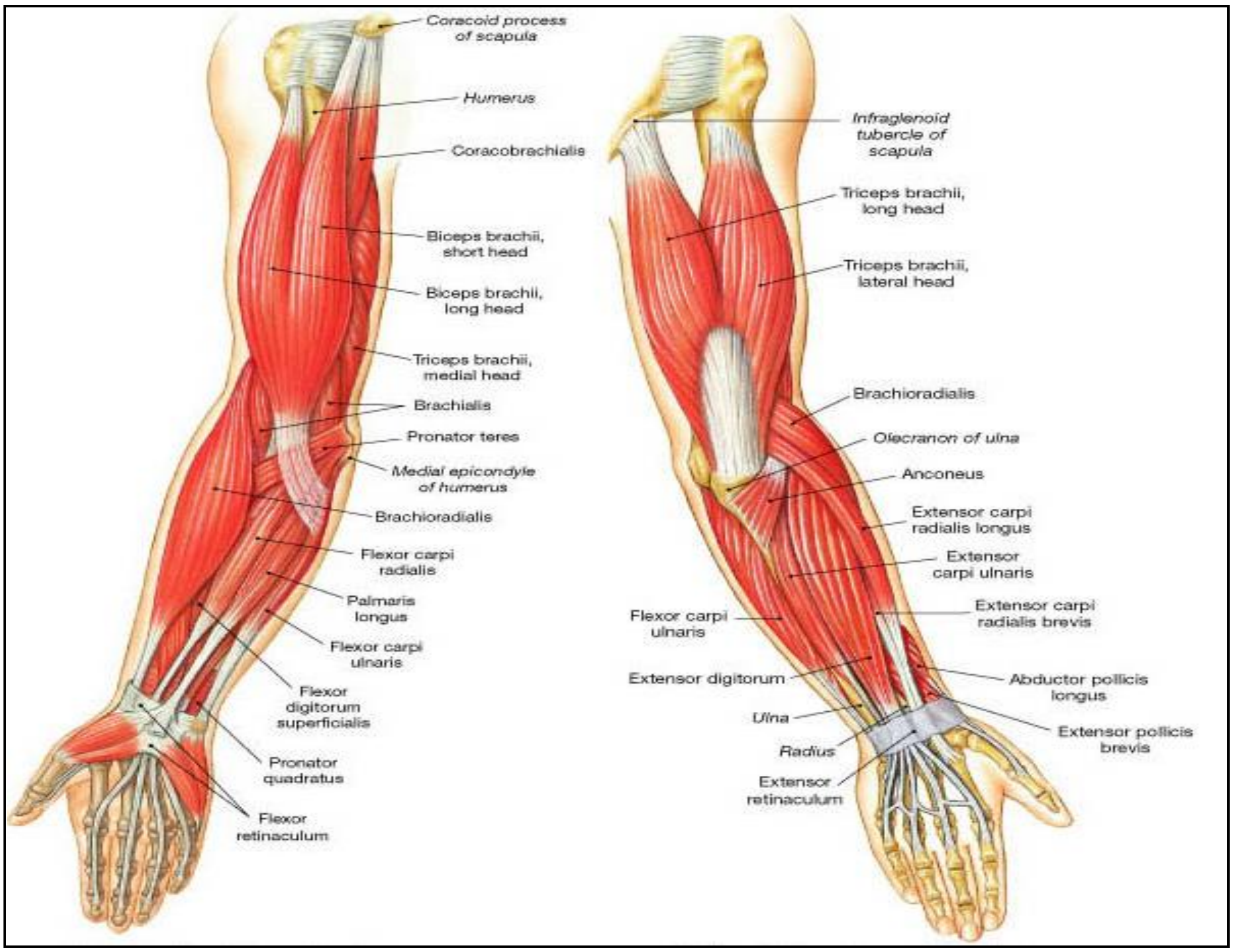


Figure 5: Front (left) and posterior (right) view of the human forearm muscle.

Adapted from Muscle that Move the Forearm (n.d)

2.2 EMG signal processing

After collecting the raw EMG signal from the test subject, techniques to process the EMG signal are needed. The raw EMG signal not only contents the useful information but also included the noise which is non desired signal. The choice of sampling frequency for EMG measurement also needed to be taken into consideration. The sampling rate of Analog/Digital kit must be at least twice as high as the maximum probable frequency of the signal. This method is known as the Nyquist's sampling theorem. Too low sampling frequency will lead to aliasing in the raw EMG signal [8].

The signal is then needed to be filtered by using filter. Filtering method such as high-pass, low-pass filter and notch filter can be used in filtering the EMG signal. The typical bandpass frequency ranges are from 10 to 20 Hz for the high pass and 500 to 1000Hz for the low pass filter. In filtering EMG signal, we need to use high pass filter because the signal will compromise of low frequency components which are less than 10Hz and the low pass filter is used to remove higher frequency components to avoid signal aliasing. Figure 6 shows the effects of low and high filters on a signal waveform.

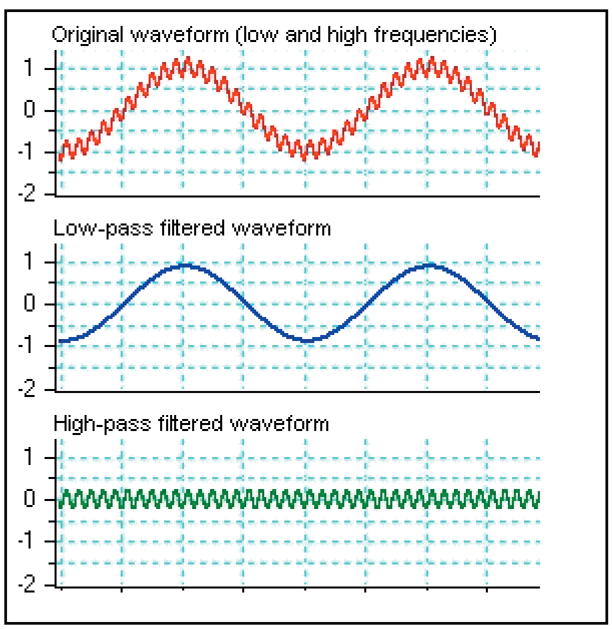


Figure 6: Effects of low and high pass filters on a signal waveform

Adapted from ADInstrumentS. S.S Young(2001). *Signal Filtering*.

The steps to process the EMG raw signal from the test subjects are showed as the Figure 7.

Figure 7: Process of Raw EMG signal

2.3 Feature Extraction

Feature extraction is an important step to better classification results. Feature extraction is needed in order to highlight the useful information or data from the signal. EMG signals can be represented in both time domain and frequency domain features [9]. Time domain features are amplitude versus time representation of the signals. Signal processing application requires additional information that is not present in the time domain representation, thus signals are usually analyze in frequency domain.

2.3.1 Time Domain Features

Root mean square, mean absolute value, zero crossings, and waveform length are the time domain features which are commonly applied in EMG feature extraction. Although the variance in the time structure of these signals is high, waveform statistics may be stable enough to allow pattern recognition.

2.3.1.1 Root Mean Square

Root mean square is calculated by squaring each data point, summing the square, dividing the sum by taking the number of samples and taking the square root. It is defined as:

$$RMS = \sqrt{\frac{1}{N}\sum_{n=1}^{N} {x_n}^2}$$

2.3.1.2 *Mean Absolute Value*

This feature take the average of the absolute signal of k samples, where the function can be shown as below

$$\bar{X}_i = \frac{1}{N}\sum_{k=1}^{N} |x_k|$$

The function below gives the difference of two MAV samples [9]:

$$\Delta\bar{X}_i = \bar{X}_{i+1} - \bar{X}_i$$

2.3.1.3 *Zero crossing*

The frequency provided from the signal is counted from the number of times zero crossing of the waveform happens. A threshold (σ) is included to reduce noise induced zero crossings. Let's get the two consecutive samples x_k and x_{k+1} , the increase of the zero crossing count, if [9]:

$$\{xk > 0 \; and \; xk{+}1 < 0\} \; or \; \{xk < 0 \; and \; xk{+}1 > 0\} \;\; \text{and} \;\; |xk - xk{+}1| \geq \sigma$$

2.3.1.4 *Waveform length*

Waveform length provides the features from the waveform frequency, amplitude and duration. The length of the waveform is the accumulation of the over each breakdown. The parameter of waveform length as show below [9]:

$$l_o = \sum_{k=1}^{N} |x_k - x_{k-1}|$$

2.3.2 *Time Frequency Features*

2.3.2.1 Wavelet Transform

Wavelet transform represent in two dimensional time frequency domain. Wavelet transform is an effective feature extraction technique for examination of fast transient response and non-stable signal. This method gives better benefits where it can be able to generate useful subset components of the frequency from the EMG signals [10]. Through the selection of the useful frequency components, it can remove efficiently the noise and unusable components in the signal. A single basic wavelet $\psi(t)$ which is known as mother wavelet was used to generate wavelet function and the definition of this algorithm are below [11]:

$$\psi_{a,b}(t) = \frac{1}{\sqrt{a}}\psi\left(\frac{t-b}{a}\right), a, b \in R; a \neq 0$$

where a, b are the scale and translation factors and,

$\frac{1}{\sqrt{a}}$ gives the energy normalization across the different scales

Wavelet transform are generally represent in two different types, first is the discrete wavelet transform (DWT) and continuous wavelet transform (CWT). CWT represents the wavelet in continuous time function. The scaling and translating scales in DWT are used to overwhelm the excessive information in continuous wavelet. The DWT scaling function are shown as follow [10]:

$$d_{j,k} = \langle f, \psi_{j,k} \rangle, \psi_{j,k} = a_o{}^{-\frac{j}{2}} \psi\left(a_o{}^{-j} t - k b_o\right)$$

where j, k are integers, $a_o > 0$ is fixed dilation step

b_o is the translation factor is dependent on a_o

DWT is often used in real-time engineering applications. DWT can transform a signal into multi-resolution of wavelet coefficient subset.

In wavelet transform, we often look at details and approximation of each signal. The detail components consist of low scale and high frequency element while approximation consists of high-scale and low frequency element in the signal.

One signal is broken down into lower-resolution elements from the approximations of level decomposition in wavelet analysis [12]. The wavelet decomposition tree is shown in Figure 8 where S is the original signal while cA is the approximation coefficient and cD is the detail coefficient.

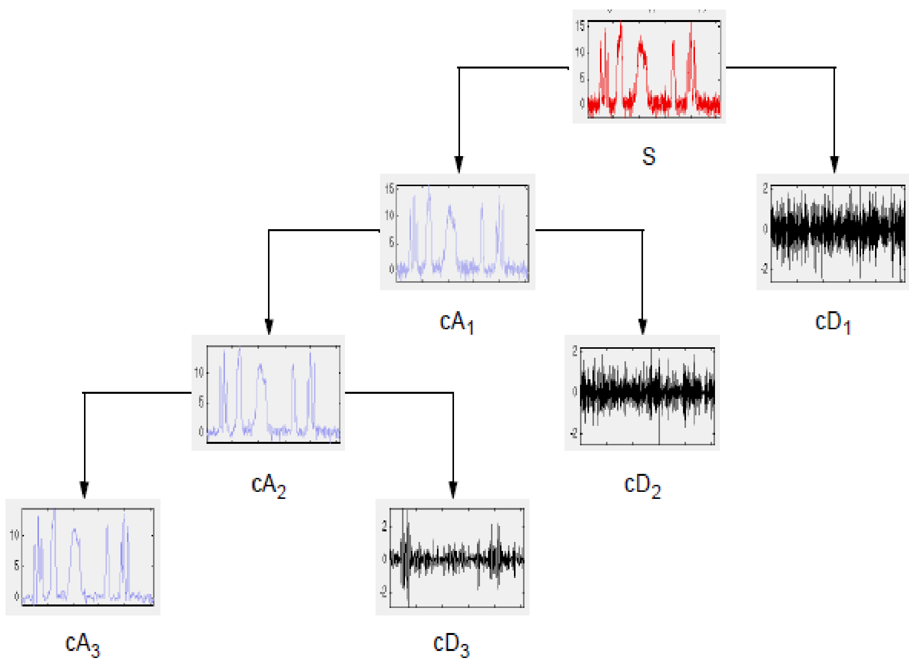


Figure 8: Wavelet decomposition tree. Adapted from

M. Misiti, Y. Misiti, G. Oppenheim, J.M Poggi,

Wavelet Toolbox for use with MATLAB

In wavelet transform, decomposition can decompose into coefficient approximation and coefficient detail. The coefficient components can be assembled back into the original signal without any loss of important information from the signal itself. This is known as wavelet reconstruction techniques in wavelet transform. The process in wavelet reconstruction involves of upsampling and filtering techniques. Upsampling here is used to lengthening signal components.

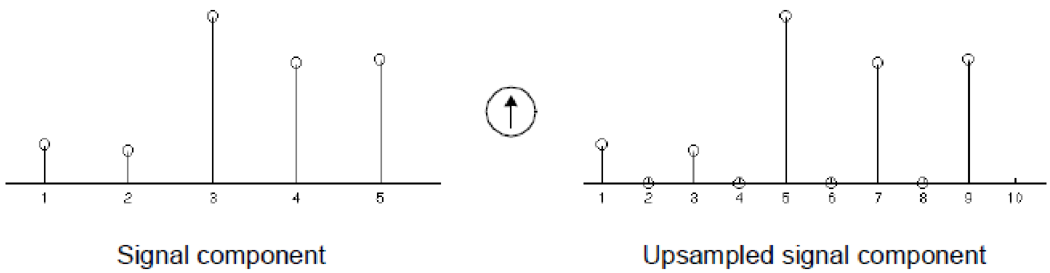


Figure 9: Wavelet reconstruction upsampling signal component techniques

Adapted from M. Misiti, Y. Misiti, G. Oppenheim, J.M Poggi,

Wavelet Toolbox for use with MATLAB

In wavelet reconstruction process, the filtering techniques are important in order to achieve the perfect reconstruction signal. Here, the coefficients components from the wavelet decomposition will be resemble back to the original signal by producing the approximation and details components. The wavelet reconstruction tree is shown in Figure 10.

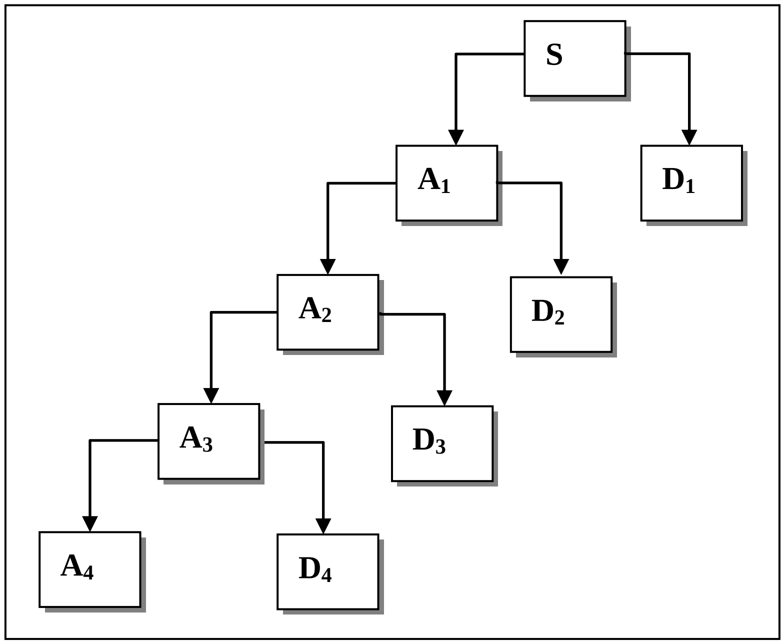


Figure 10: Wavelet reconstruction tree for wavelet transform level

2.3.2.2 Daubechies wavelet

In this research, we are focusing on Daubechies wavelet in the wavelet transform families. The names of Daubechies family wavelets are written in dbN, where the N is the order for the Daubechies wavelet families. The Daubechies represented in the scaling function. The higher the Daubechies order, the higher the scaling function for the signal. Figure 11 shows the Daubechies wavelet families from order 2 to 10.

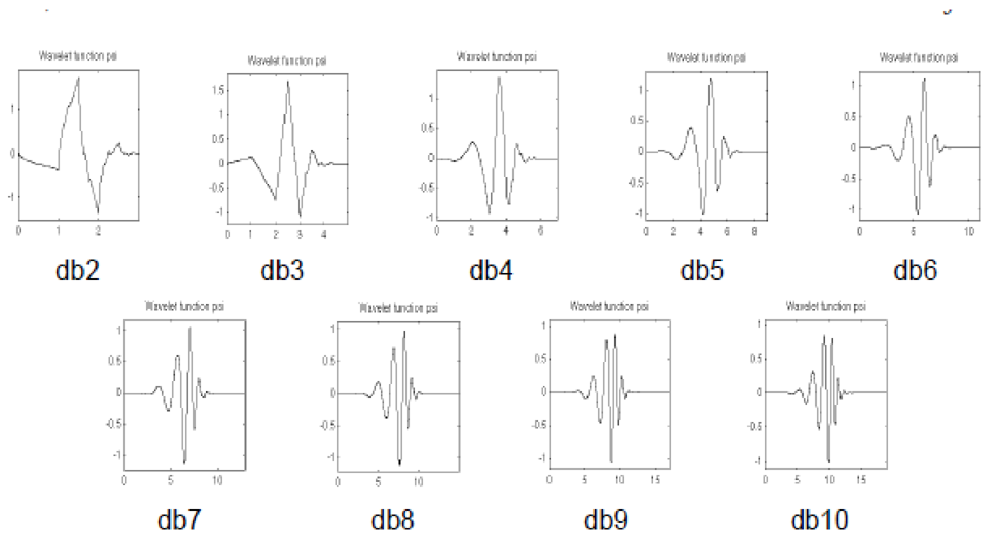


Figure 11: Daubechies wavelet families from db2 to db10

Adapted from M. Misiti, Y. Misiti, G. Oppenheim, J.M Poggi,

Wavelet Toolbox for use with MATLAB

2.4 Comparison between the feature extraction techniques

Table 2 shows the comparison between the different techniques of feature extraction from different researchers.

Table 2: Comparison between the feature extraction methods (MAV= Mean Absolute Value, ZC = Zero Crossing, SC = Slope Sign Change, WL = Waveform Length, NN= Neural Network)

No	Author	Title	Year	Method		Accuracy (%)
				Features	Classifier	
1	A.Phinyomark, C.Limsakul, P.Phukpattaranont	Application of Wavelet Analysis in EMG Feature Extraction for Pattern Classification[10]	2011	Wavelet Transform	-	-
2	Sang Wook Lee, Kristin M.Wilson, Blair A.Lock, Derek G. Kamper	Subject-Specific Myoelectric Pattern Classification of Functional Hand Movements for StrokeSurvivors[13]	2011	MAV, ZC,SC, WL	LDA	73

3	Yanjuan Geng, Long Yu, Miao You, and Guanglin Li	A pilot study of EMG pattern Based Classification of Arm Functional Movements [14]	2010	MAV,ZC, WL, SC	LDA	94
4	V. Rajesh, Dr.P. Rajesh Kumar	Hand Gestures Recognition Based on SEMG Signal Using Wavelet and Pattern Recognisation [15]	2009	Wavelet Transform + Entropy	Minimum Distance	96.66
5	Zhihong Liu, Zhizeng Luo	Hand Motion Pattern Classifier Based on EMG Using Wavelet PacketTransform and LVQ Neural Networks [16]	2008	Wavelet	NN	98
6	Matteo Arvetti, Giuseppina Gini, and Michele Folgheraiter	Classification of EMG signals through wavelet analysis and neural networks for controlling an active hand prosthesis [9]	2007	Wavelet Transform	NN	96
7	Rami N Khushaba, Adel Al-Jumaily	Fuzzy wavelet Packed based Feature Extraction Method for Multifunctional Myoelectric Control [17]	2006	Wavelet	Fuzzy	99
8	Yucel Kocyigit, Mehmet Korurek	EMG signal classification using wavelet transform and fuzzy clustering algorithms [18]	2001	Wavelet transform	Fuzzy	95.7

From Table 2, we can see that feature extraction based on Wavelet method can achieve greater classification accuracy if compare to the time domain method. The accuracy for time domain feature extraction basically can reach up to 94% , however wavelet method can give a better classification accuracy which is above 95%. Furthermore the classification accuracy can still be improved further by using the wavelet transform method with other feature extraction method.

2.5 Evaluation of Feature Extraction

In this research, evaluation criteria are used to compare the feature extraction techniques. A better class separability viewpoint will gives a better performance and enhance the feature extraction techniques [19]. The separation between the motions was measured and the minimum variation in the subject would yield a better results. In this context, we are using the statistical measurement criteria which are known as RES index method. We are investigating the performance of the feature extraction by using this statistical measurement index. Euclidean Distance (ED) is used for the separation index and Standard Deviation (SD) is used to measure the variability which is also used as a compactness index. ED is defined as [19]:

$$ED = \sqrt{(a_{ch1} - b_{ch1})^2 + (a_{ch2} - b_{ch2})^2}$$

where a and b is the feature mean of two motion from the six daily upper limb motions

ch1 is flexor capri radialis muscle

ch2 is extensor capri radialis muscle.

The SD equation is given by

$$SD = \sigma = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(x_1 - \bar{x})^2}$$

where N is the number of samples, x_1 is the MAV features

$\bar{x}$ is the mean of the MAV features.

The ratio between ED and SD is known as RES index [19].

$$RES\ Index = \frac{ED}{\bar{\sigma}}$$

The higher the RES index value, the better the class separability performance which can lead to a better classification performance.

CHAPTER 3
METHODOLOGY

The overall project can be divided into three parts, design of the experimental procedure, signal acquisition and feature extraction using hybrid techniques.

3.1 EMG signal acquisition and experiments

The correct method need to be designed in order to collect the EMG signals. In this research, there are six hand gestures will be performed by the test subject. The hand gestures are listed as in Table 3.

Table 3: List of movements needed for the experiment

Body part	Movement
Hand	Open
	Close
Wrist	Flexion
	Extension
Forearm	Pronation
	Supination

There are 10 different test subjects from the age range of 20 to 23 years old. The test subjects will be asked to perform all six movements with a rest in between the change of a movement. Subject will be asked to hold for about 5 second for one movement and rest for 5 seconds before the next movement. Each subject will be needed to perform 6 different movements with seven rests in 1 set. 2 set of EMG raw data will be taken from each subjects. Figure 12 shows the full Delsys Trigno signal acquisition system that is use for collecting the raw EMG signal from the test subject. Figure 13 shows Delsys Trigno Wireless sensor which is the hardware which is used to acquire the EMG signal from subject’s muscle.

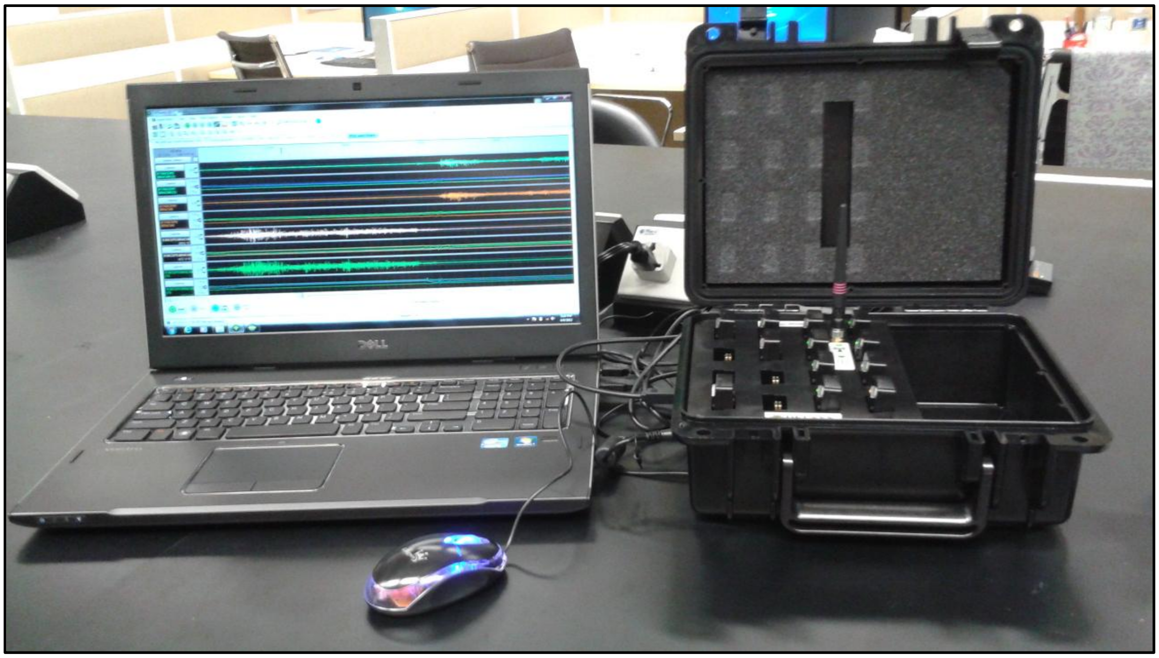


Figure 12: Delsys Trigno Signal Acquisition System

Figure 13: Delsys Trigno Wireless Sensor, Adapted from Delsys Trigno Wireless Sensor (2012)

Figure 14 shows the EMGWorks 4.0 signal acquisition software which is function as the main interface between the hardware and the acquired signal. Figure 15 shows the placement of Delsys Trigno Wireless sensor on subject’s skin.

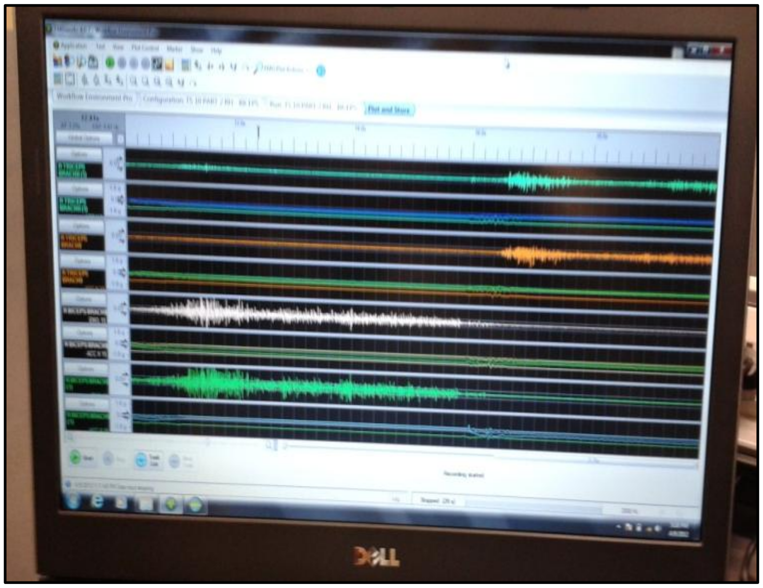


Figure 14: EMGWorks 4.0 Signal Acquisition Software

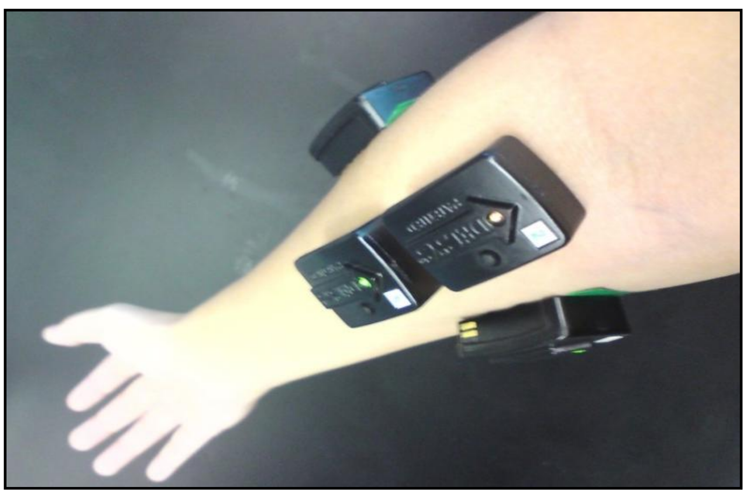


Figure 15: Placement of Delsys Trigno Wireless Sensor on subject’s skin

3.2 EMG Signal Processing

After collecting the original EMG signals from the test subjects, processing and analysis of the EMG signals are performed to obtain the required results. The raw EMG signal will be pre-process using the Delsys EMG Works analysis software to remove the unwanted noise. Here we are using Butterworth bandpass filtering techniques from 10Hz to 500 Hz to filter out the excessive noise in the signal. The output from the analysis will be further improved in MATLAB by using the wavelet techniques. In this research, we are using Daubechies wavelet due to its effectiveness in extracting the important information from the EMG signal. Multi-level of Daubechies wavelet will be used here from Daubechies order 4, 7 and 10. Figure 16 shows the wavelet toolbox main menu which is used for wavelet analysis.

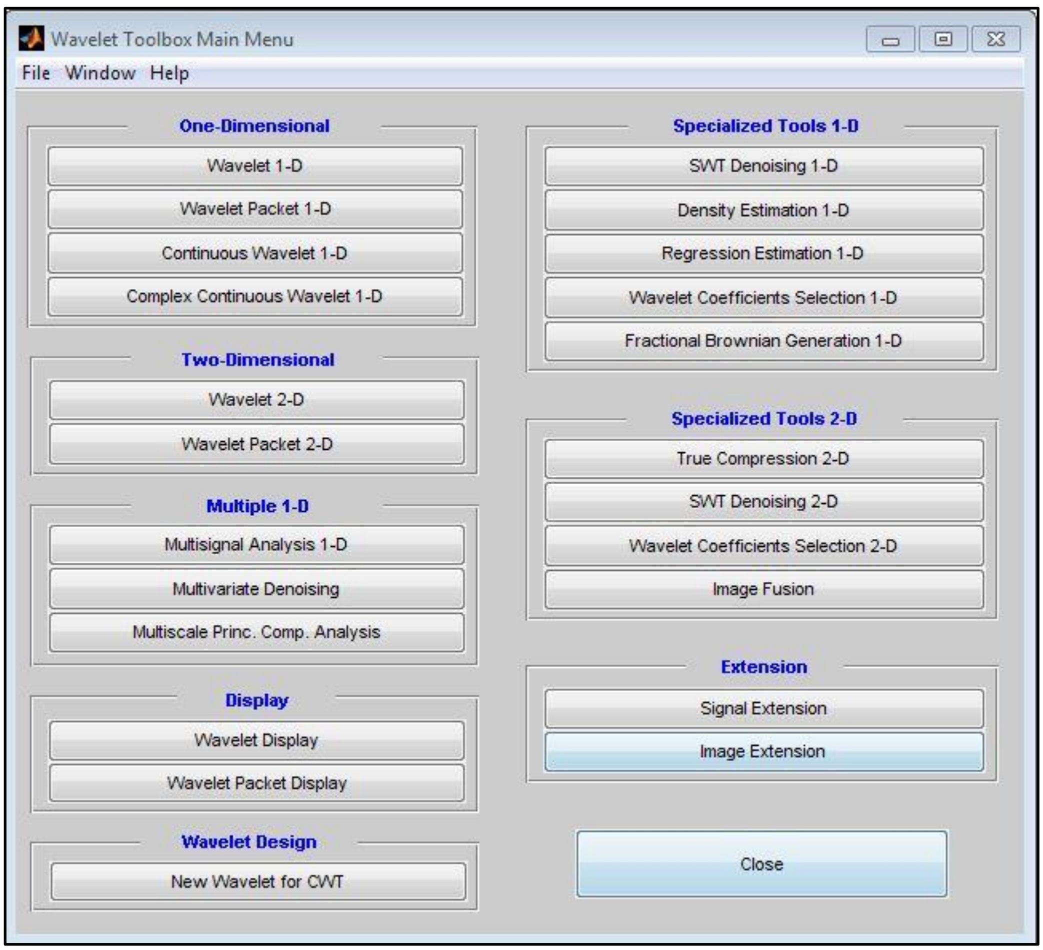


Figure 16: Wavelet Toolbox Main Menu

Figure 17 shows the wavelet analysis using the wavelet toolbox for Daubechies wavelet order 4 level 2. The overall process flow chart for this project are shown at Figure 18.

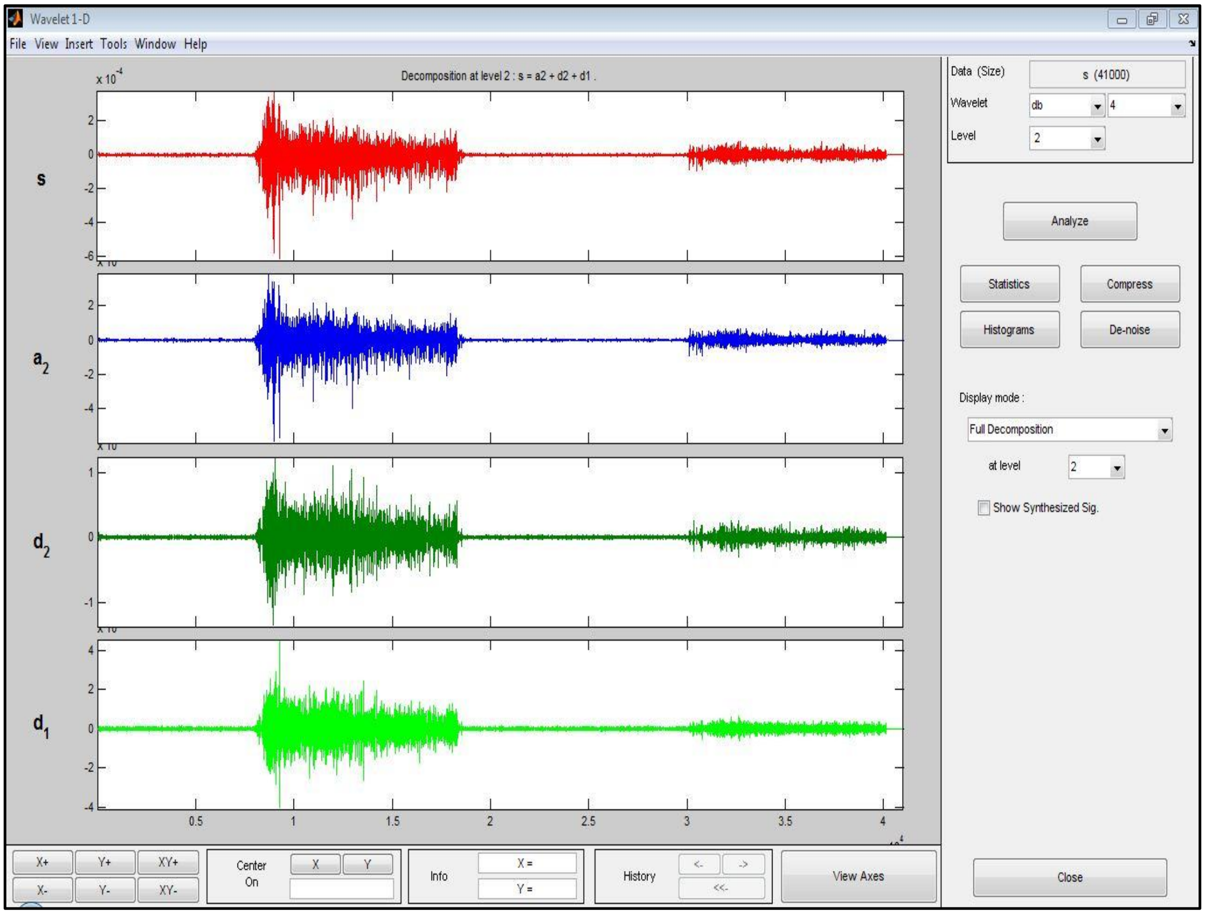


Figure 17: Daubechies wavelet order 4 level 2 using wavelet toolbox.

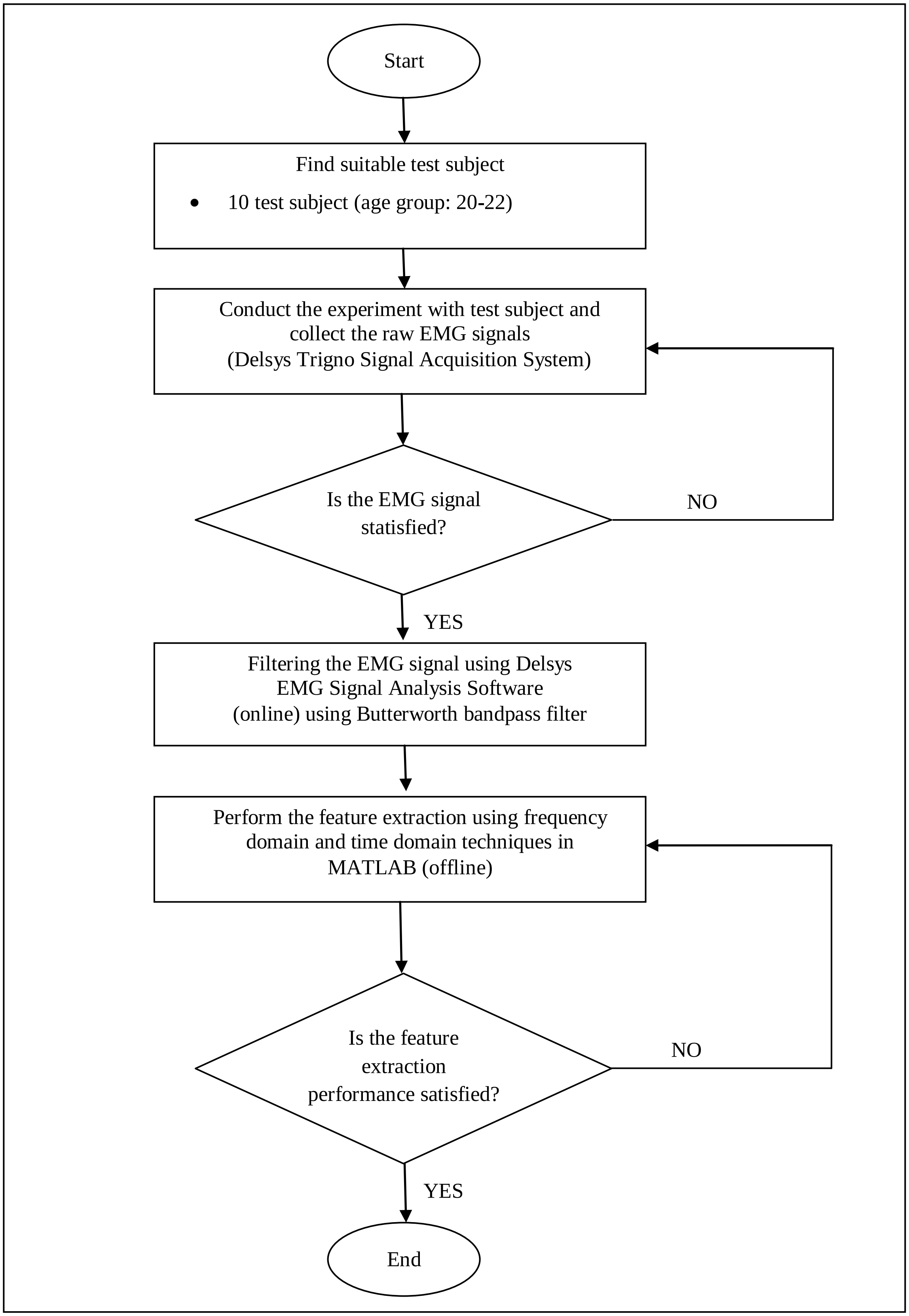


Figure 18: Process Flow Chart of EMG signal process

Once we obtained the signal after performing wavelet analysis, we will further extract the information by performing MAV or RMS features to the signal itself. Here we are using Daubechies wavelet transform as the main input to enhance the feature extraction method. In wavelet analysis, we often look at wavelet reconstruction and wavelet decomposition techniques. In this research we will be looking at the different aspects of feature extraction by using MAV or RMS and Daubechies only. Overview of the feature extraction enhancement techniques are shown in Figure 19.

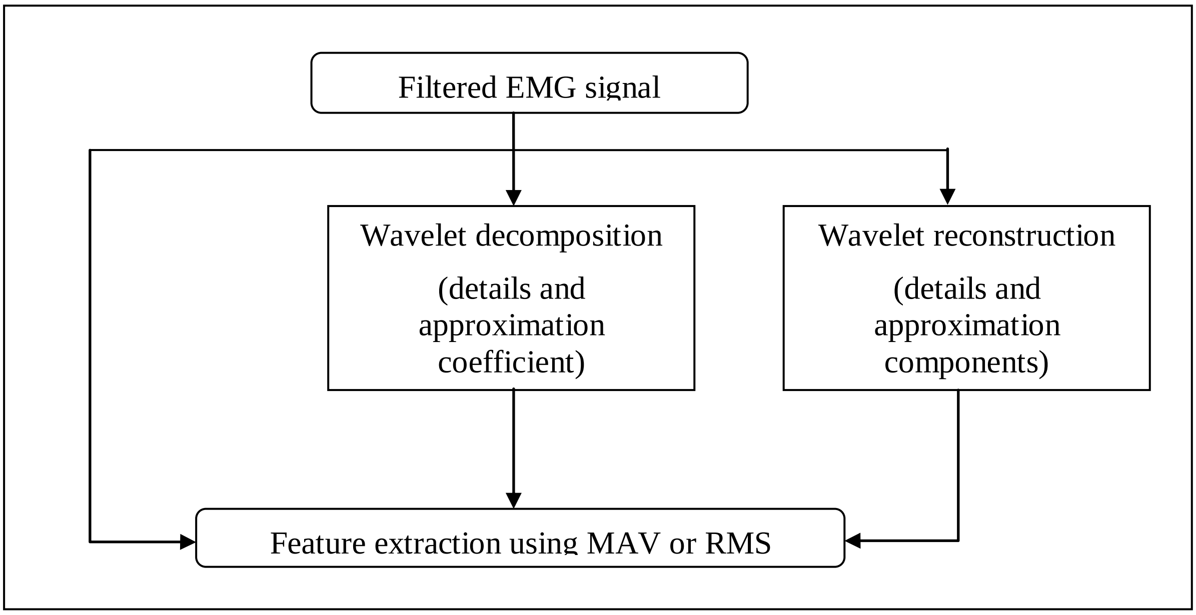


Figure 19: The procedure for feature extraction enhancement by using wavelet decomposition and wavelet reconstruction techniques with MAV or RMS features.

CHAPTER 4

RESULTS AND DISCUSSIONS

4.1 Signal Acquisition

The data acquisition for this research has been conducted and the raw EMG signals for upper limb movements are shown in Figure 20 to Figure 23. The signal shown here is the raw signal from one of the test subject. The rest of the test subject's signal gives the same pattern as shown in Figure 20 to Figure 23.

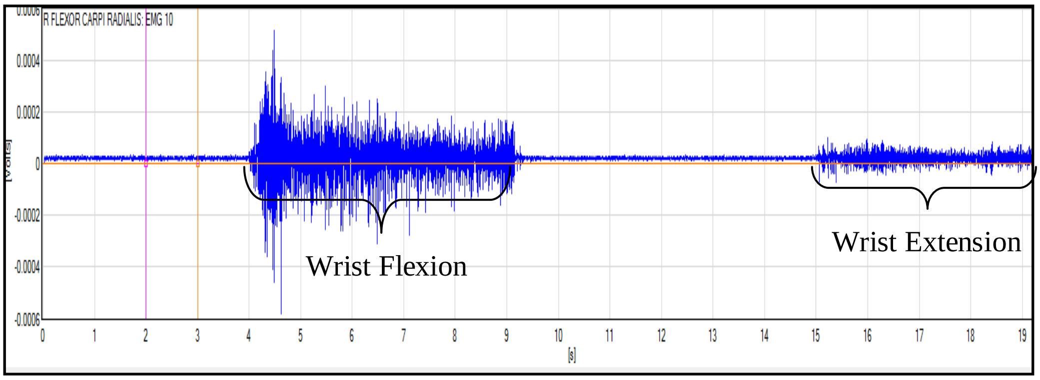


Figure 20: Signal for wrist flexion movement in flexor capri radialis muscle

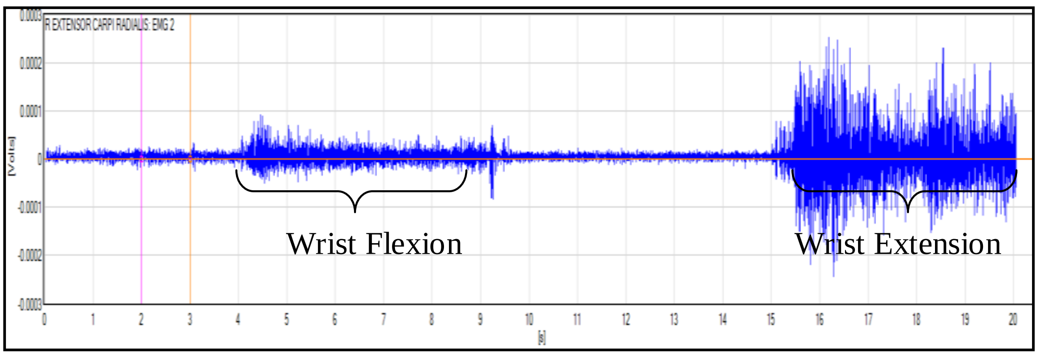


Figure 21: Signal for wrist extension movement in extensor capri radialis muscle

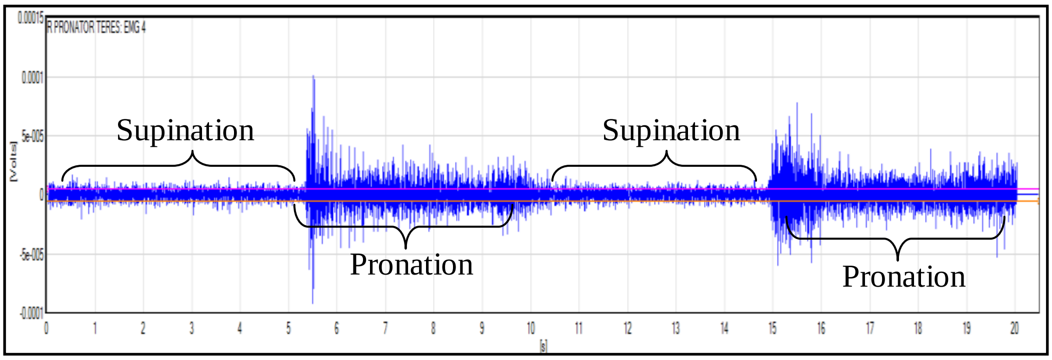


Figure 22: Signal for forearm supination and pronation in pronator teres muscle

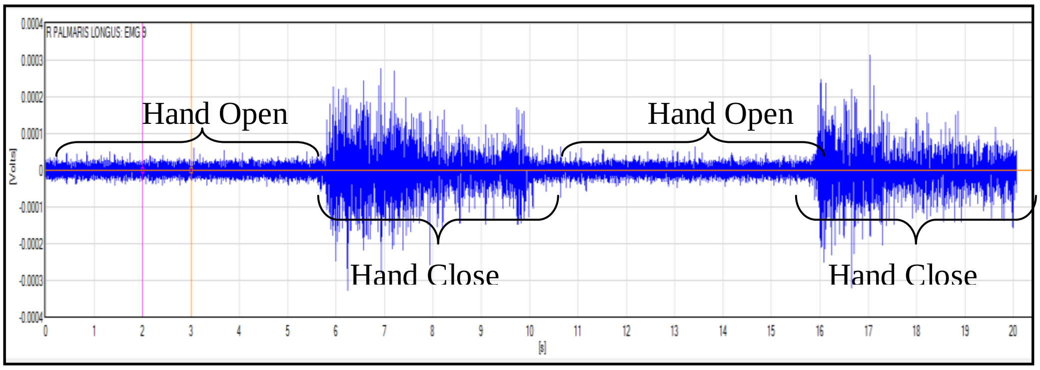


Figure 23: Signal for hand open and close in palmaris longus mucls

4.2 Feature Extraction using Frequency Domain Technique

Here, we are using Daubechies wavelet order 4, 7 and 10. Figure 24 to Figure 30 shows the signal analysis of Daubechies wavelet order 4 for level 1, 2, 3, 4, 5, 7 and 9 using MATLAB.

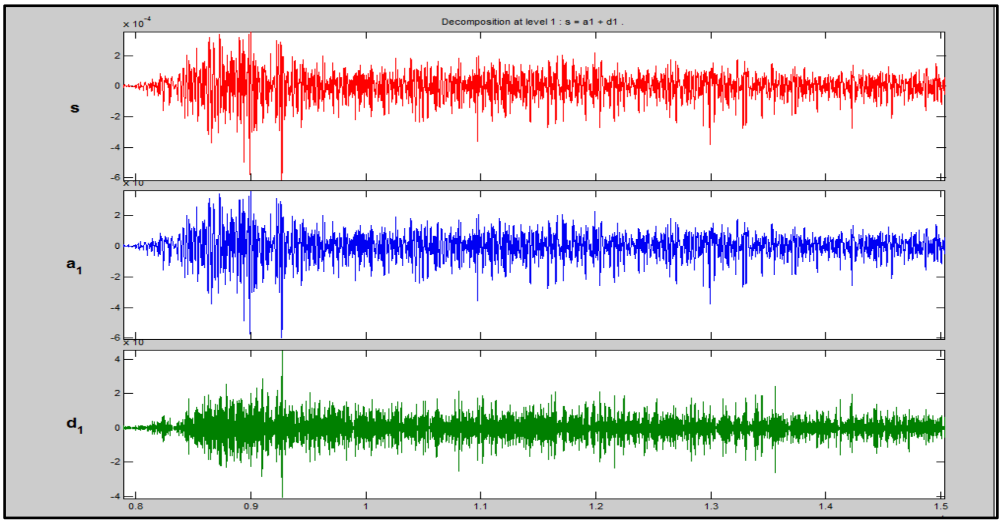


Figure 24: Daubechies wavelet order 4 level 1

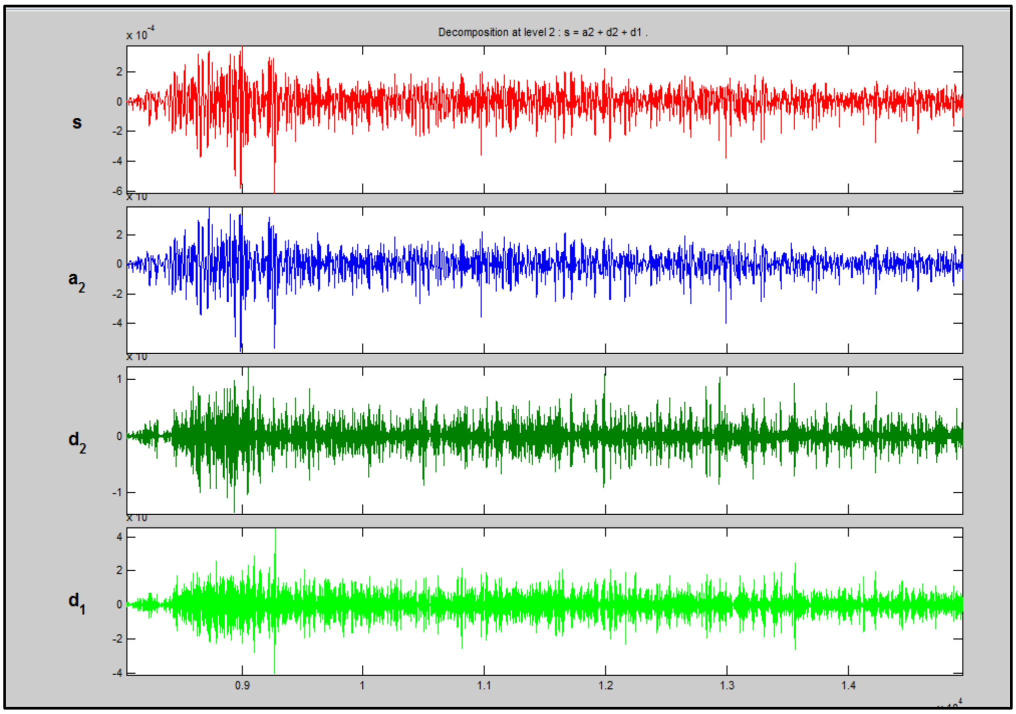


Figure 25: Daubechies wavelet order 4 level 2

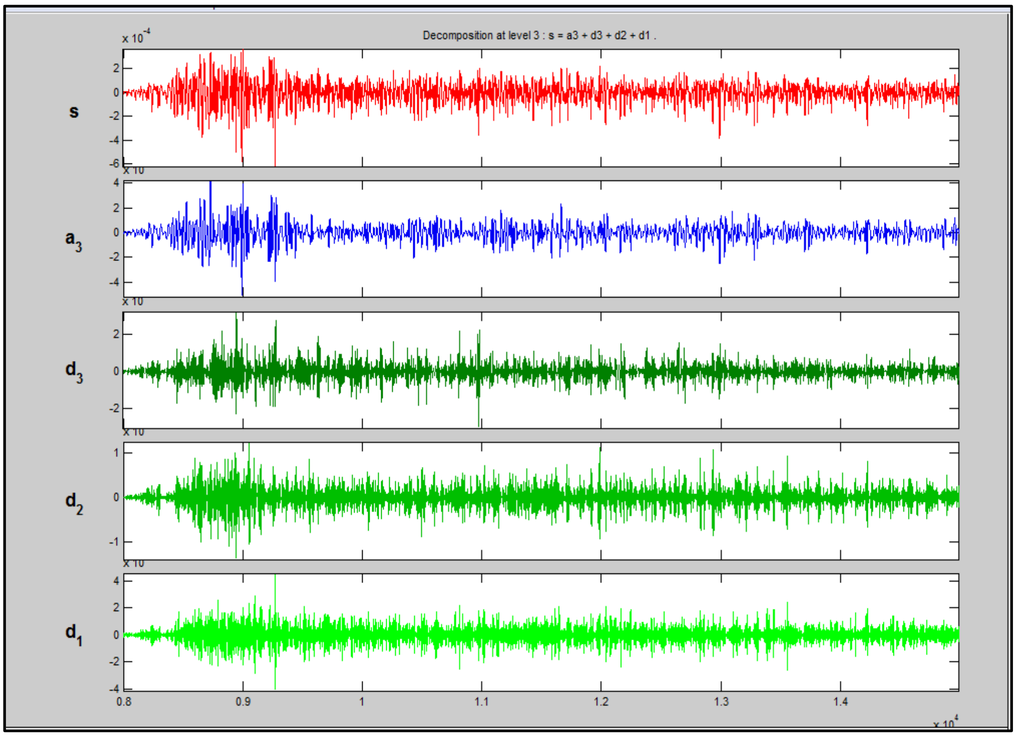


Figure 26: Daubechies wavelet order 4 level 3

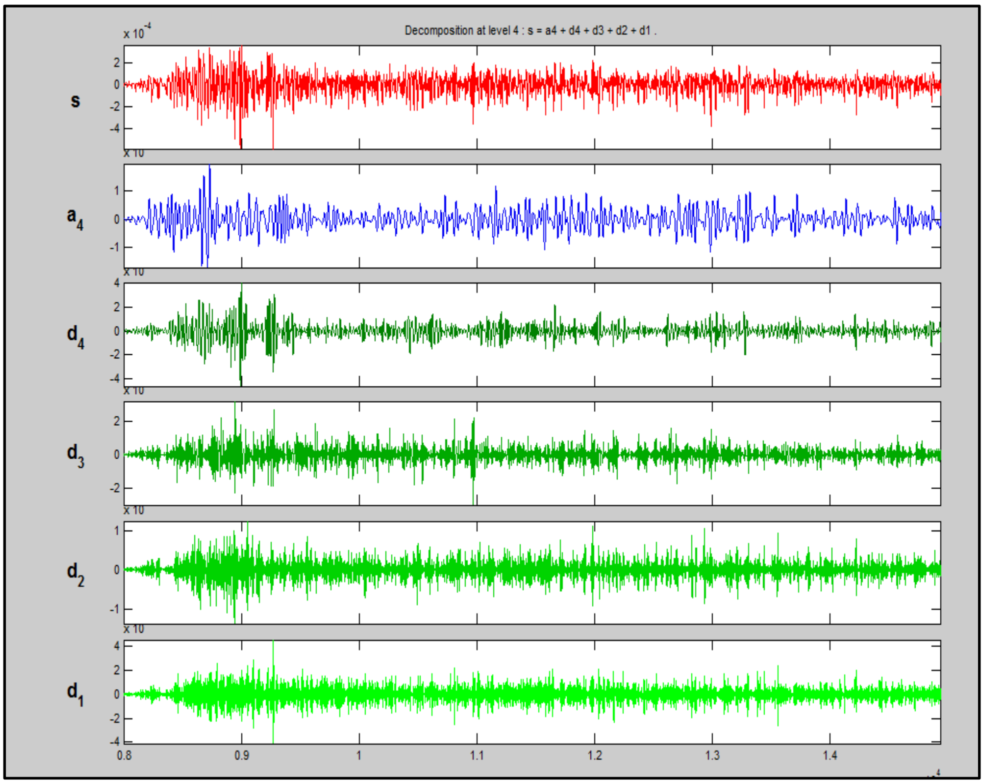


Figure 27: Daubechies wavelet order 4 level 4

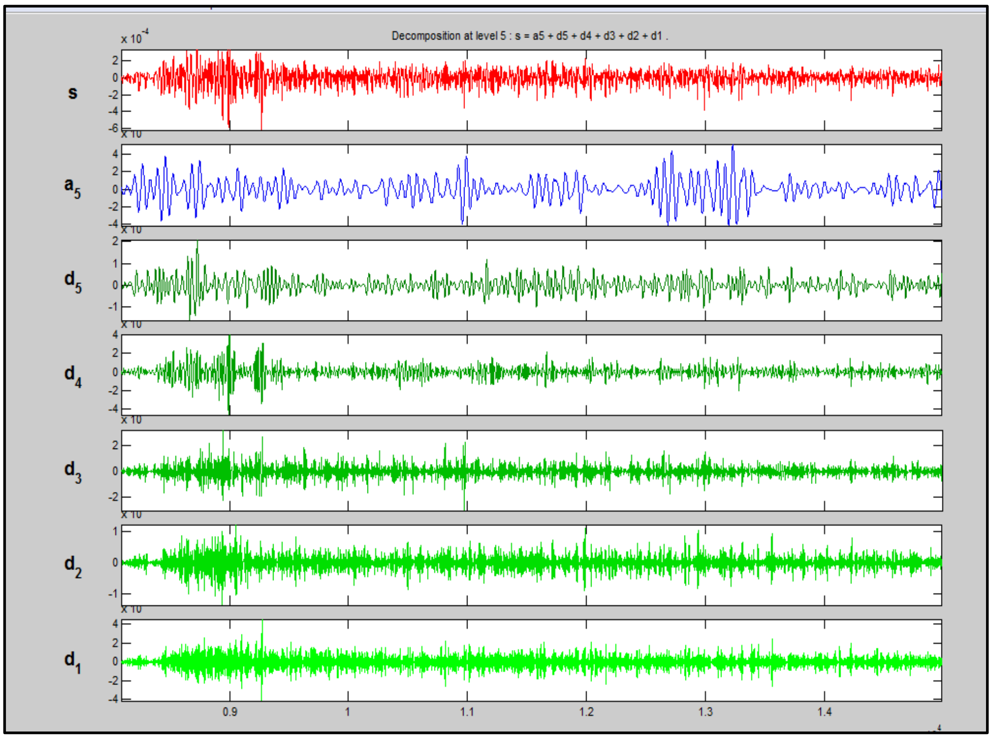


Figure 28: Daubechies wavelet order 4 level 5

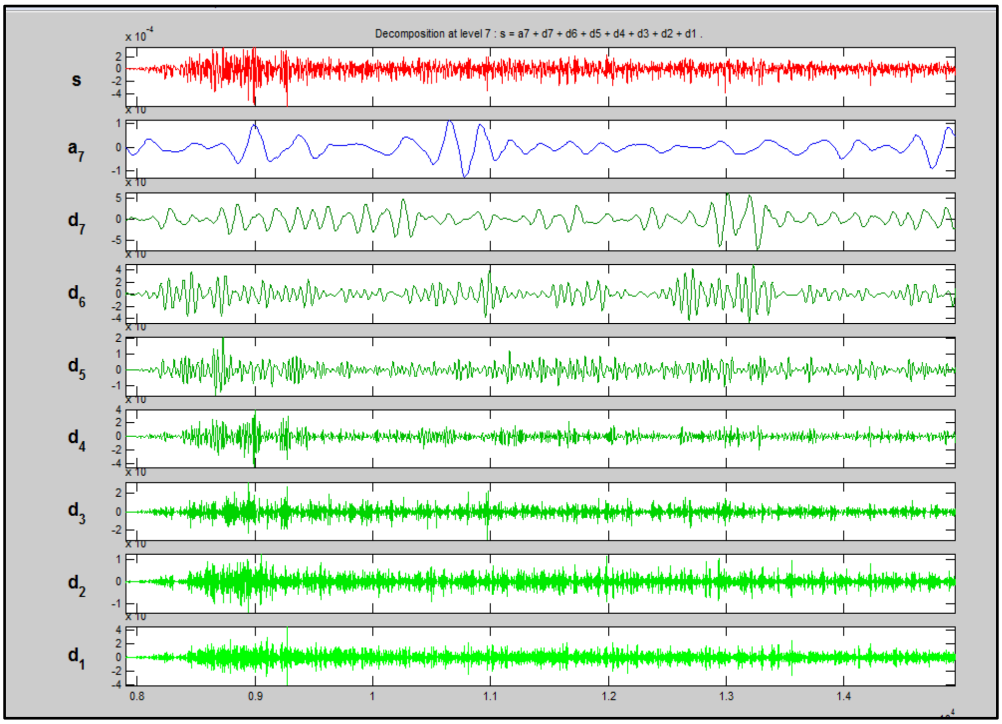


Figure 29: Daubechies wavelet order 4 level 7

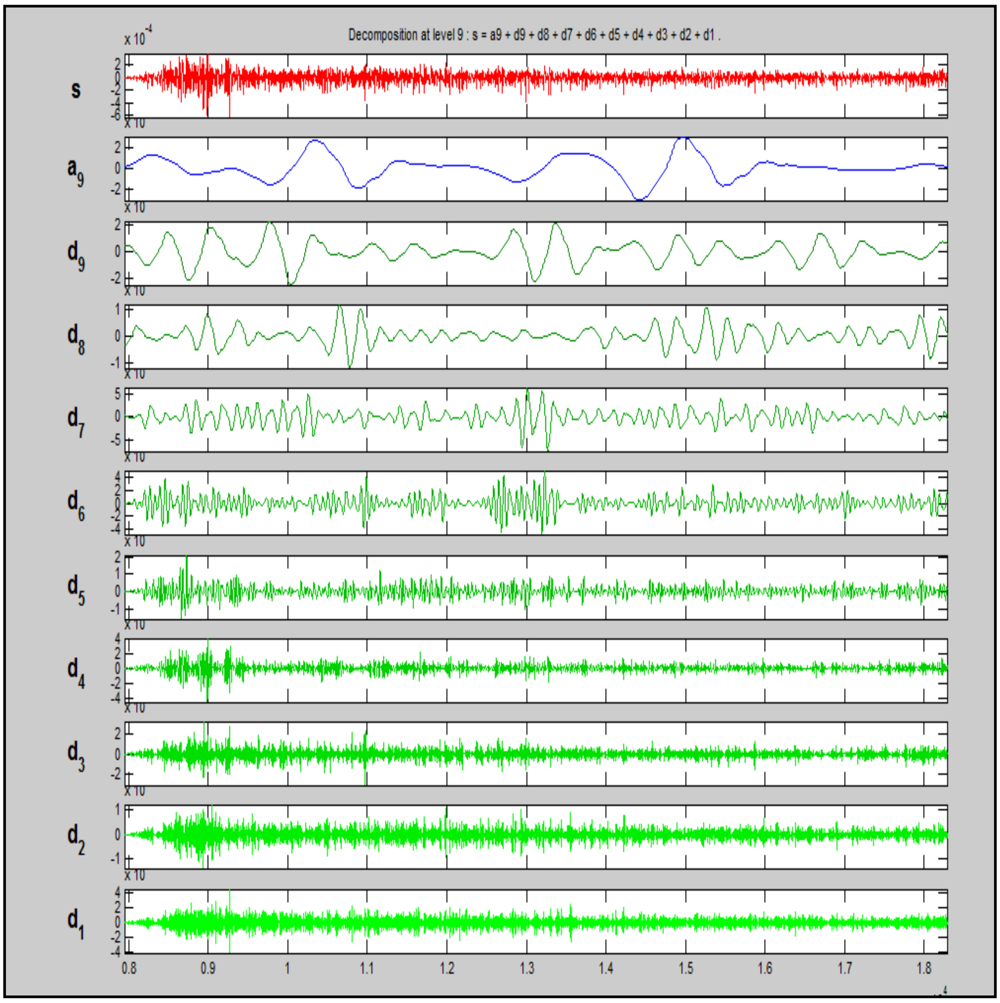


Figure 30: Daubechies wavelet order 4 level 9

Figure 31 to Figure 37 shows the Daubechies wavelet analysis for order 7 using MATLAB with various levels.

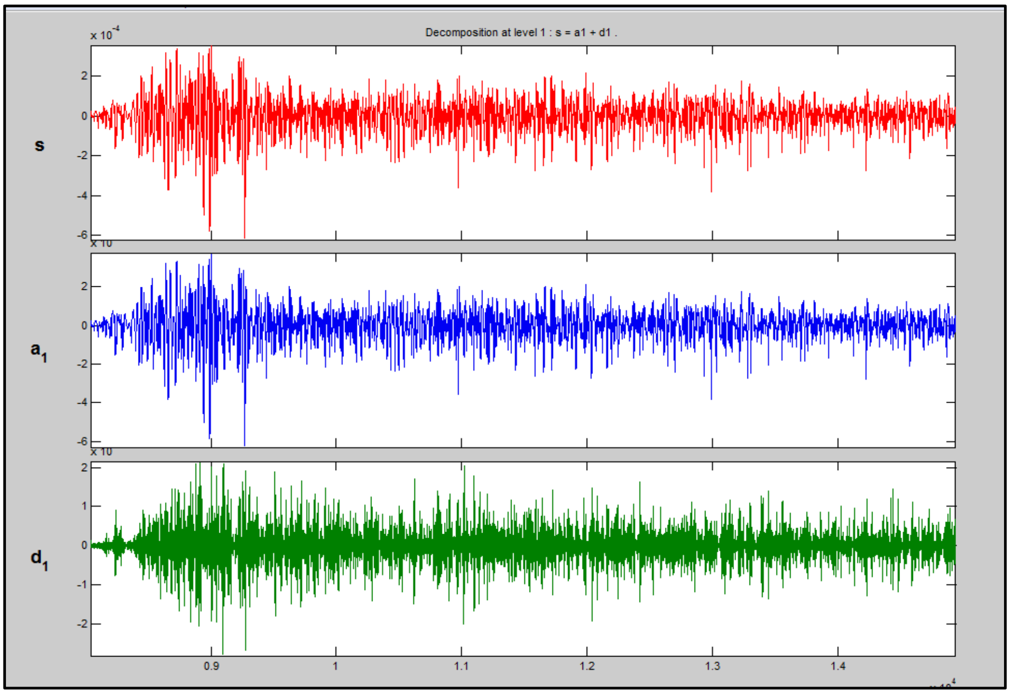


Figure 31: Daubechies wavelet order 7 level 1

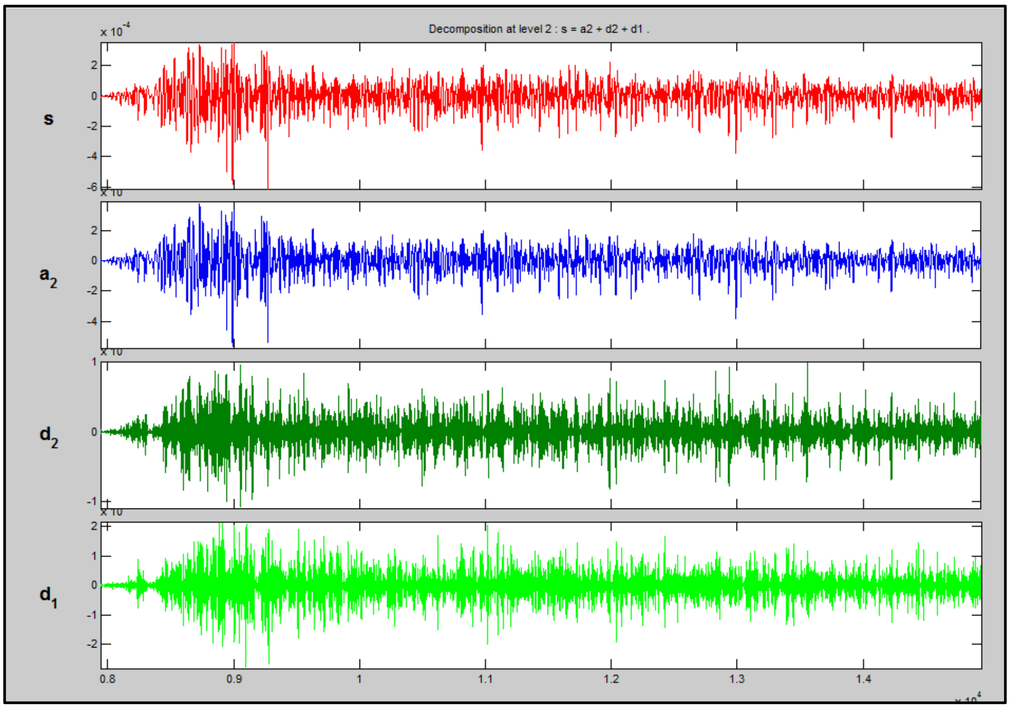


Figure 32: Daubechies wavelet order 7 level 2

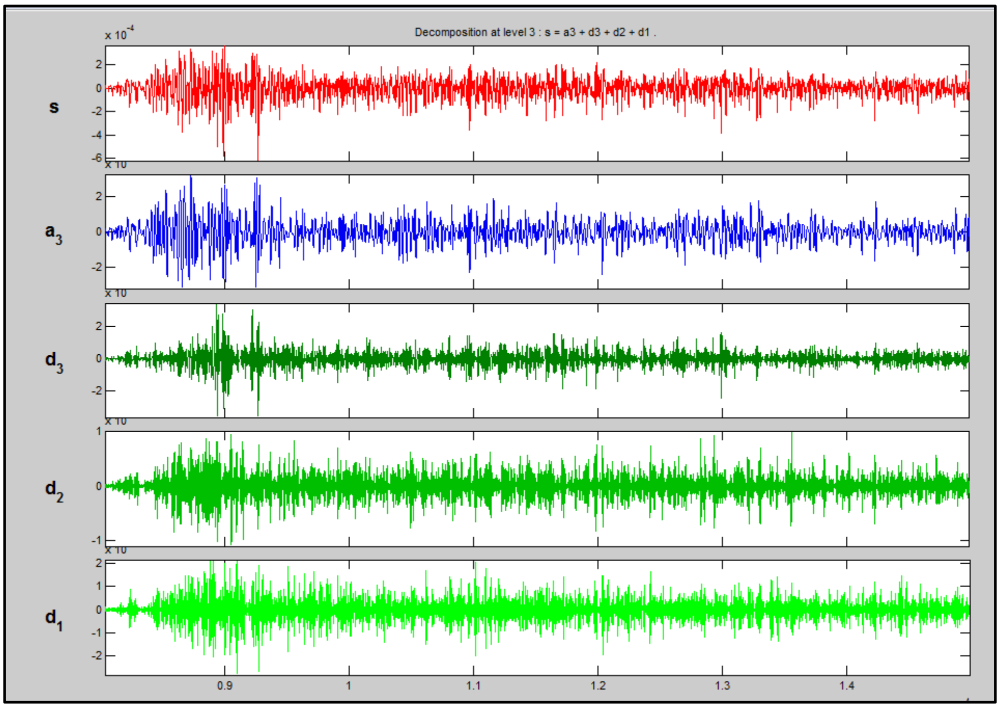


Figure 33: Daubechies wavelet order 7 level 3

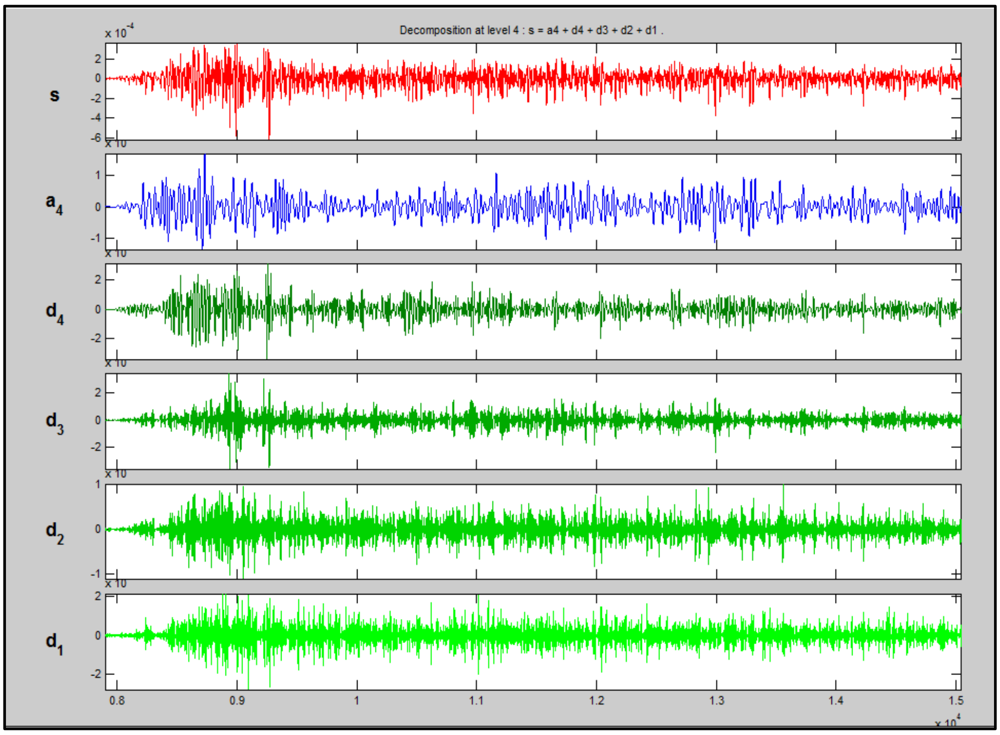


Figure 34: Daubechies wavelet order 7 level 4

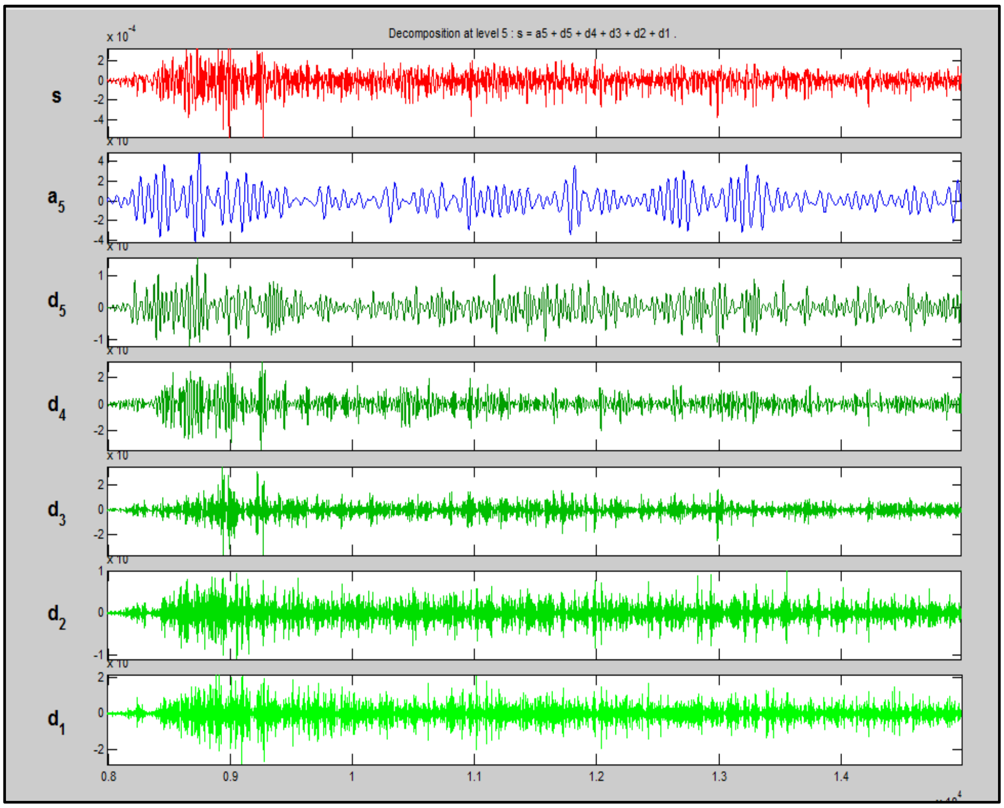


Figure 35: Daubechies wavelet order 7 level 5

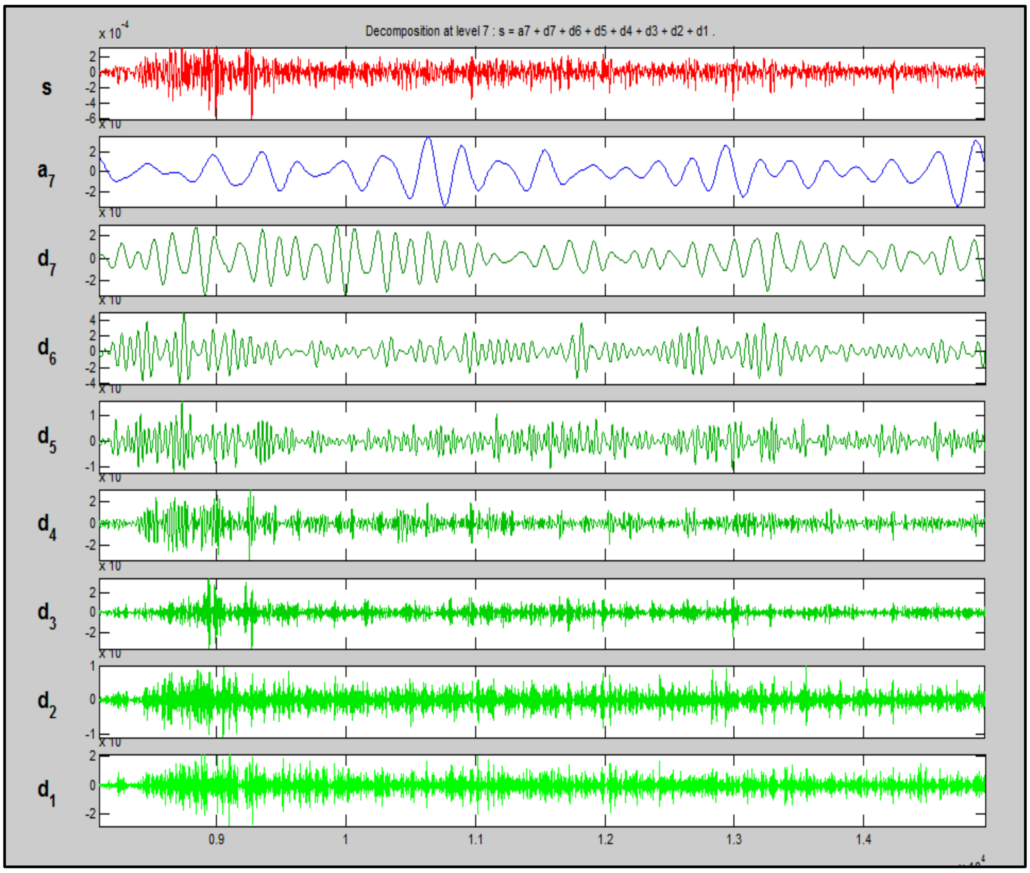


Figure 36: Daubechies wavelet order 7 level 7

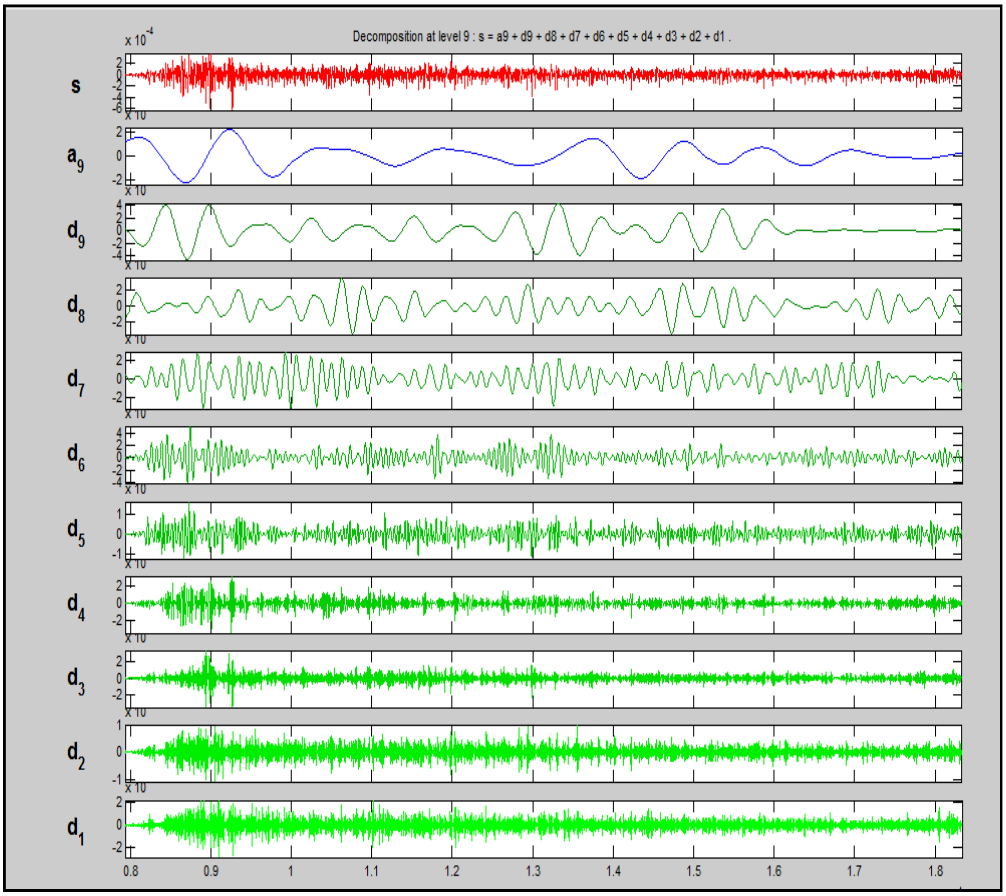


Figure 37: Daubechies wavelet order 7 level 9

Figure 38 to Figure 44 shows the Daubechies wavelet analysis for order 10 using MATLAB with various levels.

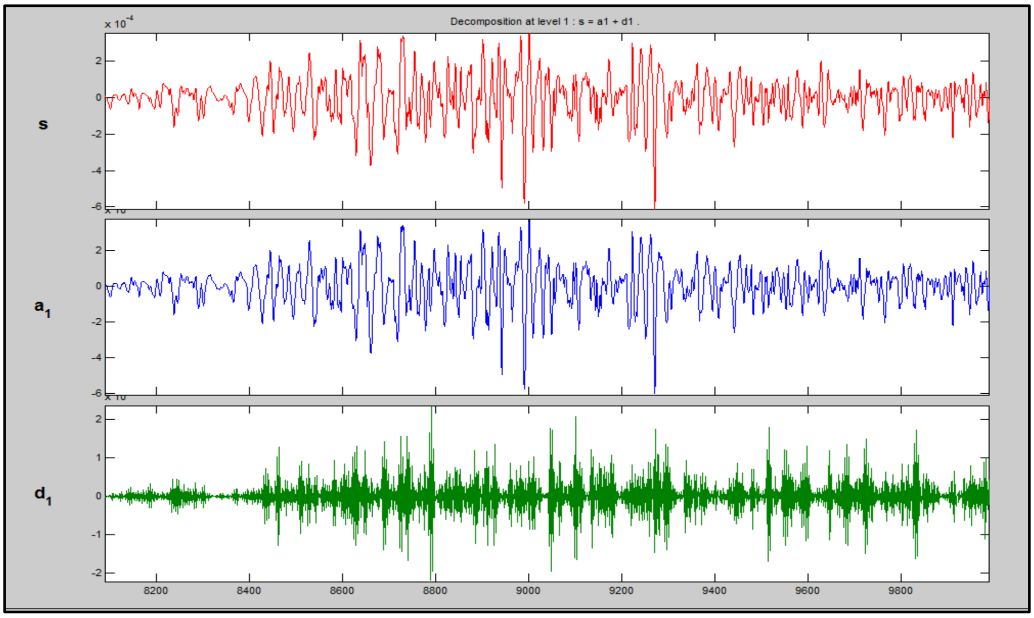


Figure 38: Daubechies wavelet order 10 level 1

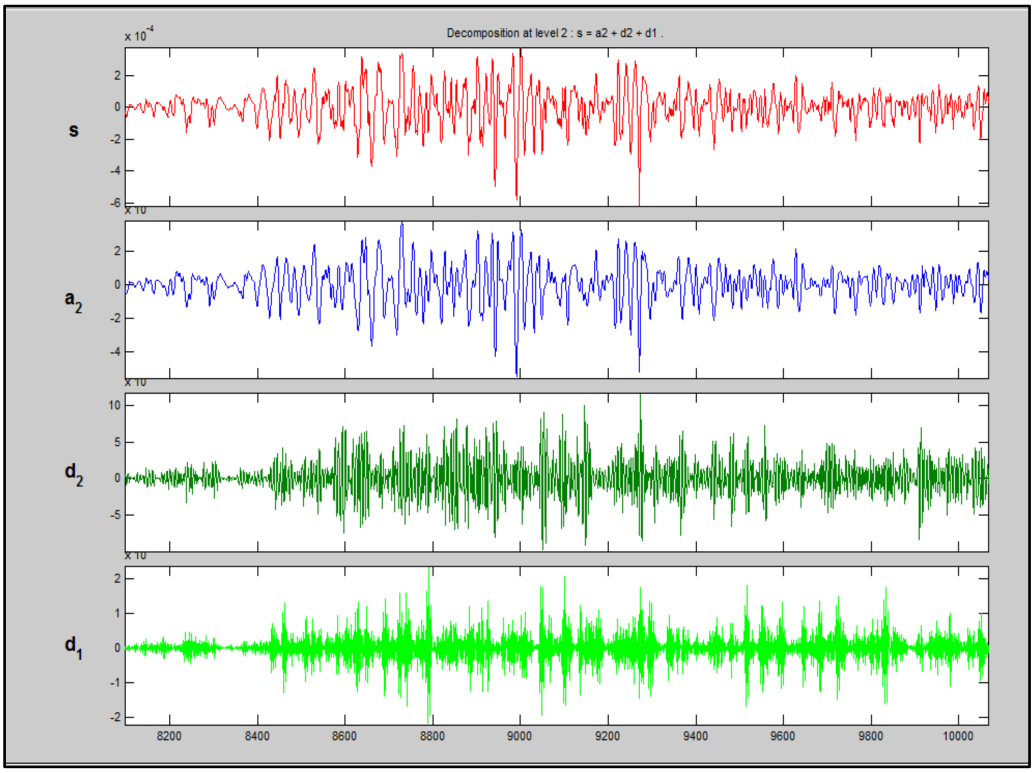


Figure 39: Daubechies wavelet order 10 level 2

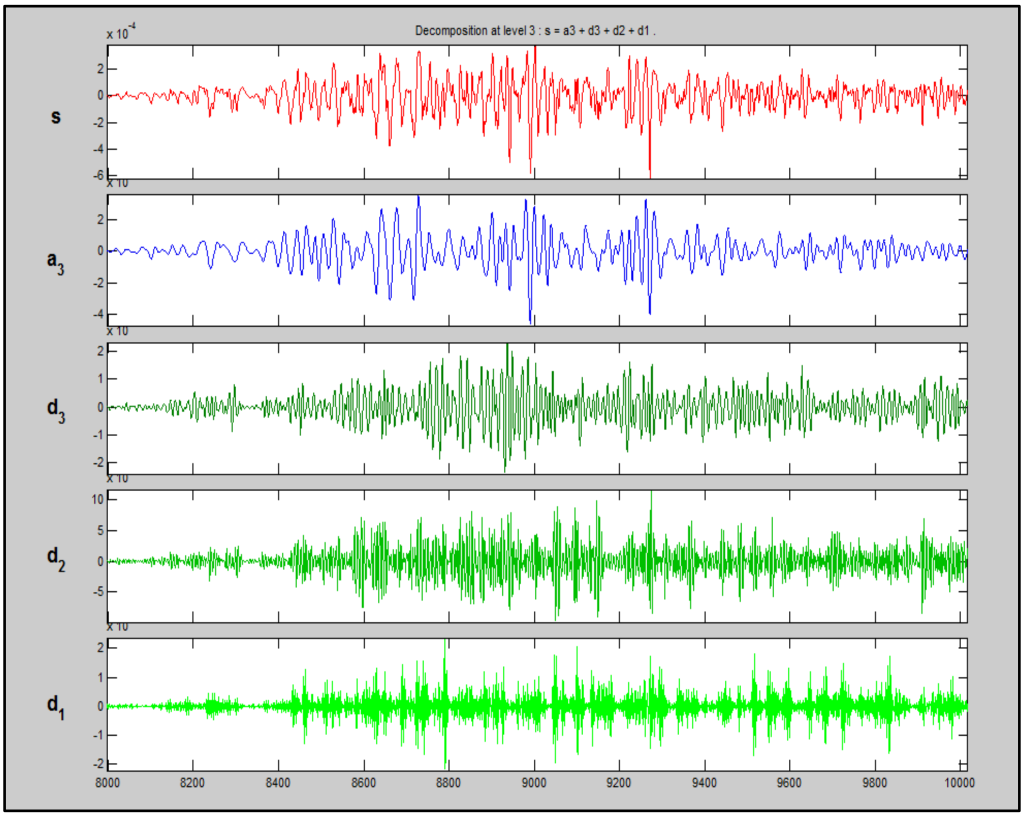


Figure 40: Daubechies wavelet order 10 level 3

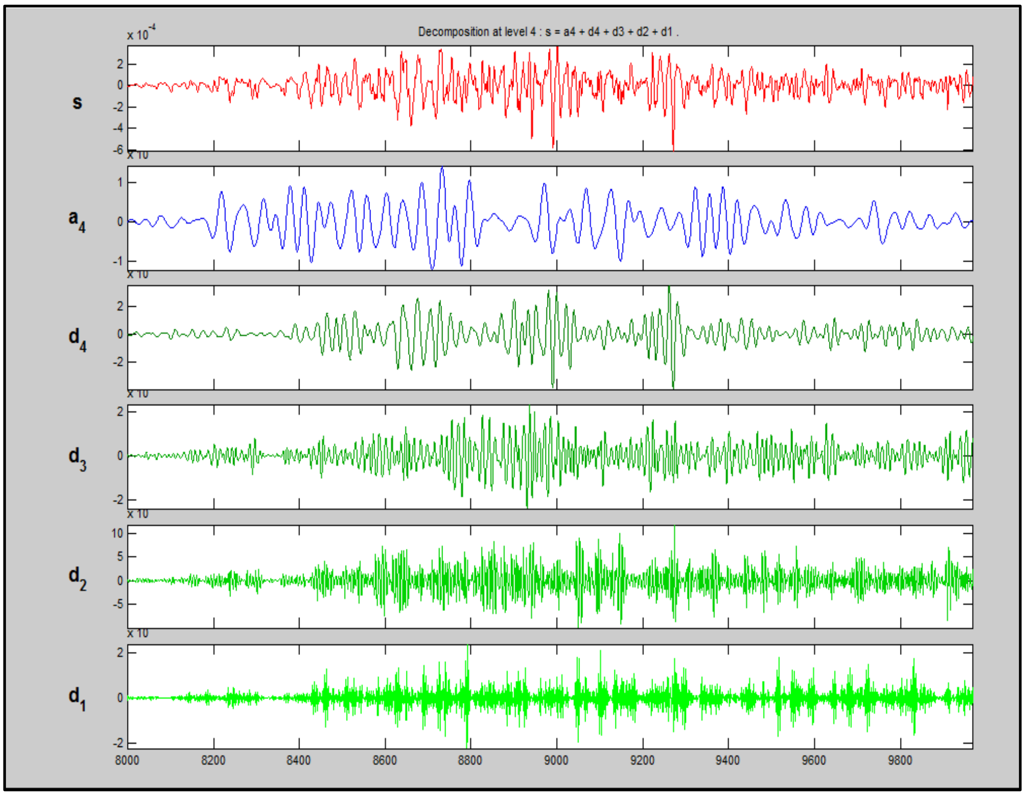


Figure 41: Daubechies wavelet order 10 level 4

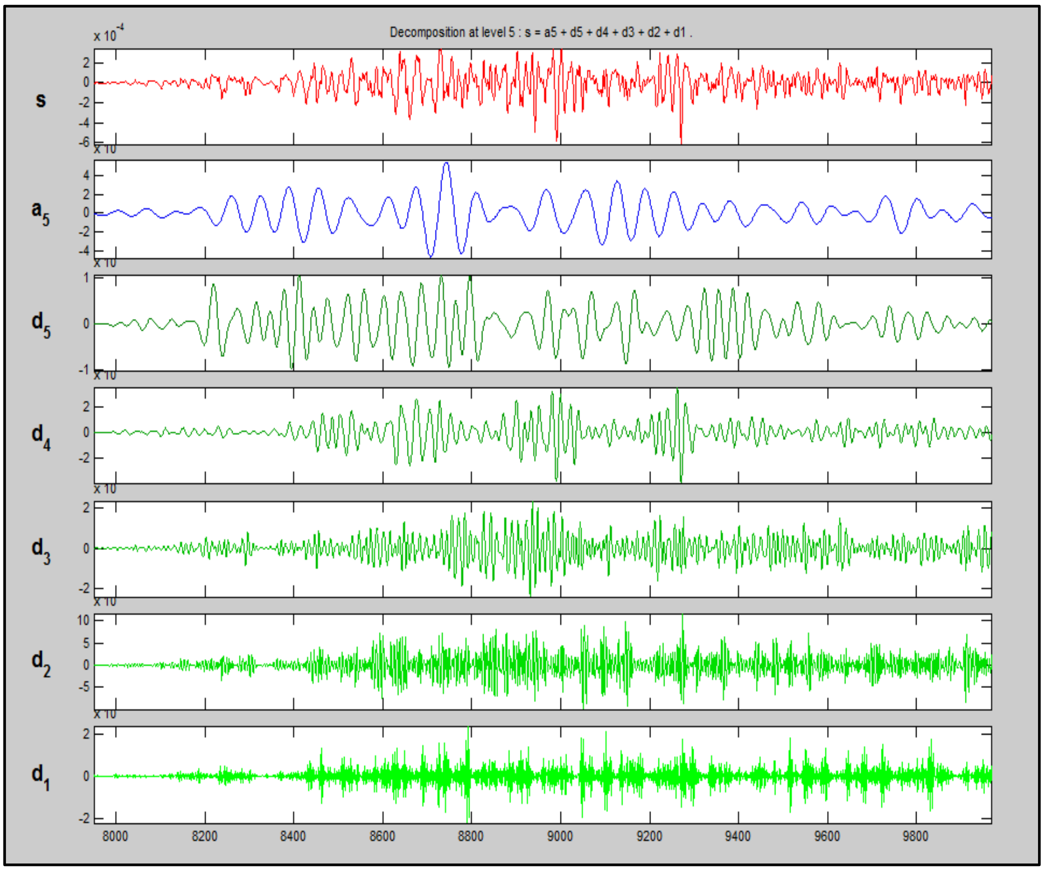


Figure 42: Daubechies wavelet order 10 level 5

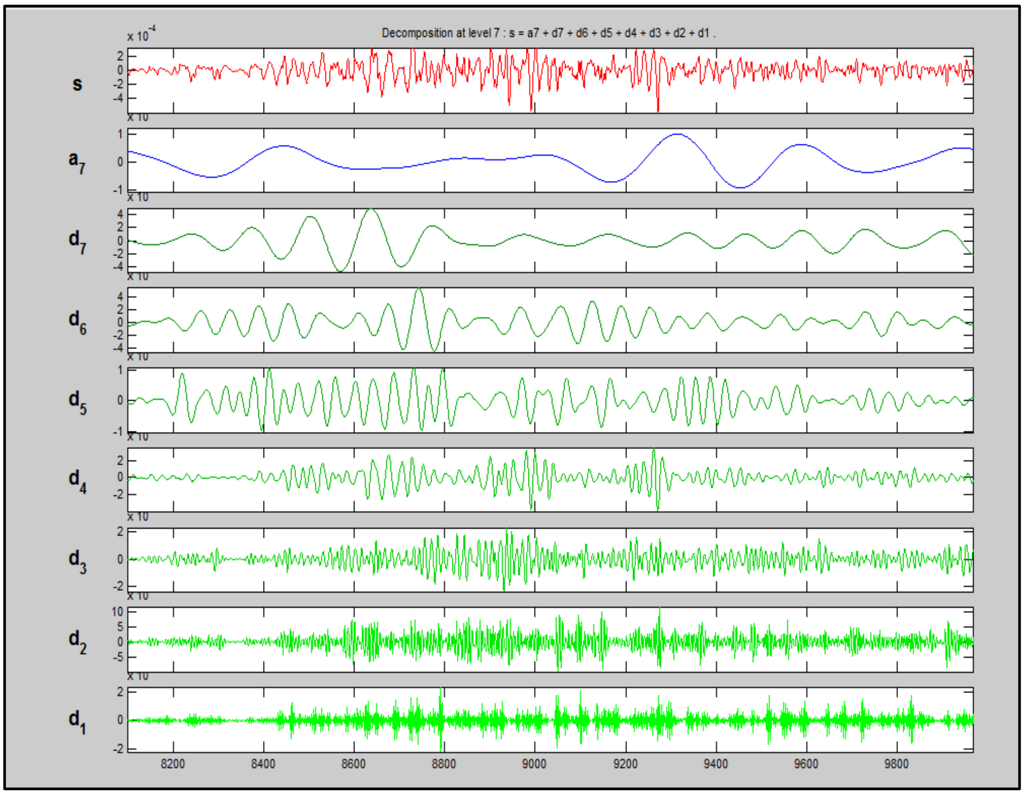


Figure 43: Daubechies wavelet order 10 level 7

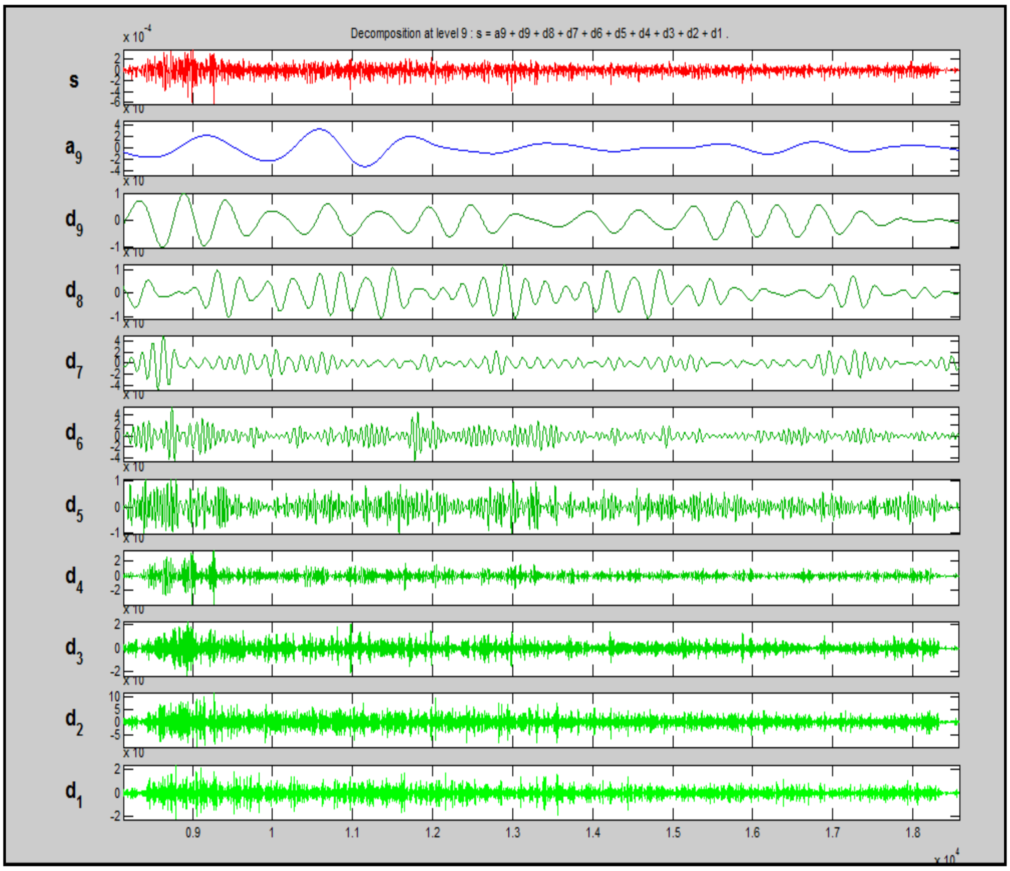
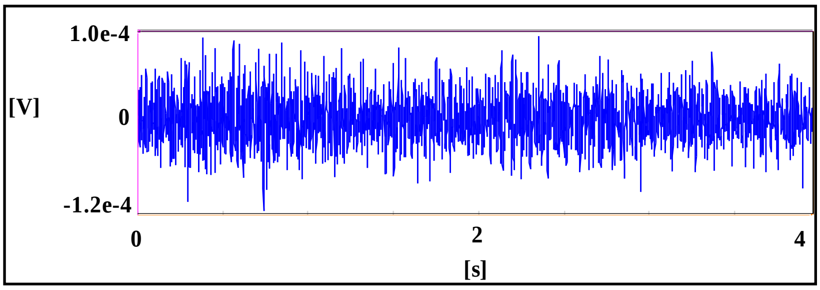


Figure 44: Daubechies wavelet order 10 level 9

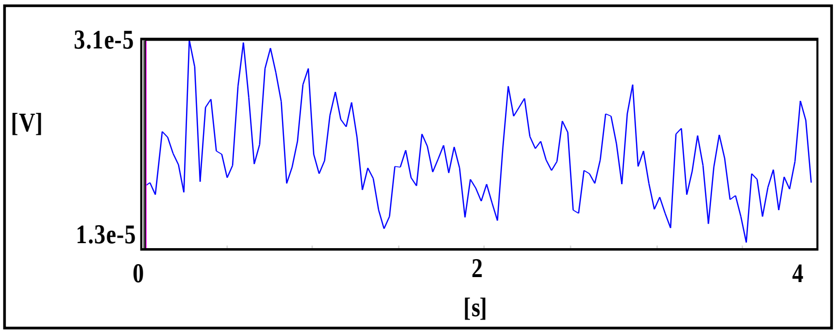
From 24 to Figure 44, Daubechies order 4, 7 and 10 were being used for this research due to it gives a better feature extraction results. From the results, we observe that the higher the levels of decomposition, the more information loss happen. For decomposition in level 1, the detail (D1) and approximation(A1) is more like similar to the original signal (S) where the EMG signal still consists the important information of the signal itself. This result is the same as decomposition level 2. In level 1 and 2 we can observe that the details and approximation signal still resembled the original signal while it removing the noise. The decomposition level 5 and 7 gives more clean signal but the details and approximation signal shows a very smooth signal which do not follow the pattern of the original signal. This shows that there are information losses in the higher level of decomposition. Thus, decomposition level 1 and 2 shows better results for feature extraction compare with other levels. This Daubechies wavelet analysis using MATLAB is to gives us more data on which Daubechies wavelet are more suitable to be use.

4.3 Feature Extraction using Frequency Domain and Time Domain Techniques

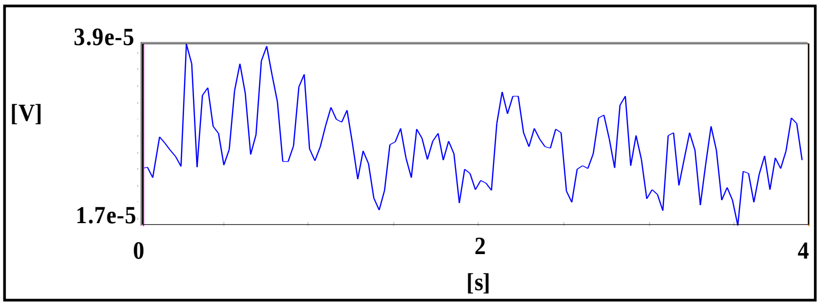
In this research, Daubechies wavelet has been chosen for feature extraction techniques. Here, the filtered EMG signal will be further processes by performing the Daubechies wavelet in MATLAB in order to remove the unwanted noise more effectively. Butterworth filtering techniques alone does not remove the extra noises in the EMG signal effectively. The wavelet decomposition and reconstruction of level 1, 2, 3, 4, 5, 7 and 9 in Daubechies order 4, 7, and 10 are being used for a better comparison. After obtaining the decomposed and reconstructed signal, we further extract the signal by using the MAV features to gives a better feature extraction results. The results of EMG signals feature extraction by using MAV and RMS techniques are shown in Figure 45.



(a) Raw EMG Signal



(b) EMG signal after perform MAV features



(c) EMG signal after perform RMS features

Figure 45: Comparison of features using MAV and RMS feature extraction (a) Raw EMG signal (b) EMG signal after perform MAV features (c) EMG signal after perform RMS features

We observe that MAV and RMS features yield almost the same result but MAV gives slightly better result as compared to RMS features. The tabulated RES index for both techniques is shown in Figure 46. We can see that MAV RES index is slightly higher than RMS. As the MAV techniques would lead to better class separability performance, we are using MAV to perform the feature extraction for the Daubechies wavelet.

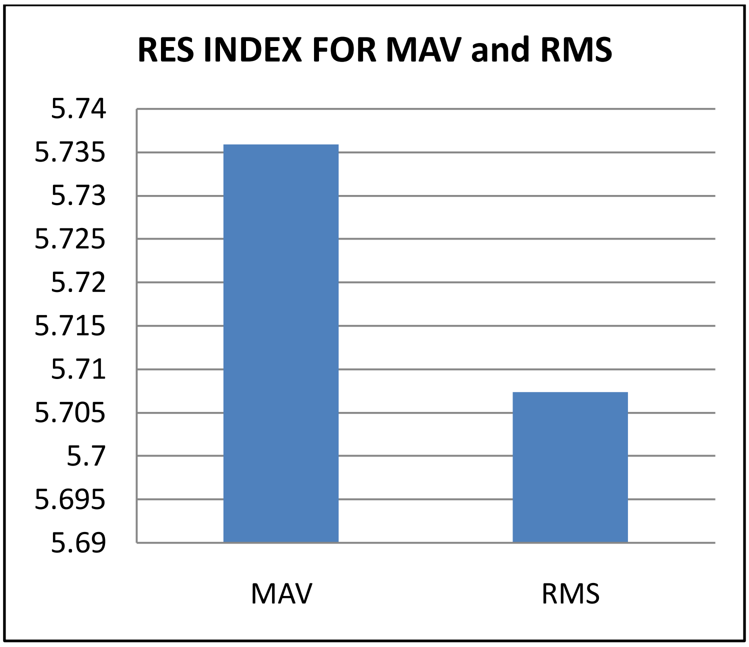
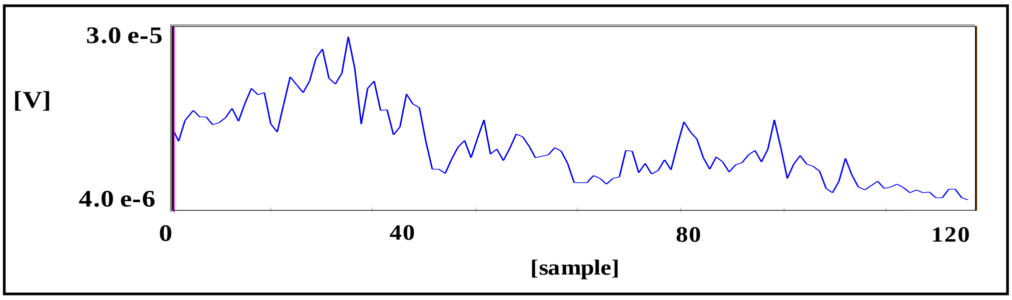
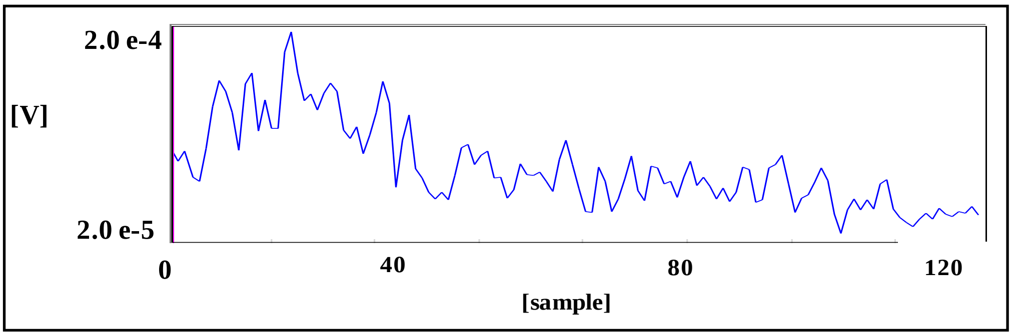


Figure 46: RES Index bar chart for MAV and RMS features

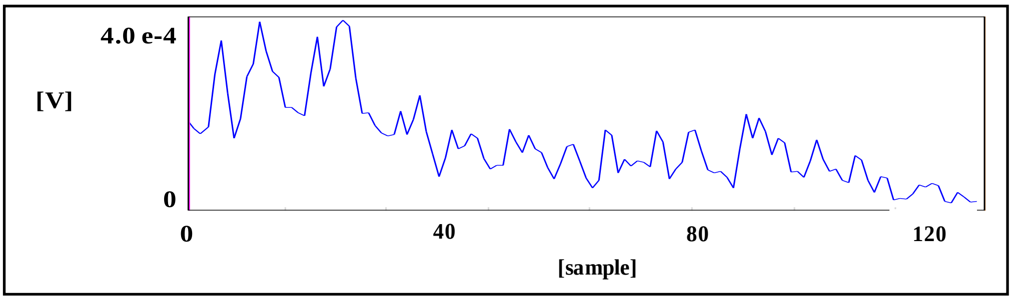
Figure 47(a) to (g) shows the MAV features of EMG signals after performing Daubechies DB7 wavelet reconstruction for details ccomponents (D1, D2, D3, D4, D5, D7 and D9). Here we can observe that D1 and D2 levels resemble the original MAV features without any further filtering techniques. Meanwhile, D5, D7 and D9 levels are slowly losing its information as the levels of Daubechies wavelet increasing. This shows that there are more information loss as the Dauchecies wavelet levels is increasing.



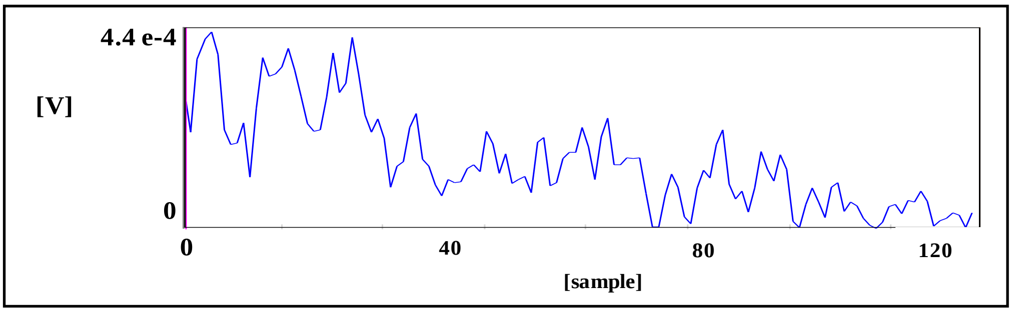
(a) Detail component (D1) level 1



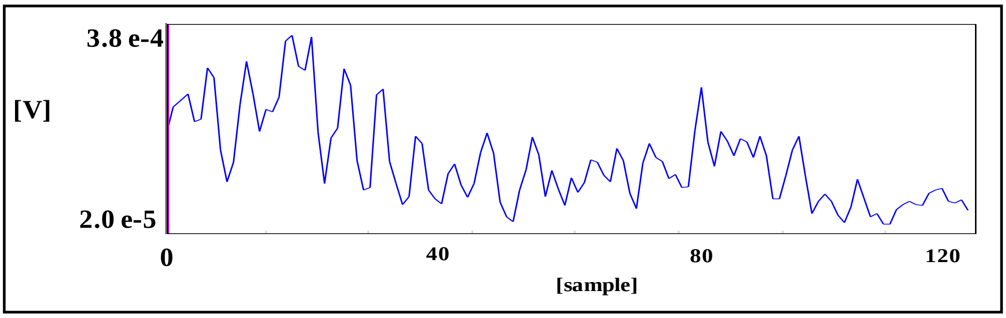
(b) Detail component (D2) level 2



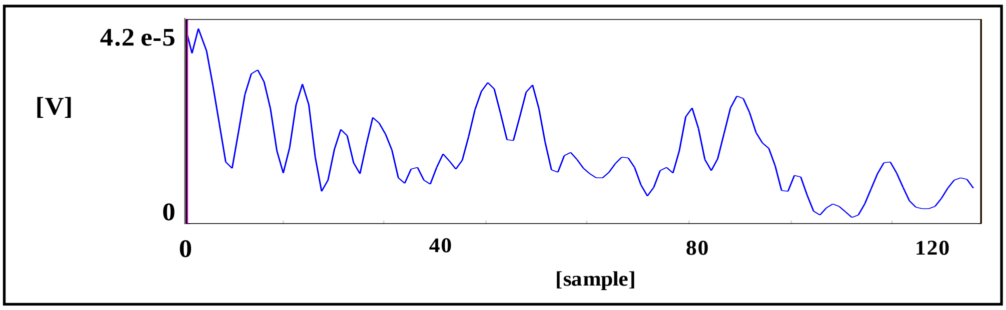
(c)Detail component (D3) level 3



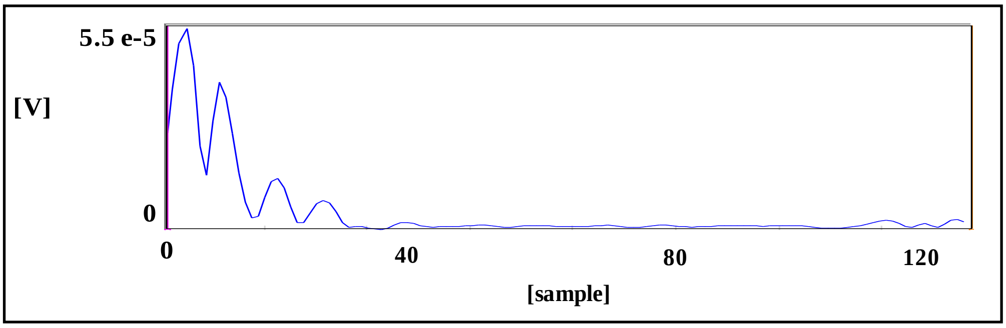
(d) Detail component (D4) level 4



(e) Detail component (D5) level 5



(f) Detail component (D7) level 7



(g) Detail component (D9) level 9

Figure 47: MAV features for detail component after performing wavelet reconstruction for DB7 (D1,D2,D3,D4,D5,D7 and D9)

The results of RES index for Daubechies wavelet was achieved from DB4, DB7 and DB10. The bar chart in Figure 48 shows that the RES index gives a better performance from the detail component in the first and second level (D1 and D2) compared to the signal with the MAV feature extraction only. We found that DB7 gives a better performance in term of the detail signal in the first and second level (D1 and D2) compared to DB4 and DB10. From the bar chart, we also can observe that Daubechies wavelet reconstruction in the first level, D1 shows better results compare to other level. In this context, the feature extraction using Daubechies wavelet reconstruction from the first level and second level in DB7 would gives a better class separability performance.

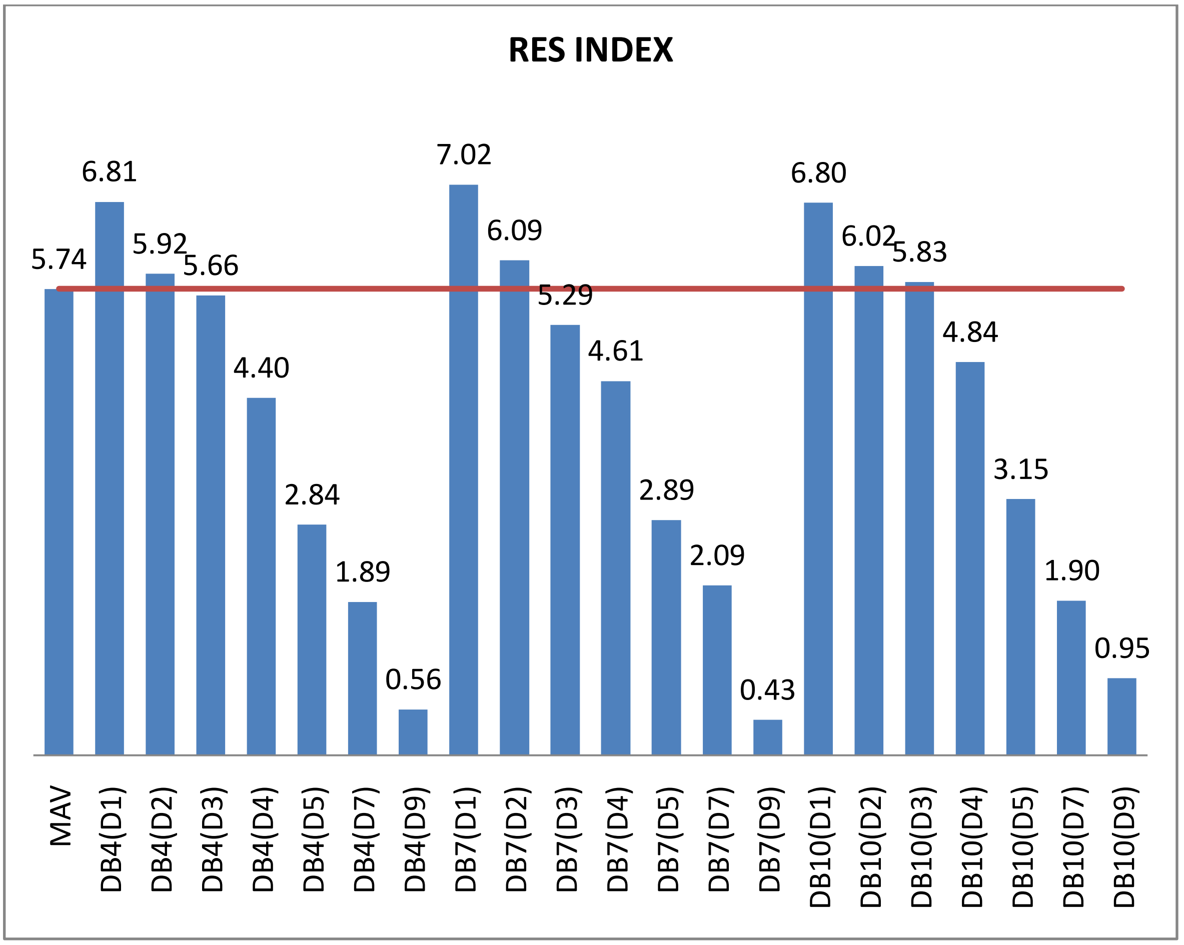
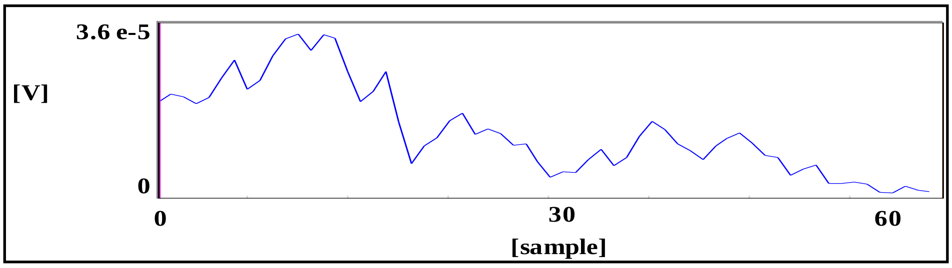
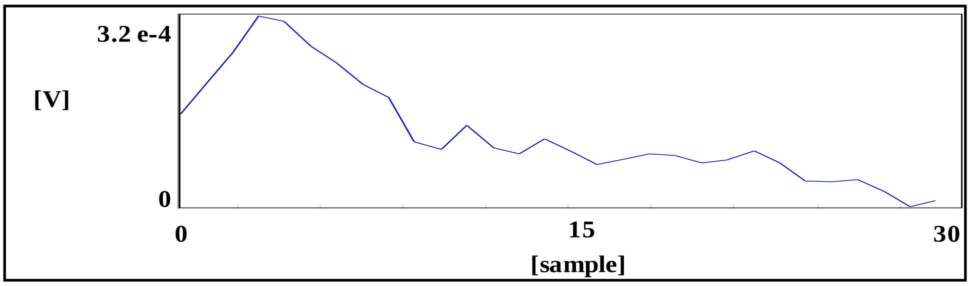


Figure 48: Bar Chart for D1, D2, D3, D4, D5, D7 and D9 (DB4, DB7 and DB10) RES index

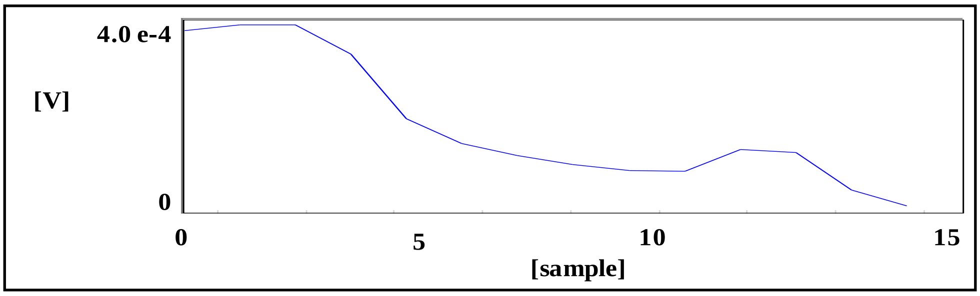
Figure 49 (a) to (g) shows the MAV features for the detail coefficient after performing wavelet decomposition for various levels using DB7. Here we have obtained cD1, cD2, cD3, cD4, cD5, cD7 and cD9 details coefficients. As we can observe from the table, the results is the same as detail components, where the higher level it is, the more information loss happens within the signal. However, for coefficients components, the sample data will be twice lesser than the original signal. This is because of the original signal has been divided into 2 subset which is details coefficient and approximation coefficients. This process is mainly dealing with the filtering techniques where the signal will be convoluted with a filter. From the result, cD1 and cD2 still preserving the information of the signal while others level are giving more flat signals where the information has been filtered out from the original signal itself.



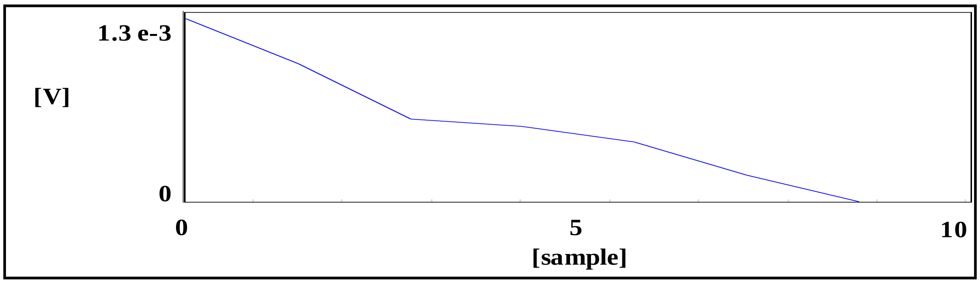
(a) Detail coefficient (cD1) level 1



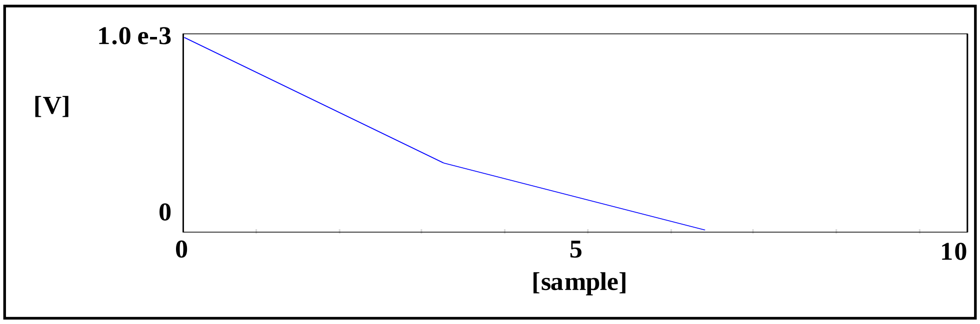
(b) Detail coefficient (cD2) level 2



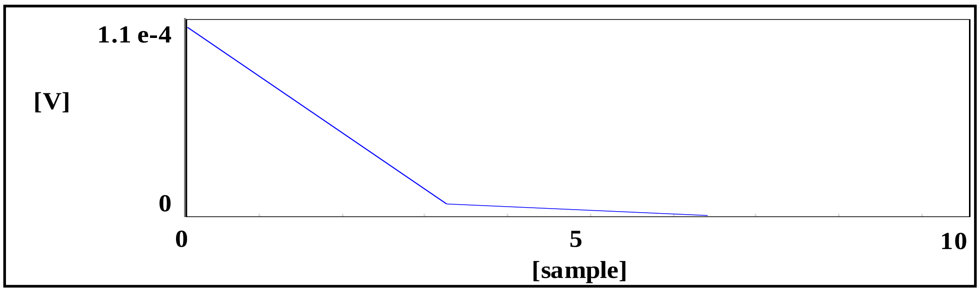
(c) Detail coefficient (cD3) level 3



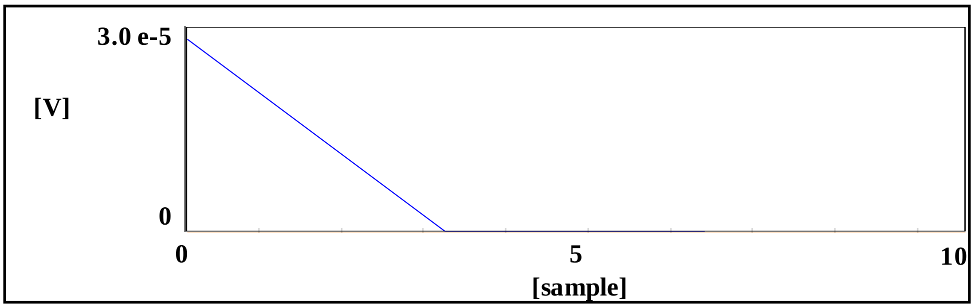
(d) Detail coefficient (cD4) level 4



(e) Detail coefficient (cD5) level 5



(f) Detail coefficient (cD7) level 7



(g) Detail coefficient (cD9) level 9

Figure 49: MAV features for detail coefficient after performing wavelet decomposition for DB7 (cD1, cD2, cD3, cD4, cD5, cD7 and cD9)

Figure 50 shows the RES index performance for the details coefficients in various levels by using DB4, DB7 and DB10. We can see that the detail coefficient for the first level of Daubechies wavelet for DB4, DB7 and DB10 are slightly better than the signal with MAV features only. This shows that the Daubechies wavelet in the first level would yield a better feature extraction result. However, for the details coefficient in level 2, only DB7 shows a better result compared to DB4 and DB10. This proven that DB7 would extract more information in the signals compared to DB4 and DB10.

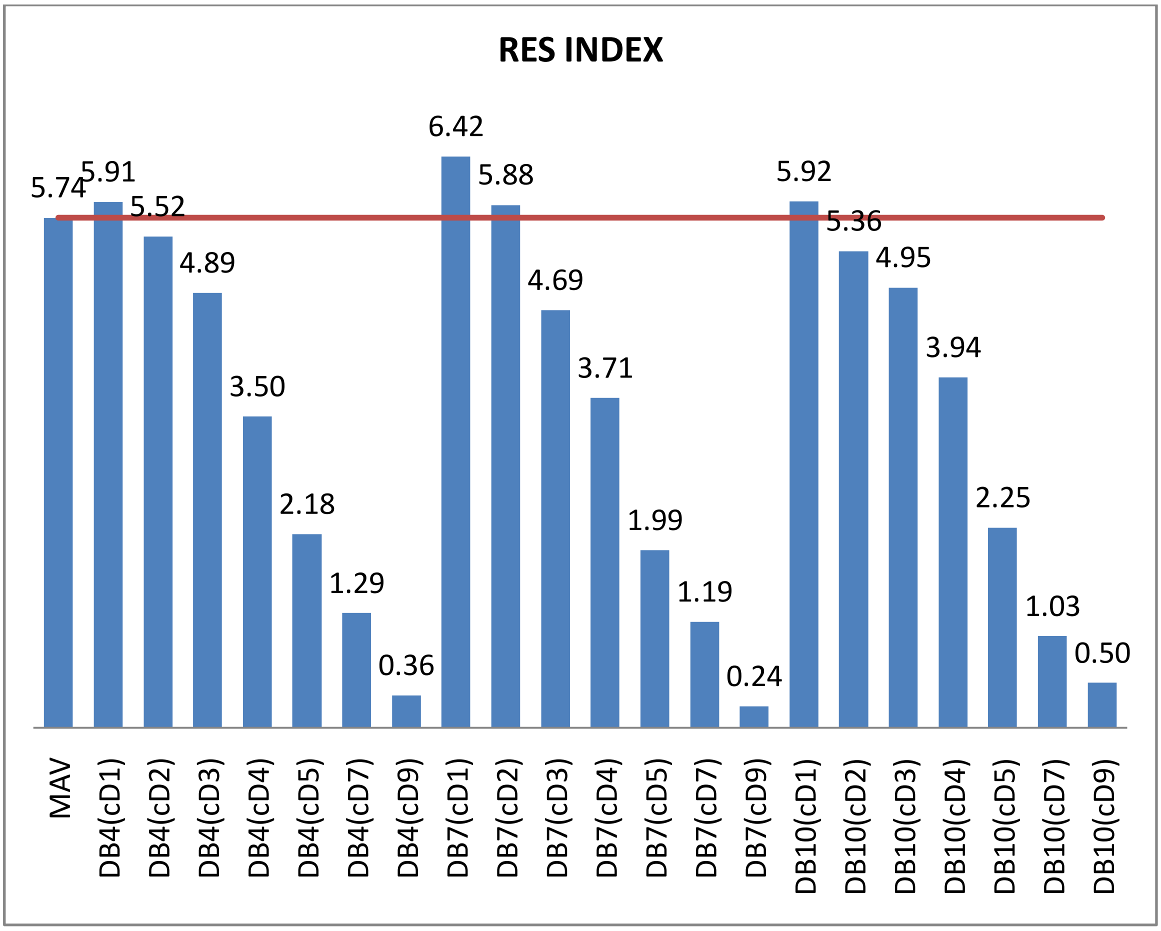
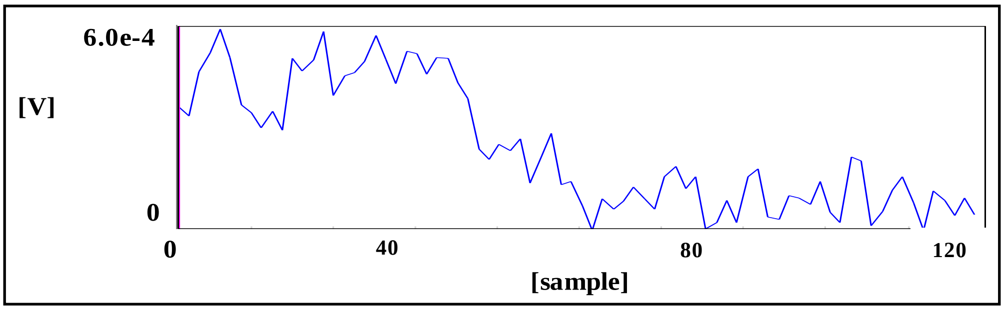
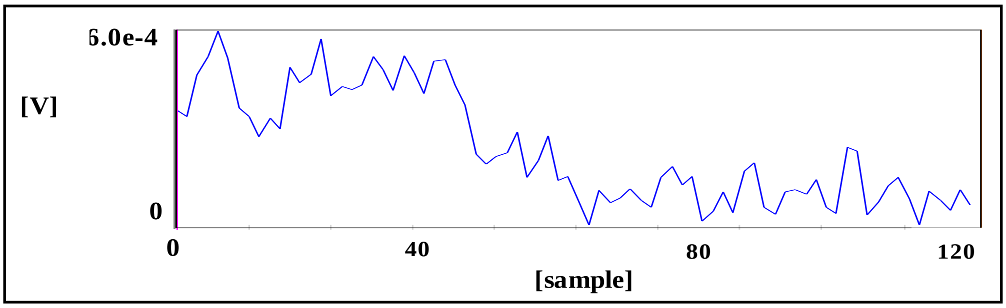


Figure 50: Bar Chart for cD1, cD2, cD3, cD4 cD5, cD7 and cD9 (DB4, DB7 and DB10) RES index

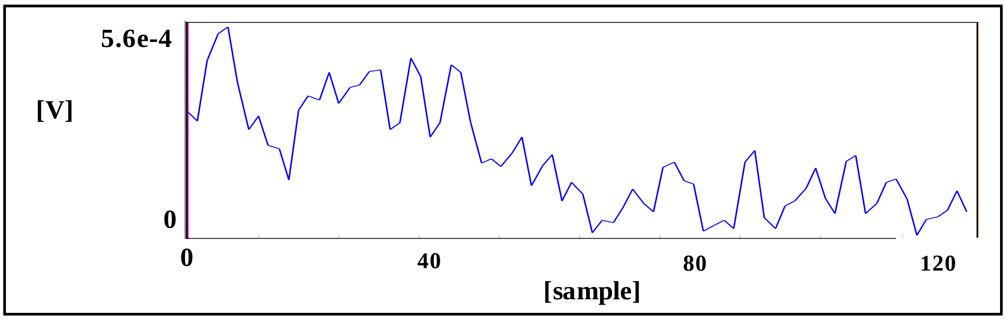
Figure 51 (a) to (g) shows the MAV features for the approximation signals after performing the wavelet reconstruction using DB7 only. Here we also observe that the approximation signals resemble the original signal. However, we can see that the signals are losing its energy once the level of Daubechies wavelet increasing. This proven once again that the higher level of Daubechies wavelet is not suitable for feature enhancement in the signal itself. The best approximation signal occurs in level 1 and 2 which is A1 and A2. A7 and A9 signals are slowly losing its energy and reaches to zero.



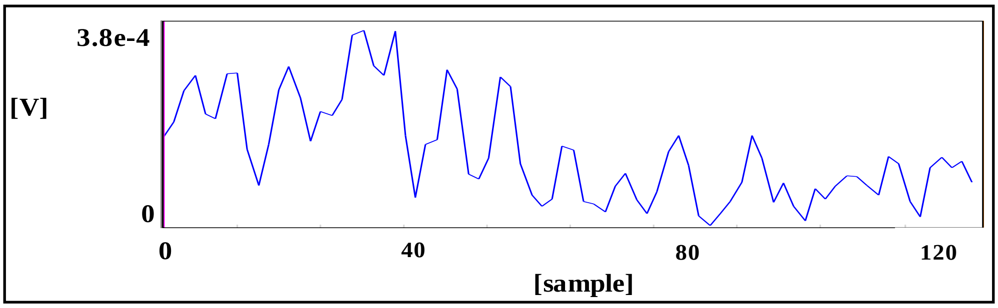
(a) Approximation component (A1) level 1



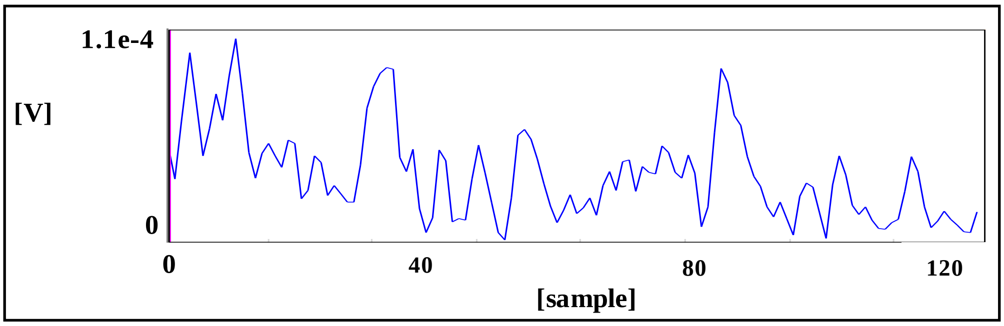
(b) Approximation component (A2) level 2



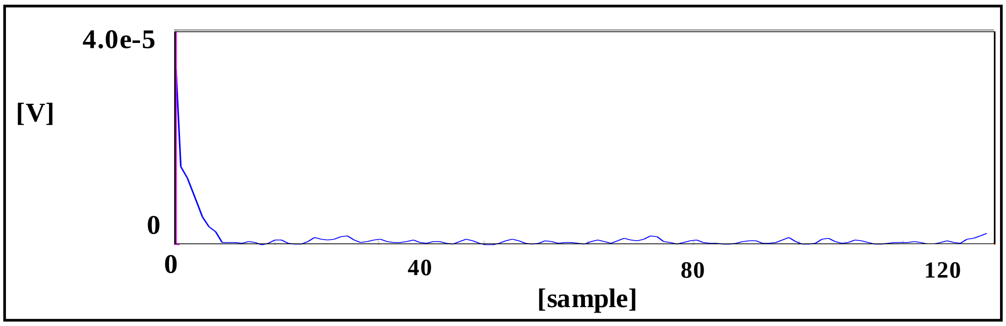
(c) Approximation component (A3) level 3



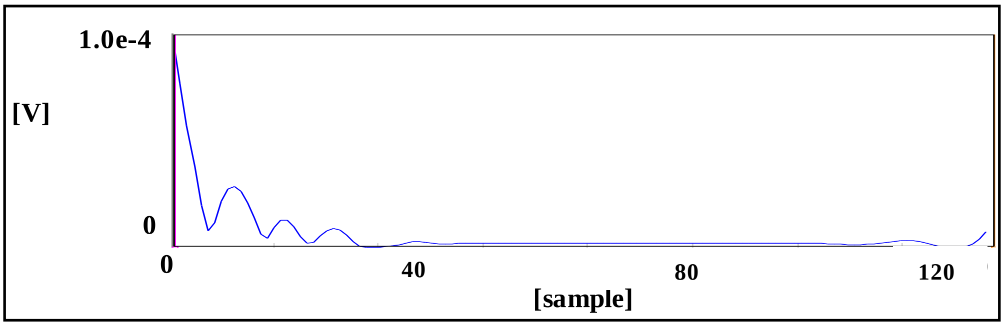
(d) Approximation component (A4) level 4



(e) Approximation component (A5) level 5



(f) Approximation component (A7) level 7



(g) Approximation component (A9) level 9

Figure 51: MAV features for approximation components after performing wavelet reconstruction for DB7 (A1, A2, A3, A4, A5, A7 and A9)

In the context of approximation signals, we can observe that it actually resembles the original signal. From Figure 52 the bar chart shows that approximation in level 1 also gives a better result compared to approximation coefficients signals. The approximation signals in the first level for DB4, DB7 and DB10 gives slightly better results compared to MAV features without any further feature extraction.

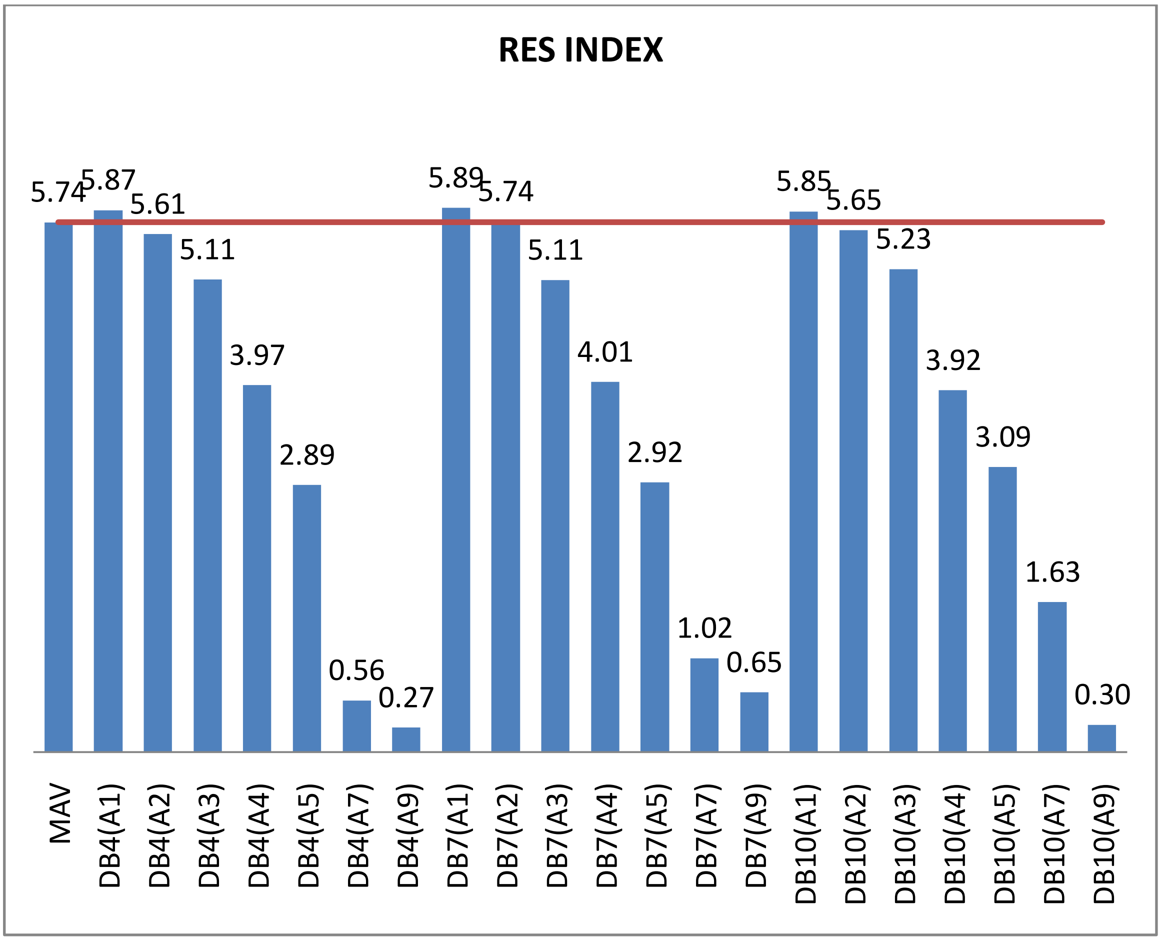
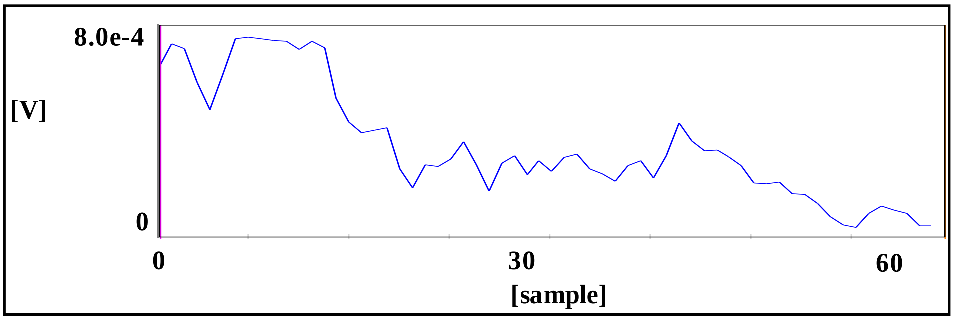
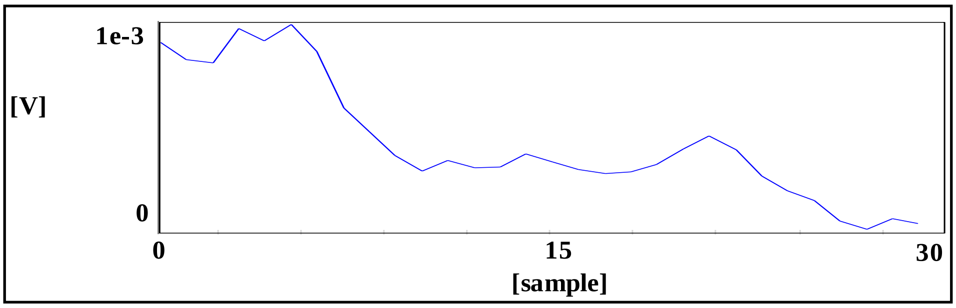


Figure 52: Bar Chart for A1, A2, A3, A4, A5, A7 and A9 (DB4, DB7 and DB10) RES index

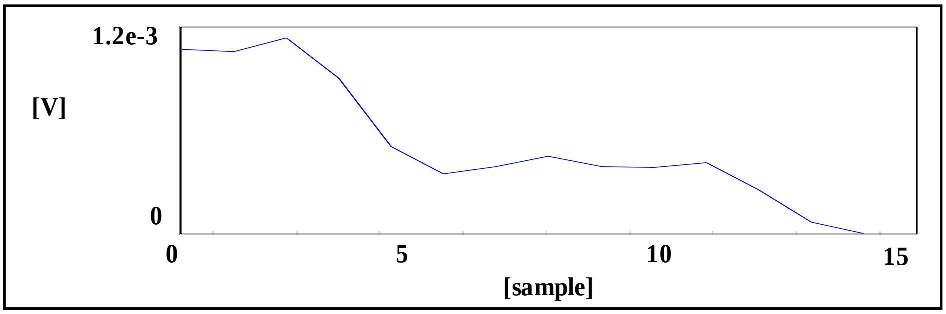
Figure 53(a) to (g) shows the MAV features for the approximation coefficients after performing the wavelet decomposition for DB7. In approximation coefficients we can observe that the sample of the signal is twice lesser than the original signal and it continues to decrease as the levels of decomposition get higher. In this research, we obtained cA1, cA2, cA3, cA4, cA5, cD7 and cA9 by performing the Daubechies wavelet decomposition. We can observe that cA1 signal is still preserving some information from the signal itself while the others levels are slowly losing its data as the level increasing. This is due to the scaling function to the wavelet itself in order to filter out unnecessary information. It results in giving smooth signals as return. The result itself is meaningless for data analysis due to the signal is losing its own information.



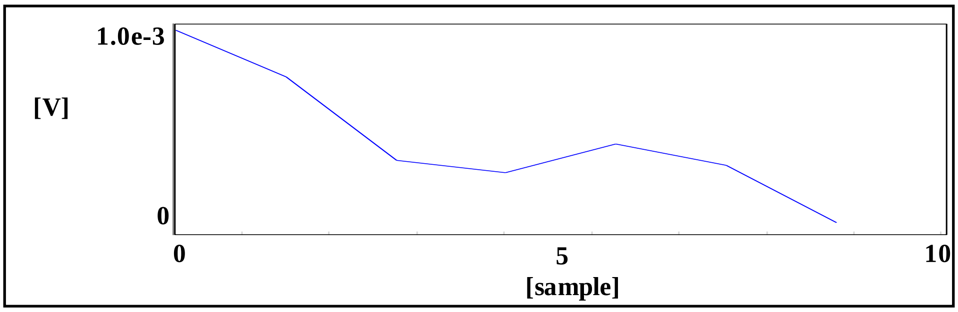
(a) Approximation coefficient (cA1) level 1



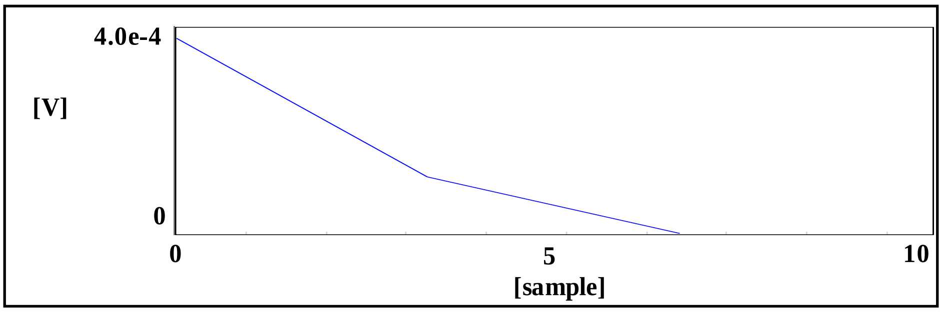
(b) Approximation coefficient (cA2) level 2



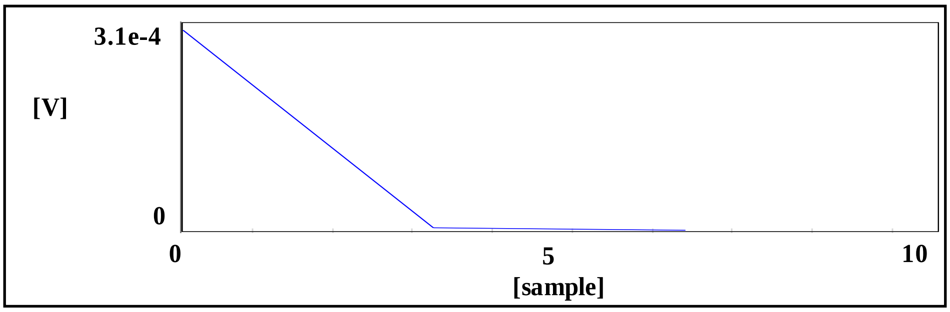
(c) Approximation coefficient (cA3) level 3



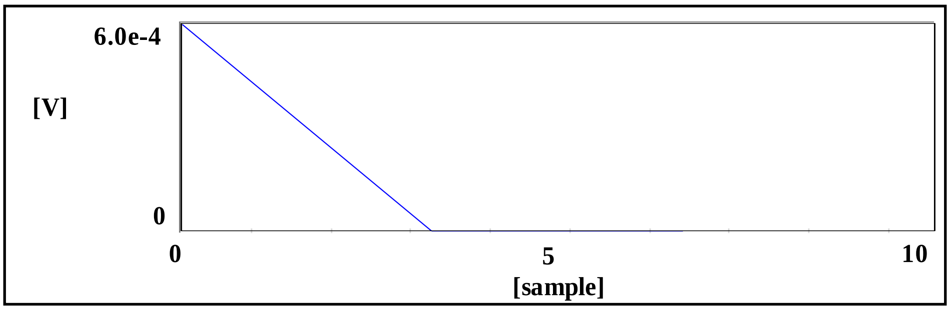
(d) Approximation coefficient (cA4) level 4



(e) Approximation coefficient (cA5) level 5



(f) Approximation coefficient (cA7) level 7



(g) Approximation coefficient (cA9) level 9

Figure 53: MAV features for approximation coefficients after performing wavelet decomposition for DB7 (cA1,cA2,cA3,cA4,cA5,cA7 and cA9)

By observing the bar chart in Figure 54, we can see that the approximation coefficients does not gives any good performance for feature extraction using DB4, DB7 and DB10. However, we still observe that cA1 and cA2 in DB7 are giving a better performance as compared to DB4 and DB10 although the results are not satisfying.

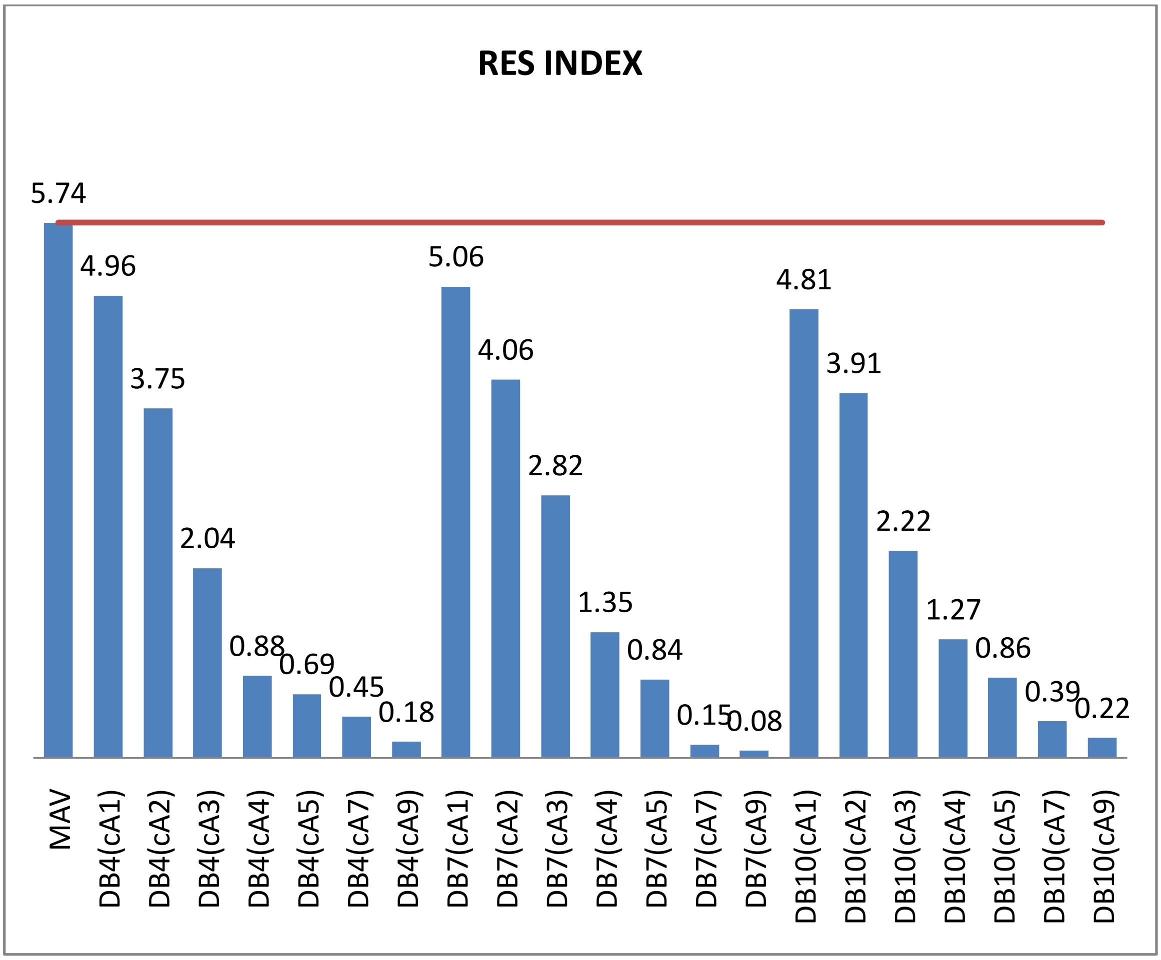


Figure 54: Bar Chart for cA1, cA2, cA3, cA4, cA5, cA7 and cA9 (DB4, DB7 and DB10) RES index

CHAPTER 5
CONCLUSION AND RECOMMENDATION

Hand gestures recognition can be applied in the powered exoskeleton arm for disable people. In order to improve or enhance the algorithms for classification, the suitable feature extraction method is important in the EMG processing. The performance of Daubechies wavelet with multi-levels reconstruction and decomposition has been investigated in our research. Here, we have selected the most successful feature extraction techniques by using MAV and also wavelet transform for EMG signal processing. It is proven that feature extraction using hybrid techniques which is the combination of frequency domain and time domain method lead to a better performance from the results. The results shows that EMG signals feature extraction gives a better performance in term of class separability by using Daubechies detail components in level 1 and level 2. The RES index has been use to evaluate the performance of the EMG feature extraction. Good feature extraction techniques can lead to higher classification accuracy. In this research, it shows that DB7 are suitable for EMG feature extraction.

Future works can be done by performing the classification techniques in order to prove that the feature extraction using hybrid technique gives good classification accuracy. Although the RES Index gives a good performance in term of the feature extraction performance but we do not know the classification accuracy until we further process it with classification techniques. Besides, there are many more feature extraction techniques which can be further explore so that there will be more data to prove that which feature extraction techniques that actually can improve the classification accuracy.

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APPENDIX A

GANTT CHART FOR FYP 1 AND FYP 2

Gantt Chart for FYP 1															
Week Number Activities	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
FYP Title selection	D														
Literature Review		D	D	D	D	D									
Design of Experimental Procedure		D	D	D	D	D									
Submission of Extended Proposal						D									
Signal Acquisition							D	D	D						
Proposal Defense									D						
Project work continues										D	D	D	D		
Submission of Draft Report														D	
Submission of Interrim Report															D
Gantt Chart for FYP 2															
Feature Extraction	D	D	D	D	D	D	D								
Submission of Progress Report								D							
Project work continues									D	D					
Pre-EDX											D				
Project work continues												D			
Submission of Draft Report													D		
Submission of Final Report														D	
Submission of Technical Report														D	
VIVA															D