

**ÇUKUROVA UNIVERSITY  
INSTITUTE OF NATURAL AND APPLIED SCIENCES**

**MSc THESIS**

**Durmuş Ali EROĞLU**

**REAL TIME ELBOW JOINT ANGLE ESTIMATION USING sEMG  
SIGNALS**

**DEPARTMENT OF ELECTRICAL AND ELECTRONICS ENGINEERING**

**ADANA, 2015**

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## **ABSTRACT**

### **MSc THESIS**

|                                                                      |
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| <b>REAL TIME ELBOW JOINT ANGLE<br/>ESTIMATION USING sEMG SIGNALS</b> |
|----------------------------------------------------------------------|

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The Surface Electromyographic (sEMG) signal is convenient for prosthetic device control due to its non-invasive acquisition and its intrinsic relation to the user's intention. This thesis presents an algorithm for estimation of the real time elbow joint angle from sEMG signals acquired from the muscles of biceps and triceps. The algorithm developed in the thesis uses time-domain feature extraction methods such as mean absolute value (MAV), root mean square (RMS) and waveform length (WL). Estimation of the joint angle using extracted sEMG features is performed by Artificial Neural Networks (ANN), specifically a Multilayer Perceptron (MLP) and a general regression neural network (GRNN). The overall system is implemented and tested in a real time hardware setup. The results indicated that developed method could be successfully used for a prosthetic arm device posture control.

**Key Words:** Surface Electromyographic (sEMG) Signals, Prosthetic Device Control, Time-Based Feature Extraction, Artificial Neural Networks.

## ÖZ

### YÜKSEK LİSANS TEZİ

#### YÜZEYEL EMG İŞARETLERİNİ KULLANARAK GERÇEK ZAMANLI DİRSEK EKLEM AÇISININ TAHMİNİ

**Durmuş Ali EROĞLU**

**ÇUKUROVA ÜNİVERSİTESİ  
FEN BİLİMLERİ ENSTİTÜSÜ  
ELEKTRİK ELEKTRONİK MÜHENDİSLİĞİ ANABİLİM DALI**

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Yüzeyel Elektromiyografik işaret, girişimsel olmayan şekilde edinilmesi ve kullanıcının isteğiyle doğrudan ilişkili olması sebebiyle protez cihaz kontrolü için uygundur. Bu tez, biceps ve triceps kaslarından edinilen Yüzeyel EMG işaretlerinden gerçek zamanlı dirsek eklem açısının tahmini için bir algoritma sunar. Tezde geliştirilen algoritma ortalama mutlak değer, ortalama karekök ve dalga boyu gibi zamana dayalı öznitelik çıkarma yöntemleri kullanır. Çıkarılan yüzeyel EMG öznitelikleri kullanılarak yapay sinir ağları özellikle Çok Katmanlı Algılayıcı ve Genel Regresyon sinir ağı tarafından eklem açısı tahmini gerçekleştirilir. Tüm sistem gerçek zamanlı donanım düzeneğinde uygulandı ve test edildi. Sonuçlar, geliştirilen yöntemin protez kol cihazının pozisyon kontrolü için başarılı bir şekilde kullanılabilirliğini göstermiştir.

**Anahtar Kelimeler:** Yüzeyel Elektromiyografik İşaretler, Protez Cihaz Kontrolü, Zamana Dayalı Öznitelik Çıkarma, Yapay Sinir Ağları.

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## LIST OF SYMBOLS AND ABBREVIATIONS

|              |                                                    |
|--------------|----------------------------------------------------|
| $^{\circ}$   | : Degree                                           |
| $\sim$       | : Approximately                                    |
| $k$          | : Segment                                          |
| $N$          | : Length of the Segment                            |
| $x_i$        | : The Value of Each Part of the Segment $k$        |
| $e$          | : Threshold                                        |
| $a_i$        | : AR coefficients                                  |
| $e_k$        | : White Noise or Error Sequence                    |
| $M$          | : Length of the Power Spectrum Density             |
| $W(t)$       | : Window Function                                  |
| $*$          | : Complex Conjugate                                |
| $w$          | : Frequency                                        |
| $x(t)$       | : Input Signal                                     |
| $y^*$        | : Complex Conjugate of the Mother Wavelet Function |
| $w_i$        | : Weight                                           |
| $x_i$        | : The Input to the Neuron                          |
| $n_{in}$     | : Input Nodes                                      |
| $n_{hidden}$ | : Hidden Neurons                                   |
| $n_{out}$    | : Output Neurons                                   |
| $d_k$        | : Error                                            |
| EMG          | : Electromyography                                 |
| sEMG         | : Surface Electromyography                         |
| MAV          | : Mean Absolute Value                              |
| RMS          | : Root Mean Square                                 |
| WL           | : Waveform Length                                  |
| ANN          | : Artificial Neural Networks                       |
| MLP          | : Multilayer Perceptron                            |

|      |                                     |
|------|-------------------------------------|
| GRNN | : General Regression Neural Network |
| MAVS | : Mean Absolute Value Slope         |
| ZC   | : Zero Crossing                     |
| SSC  | : Slope Sign Changes                |
| STFT | : Short Time Fourier Transform      |
| WT   | : Wavelet Transform                 |
| WPT  | : Wavelet Packet Transform          |
| PCA  | : Principal Components Analysis     |
| LDA  | : Linear Discriminant Analysis      |
| HMM  | : Hidden Markov Model               |
| IEMG | : Integrated EMG                    |
| VAR  | : Variance                          |
| BZC  | : Bias Zero Crossing                |
| WAMP | : Willison Amplitude                |
| AR   | : Auto Regressive Coefficients      |
| DBI  | : Davies Bouldin Index              |
| BPNN | : Back Propagation Neural Network   |
| TD   | : Time Domain                       |
| HEMG | : Histogram of EMG                  |
| MFMN | : Modified Frequency Mean           |
| FFT  | : Fast Fourier Transform            |
| KNN  | : K-nearest neighbor                |
| DFT  | : Discrete Fourier Transform        |
| SOM  | : Self Organizing Map               |
| FMN  | : Frequency Mean                    |
| FMD  | : Frequency Median                  |
| SVM  | : Support Vector Machine            |
| FCMs | : Fuzzy C-Means                     |
| K    | : Kilo                              |
| CMRR | : Common Mode Rejection Ratio       |
| dB   | : Decibel                           |

|         |                               |
|---------|-------------------------------|
| m       | : Milli                       |
| Hz      | : Hertz                       |
| G       | : Giga                        |
| M       | : Mega                        |
| ADC     | : Analog to Digital Converter |
| IAV     | : Integrated Absolute Value   |
| FR      | : Frequency Ratio             |
| $\mu$ V | : Microvolts                  |
| MSE     | : Mean Square Error           |
| SD      | : Standard Deviation          |



## 1. INTRODUCTION

Electromyogram (EMG) is defined as the measurement of electrical activity formed on the muscles during contraction or relaxation of muscles. The system that records this activity is called as electromyograph and the process of examination of muscle function through electrical signals is called as electromyography (E. Yazgan and M. Korürek, 1996).

Surface EMG (sEMG) signals are taken from skin surface and they are used in various applications. Among them, clinical diagnosis, functional electrical stimulation (FES) and prosthetic device control could be stated. Patients with defects in their arm or hand cannot perform many functions in daily life. Prosthetic devices are designed to remedy this deficiency and to regain the arm or hand functionality. In applications, raw biological signals as a result of the activation of muscles are processed with developed techniques and methods in literature and they are used as control signals in the electronic controllers to move the mechanical parts of prosthetic limbs.

However, prosthetic devices still have limitations and have needed improvements. Major subjects related to improvements are mainly categorized into three subgroups. The first one is mechanical solutions which will provide to operate arm at enough degrees of freedom. The second one is electronic circuits which will provide to move mechanical part desired speed and capability. Last but not the least one is the improvements in the production of control signals for prosthetic uses.

The control signals from sEMG are mainly obtained by performing feature extraction and classification techniques. The yielded information is used for postural and torque estimations for prosthetic device. In postural estimations, accurate real-time joint angle estimation have important role in device control since it is used as set point value. However, the real-time joint angle estimation still needs improvements in terms of accuracy and response time.

In this thesis, it is aimed to bring an improvement to above estimation issues. To do that, a real time elbow joint angle estimation method by processing and classifying two different EMG signals which are taken from the biceps and triceps

muscles is proposed. In the scope of thesis, it aimed to collect EMG data which is measured from muscles of biceps and triceps correctly, to extract feature vector as real time, to choose correct classification algorithm and to compare with different classification algorithm, in an integrated structural form.

The material in this thesis is organized as follows:

Section 2 provides a brief historical overview of previous and current work related with the area of sEMG signal processing and prosthesis control uses.

Section 3 progresses into the actual analysis of the EMG data. Feature extraction of the relevant information and the classification strategies which are used in this thesis are discussed. The various algorithms are briefly summarized and the final EMG Classifier program is presented.

Section 4 concludes and summarizes the results of this thesis and compares different methods.

Finally, Section 5 summarizes all the work done in this thesis. Future work planned on the thesis topic and possible improvements for a more robust design are in this chapter.

## 2. PRELIMINARY WORKS

Surface electromyography (sEMG) is used to assess and record the electrical activity of muscles. It is a noninvasive technique and this technique has applied for different applications which are used in clinical neurological problems and control of prosthesis devices. Control of prosthesis is based on pattern recognition.

The analysis of pattern recognition in sEMG mostly occurs from two sections, that is feature extraction and classification. Feature extraction is the reduction of the raw sEMG input dimension to compose a feature vector. It is important to choose accurate features because the accuracy of the pattern classification system nearly is conditional on the choice of these features. Researchers have done studies with different features which are used in pattern recognition including time, frequency and time frequency domain features.

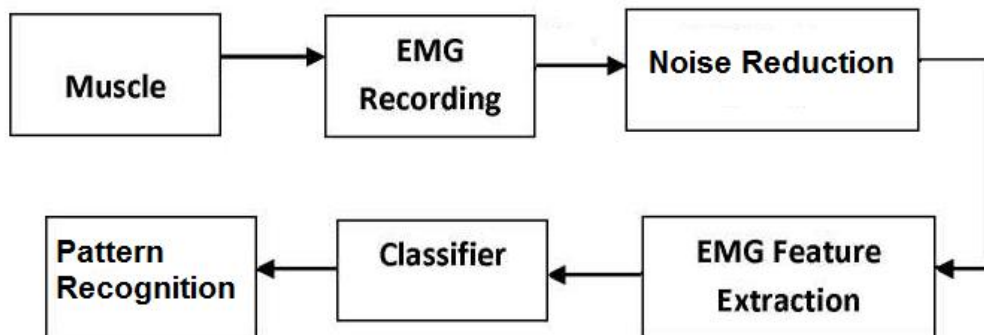


Figure 2.1. Block Diagram of the Process of EMG Classification System (Chowdhury et al., 2013)

Process which starts from EMG measurement part to pattern recognition part is given at Figure 2.1. The stages are EMG recording, noise reduction, EMG feature extraction, classifier and pattern recognition in the process of EMG classification. Each one of subjects in these stages was studied on and made progress.

It was done scientific research that used feature extraction and classification methods together. Oskoei et al. (2007), Ramirez et al. (2011), Chowdhury et al. (2013) and Hakonen et al. (2015) mention about the most recent developments and

research studies related with the topics mentioned above at their studies. Some of these studies are listed in following sections:

Hudgins et al. (1993) applied EMG signals with five time domain features for classification. The features which they used in their studies were the mean absolute value (MAV), mean absolute value slope (MAVS), zero crossing (ZC), slope sign changes (SSC), and waveform length (WL). This study resulted with accuracy ratio of 91% using MLP neural networks.

Englehart et al. (1993, 2001) used feature projection in their works to contrast accuracy of time domain features applied in study of Hudgins and friends with time scale features which were formed a short time Fourier transform (STFT), wavelet transform (WT), and a wavelet packet transform (WPT). Using principal components analysis (PCA) initially decreased dimension of features. The best accuracy was gotten by features of WPT, PCA reduction, and LDA classification. An average error in their studies was 0.5% in four class, and 2% in six class classification problems. This was an important development with reference to Hudgins et al..

Chan and Englehart (2005) studied over Hidden Markov Model (HMM) to process EMG signal with four channels that separated six classes of limb movement. It was obtained an average accuracy of 94.63% from HMM classification of continuous EMG signals.

Huang and Chen (1999) used EMG time domain features (integrated EMG (IEMG), waveform length (WL), variance (VAR), slope sign changes (SSC), Willison amplitude (WAMP), and bias zero crossings (BZC)) and frequency domain features of EMG (fourth order auto regressive coefficients (AR)) to contrast the performance of them and also to discriminate hand movements. There were two sections in their studies. In the first section, they applied the index of Davies Bouldin (DBI) which is a measurement that shows the overlapping degree of the clusters according to their closest neighbors. Davies Bouldin index's lower value indicates higher degree of separability to asses each feature. It gave result that IEMG, WL and VAR had better separability than other features. In the second section, the best features (IEMG, WL and VAR) detected in the first section were added with other chosen features (AR of second order, WAMP and BZC) to obtain the best accuracy.

Two feature vectors were applied in the neural network to test the results. The first feature set occurred from WL, WAMP, IEMG and VAR; and the second set consisted of second order AR model parameters, VAR, IEMG, WAMP, WL and BZC. The feature set of second order AR model parameters, VAR, IEMG, WAMP, WL and BZC gave the best accuracy for the hand movements' classification. Huang and Chen developed a system of EMG separation system for a prosthetic hand and did eight kinds hand movements classification such as wrist flexion, power grasp, three jaw chuck, lateral hand, cylindrical grasp, hook grasp, flattened hand and centralized grip. It is applied a back propagation neural network (BPNN) for separation of the feature sets. The neural network structure occurred from one hidden layer and one output layer. Nonlinear sigmoid function was the transfer functions for output layer neurons and hidden layer neurons. Accuracy ratio for offline test was 85% and accuracy ratio for online test was 71% in their studies.

Huang et al. (2005) did a comparison of three feature sets in EMG classification. Root mean square (RMS), autoregressive (AR) coefficients and Hudgins' time domain (TD) features were the feature sets used in their works. A combination of a six order AR coefficient and RMS gave higher accuracy rates. It is obtained a 3.7% average error rate in RMS - AR feature set and 3.1% average error rate in TD - AR - RMS feature set for six classes of limb movements. Furthermore, the RMS - AR feature set was also used by Chan and Englehart (2005) and resulted in a high performance rate around 94%.

Phinyomark et al. (2009) used eighteen time domain features (mean absolute value (MAV), integrated EMG (IEMG), modified mean absolute value 1 (MMAV1), mean absolute value slope (MAVS), modified mean absolute value 2 (MMAV2), simple square integral (SSI), root mean square (RMS), variance (VAR), waveform length (WL), slope sign changes (SSC), zero crossings (ZC), histogram of EMG (HEMG) and Willison amplitude (WAMP)) and frequency domain features (frequency mean, frequency median, modified frequency median, modified frequency mean and autoregressive coefficients) to compare each other in a noisy condition that it purposed to detect which one has a better white Gaussian noise performance. Their results showed that from the point of view of white Gaussian

noise, modified frequency mean (MFMN) was the best feature comparing with others on the quality of the robustness of EMG features. MFMN had an average error of 6% on strong EMG signals and 10% on weak EMG signal; also MFMN had an average error of 0.4% in both strong and weak EMG signal. In addition, MFMN and other robust features (WAMP and HEMG) were used as an input to the EMG pattern recognition. The experiment showed that these features were excellent candidates for a multi-source feature vector.

Karlik et al. (2005) compared different signal processing methods which are used to find EMG feature vector. These methods were Fast Fourier Transform (FFT), Auto Regressive (AR) parameters and Wavelet Transform (WT). EMG signal is classified using Back Propagation Neural Network (BPNN) algorithm which has many layers. According to results, they found more successful to use WT in EMG classification.

Peleg et al. (2002) applied K-nearest neighbor (KNN) as a classifier and Generic Algorithm (GA) as a feature selection for EMG signals in finger motions to be used in a robotic prosthesis hand. The characteristic features were obtained from discrete Fourier transform (DFT) of the EMG signal and coefficients of an eleventh order autoregressive (AR) model. The method was resulted in a probability of error of less than 2%.

Chu et al. (2006) studied over real time EMG classification for control of a multifunction myoelectric hand via four channel EMG signals. They used a wavelet packet transform to extract a feature vector from the EMG signal. They also used a linear and nonlinear feature projection which consisted of principal components analysis (PCA) and a self organizing map (SOM). They employed to classify a multilayer perceptron (MLP) with an input layer constructed from the eight outputs of the SOM for four channels, two hidden layers which each hidden layer has nine neurons and an output layer with nine neurons for the nine hand motions to be recognized. The average classification success rates of the MLP were 97.024% when PCA+SOM were used, 97.785% when SOM was applied and 95.759% when PCA was employed. Their experimental results which showed that all processes and included virtual hand control were completed within 125 ms.

Oskoei and Hu (2006) used advanced subset search algorithms to evaluate EMG features of upper limb. These algorithms consisted of a genetic algorithm Davies Bouldin index and Fishers linear discriminant index. An artificial neural network was implemented as the classifier in the upper limb EMG system. They evaluated EMG time domain features such as mean absolute value (MAV), mean absolute value slope (MAVS), root mean square (RMS), variance (VAR), waveform length (WL), zero crossings (ZC), slope sign changes (SSC), Willison amplitude (WAMP), auto-regressive coefficients (AR) and EMG frequency domain features such as frequency mean (FMN), frequency median (FMD) and frequency ratio (FR). As a result, they found that WL demonstrated high capability in providing discriminating information for EMG classification; after that MAV and RMS were placed in second grade and AR in third grade.

Oskoei and Hu (2008) compared SVM, LDA and multilayer perceptron neural network (MLP) in classifying upper limb motions using myoelectric signals. They used four kernels (radial-basis, linear, polynomial and sigmoid) in SVM and two multilayer perceptron neural networks, one with one hidden layer (MLP1) and the other one with two hidden layers (MLP2). The average accuracy for all kernels in SVM was approximately  $95.5 \pm 3.8\%$ . The LDA was placed after SVM with the average performance of  $94.5 \pm 4.9\%$ . The MLP2 performed a similar accuracy to the SVM and LDA, while the accuracy of MLP1 dropped approximately 6%.

Wei and Hu (2010) designed a human machine interaction (HMI) for hands free control of a wheelchair, employing forehead EMG signals and color face image information. They used five recognizable movements: SJC (single jaw clenching), DJC (double jaw clenching) and CJC (continuous jaw clenching) from jaw movements and LEC (left eye close) and REC (right eye close) from eye movements. SJC and DJC patterns were recognized using a threshold based strategy; while CJC, LEC and REC were separated using SVM with a radial basis function kernel. The result achieved by SVM had an accuracy rate of over 93%.

Subasi et al. (2006) compared back propagation neural networks (BPNN) and wavelet neural networks (WNN) for classifying neuromuscular disorders of EMG recordings. They used an auto regressive (AR) model of EMG signals as an input to

classification system. The BPNN was designed with AR spectrum of EMG signal in the input layer; the output layer consisted of three nodes representing normal, myopathic or neurogenic disorder. On the other hand, the WNN was designed with mono hidden layer forward neural network with its node activation function based on dyadic discrete Morlet wavelet basic function to locate the three classes. The success rate for the WNN technique was 90.7% and for the BPNN technique 88%.

Firoozabadi et al. (2008) developed hands free control system for operating a virtual wheelchair which was based on forehead multi channels EMG signals. SVM was used for classifying the motion control commands (forward, left, right, backward and stop). Three subjects (one adult and two children) participated in controlling a virtual wheelchair using interface software on a personal computer. The accuracy percentages of SVM classification were: 100% for the adult and 89.75% and 97.49% for the two children.

Lucas et al. (2008) proposed a multi channel supervised classification of EMG signals with the aim of controlling myoelectric prostheses. The classification of six hand movements was performed with SVM approach in a multi channel representation space. The results showed an average misclassification rate of 5%.

Kiguchi et al. (2004) developed a robotic exoskeleton for human upper limb motion assist. It was controlled using EMG signals. A hierarchical neuro fuzzy controller which consisted of three stages: input signal selection, posture region selection stage and neuro-fuzzy control was used as a classifier. Three membership functions were used for the elbow and shoulder regions: flexed angle (FA), intermediate angle (IA) and extended angle (EA). By applying these membership functions, the appropriate controllers were moderately selected in accordance with the arm posture of the robot user. Two kinds of nonlinear functions were applied to express the membership function of the neuro fuzzy controller. The initial fuzzy IF-THEN control rules were designed based on the analyzed human elbow and shoulder motion patterns, then they were transferred to the neural network form.

Ajiboye and Weir (2005) presented a heuristic fuzzy logic approach to multiple EMG pattern recognition for multifunctional prosthesis control. Basic signal statistics (mean and standard deviation) were used for membership function

construction and fuzzy c-means (FCMs) data clustering was used to automate the construction of simple amplitude driven inference rule base. The multi input single output fuzzy system consisted of three parts: input membership functions that fuzzify numerical inputs, converting them to linguistic variables; an inference rule base that performs pattern classification by processing the linguistic inputs, returning linguistic outputs and associated degrees of truth and an output membership function that defuzzifies the inference rule base linguistic outputs, converting them to one numerical value. Four fuzzy sets were defined of signal gradation (OFF, LOW, MED, HIGH). Overall classification rates ranged from 94% to 99%.

Results of feature extraction and classification methods which are mentioned above studies was begun to be implemented as a control signal for rehabilitation devices. In control of devices, joint angle estimations have an important role to control a rehabilitation device so many researchers did scientific studies about this subject. Some of these studies are listed below:

Pang et al. (2015) applied an upper limb elbow joint representation method that used only single channel EMG signals. EMG signals were recorded from the biceps muscle and a discretized recursive filter was implemented to calculate the muscle activation level from signals. A modified Hill type muscular model was implemented to build a quantitative relationship between the elbow joint angle and the muscle activation level (or EMG signals). Experimental results indicated that this method could provide suitable prediction results with RMS errors of below  $10^\circ$  in continuous motion and RMS errors of below  $10^\circ$  in stepping motion with  $20^\circ$  and  $30^\circ$  increments.

Raj et al. (2015) made to estimate the elbow joint angle from surface Electromyography (SEMG) signal during dynamic contraction using Fuzzy logic technique. SEMG signals were taken from the biceps brachii of subjects during flexion and extension of elbow. To estimate the elbow joint angle, the SEMG signals were segmented into 250ms by adjacent window technique and two time domain parameters such as Integrated EMG (IEMG) and Zero crossing (ZC) were extracted from windowed raw EMG signals. The estimated values of elbow joint angles were compared with the actual angle values. Two dimensional robotic arm animations

were also coded using LabVIEW and incorporated to the output of fuzzy logic system to simulate the estimated angle. Regression value obtained from the experiment was 0.7975.

Aung et al. (2012) improved a sEMG based back propagation neural network (BPNN) and a virtual human model (VHM). Four sEMG signals were collected from each of four healthy subjects and then sent to a BPNN controller to estimate the upper limb joint angle. The estimated angle was then displayed by the developed VHM. The evaluation results showed that the developed BPNN could represent the relationship between sEMG and joint angle successfully and the simulation of VHM mimicked the human arm movements.

It is aimed a study which is related to real time elbow joint angle estimation in this thesis. Firstly, two different EMG signals which are measured from the biceps and triceps muscles are processed using band pass filter and notch filter. Secondly, it is extracted features from these processed EMG data. It is used mean absolute value (MAV), root mean square (RMS) and waveform length (WL) which are from time domain feature extractions in this thesis as feature extraction and it is occurred feature vectors. Then, these feature vectors are classified using multilayer perceptron (MLP) and general regression neural network (GRNN). Finally, real time estimation of elbow joint angle which is result of neural networks compared with each other.

### 3. MATERIALS AND METHODS

#### 3.1. Introduction

Previous literature surveys state that an sEMG classification system is mainly composed of three sub blocks. (Rechy - Ramirez and Hu, 2011). These blocks are sEMG measurement and data acquisition unit, feature extraction unit and pattern classifier unit. A general overview of the system developed in this thesis for real-time joint angle estimation is given in Figure 3.1. In the system there is a goniometer which is used in training phase of classifiers and in final accuracy tests. The software for the overall system is implemented in MATLAB package at a desktop PC.

First of all, the measurement and data acquisition phase takes place. sEMG signals are collected by electrodes placed on the skin over a user's muscle. Signals are then amplified, filtered, digitized via standard EMG instruments (BIOPAC), and transferred to a feature extraction which computes and presents preselected features for a classifier. Next, the features are fed into a classifier to improve classification efficiency. Selection or extraction of highly effective features is one of the most critical stages in estimation elbow joint angle. The last component is pattern classification module which recognizes signal patterns. Due to the complexity of biological signals, and the influence of physiological and physical conditions, the classifier should be adequately robust and intelligent. It is aimed to be able to adapt itself to changes during long-term operation, by exploiting offline and/or online training.

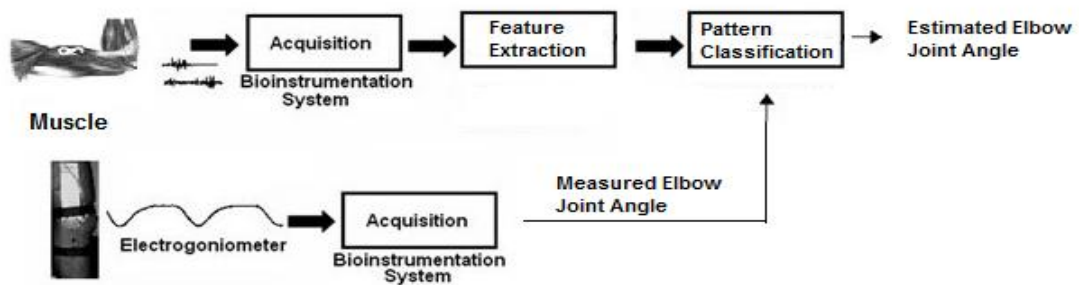


Figure 3.1. Block Diagram for the Estimation of Elbow Joint Angle (Delis et al., 2009)

### 3.2. EMG Signal

The sEMG signal is a superposition of individual motor unit action potentials (MUAPs) within the pick-up range of the surface electrodes. In the example given below Figure 3.2 a raw surface EMG recording (sEMG) was done for three static contractions of the biceps brachii muscle (Konrad, 2006).

Raw sEMG can range between  $\pm 5000$  microvolts and typically the frequency contents ranges between 6 and 500 Hz, showing most frequency power between  $\sim 20$  and 150 Hz (Konrad, 2006).

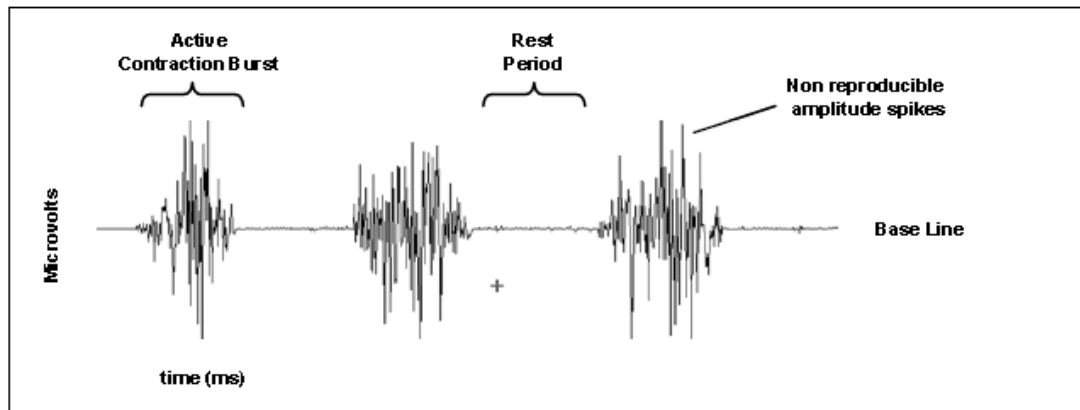


Figure 3.2. The Raw EMG (Konrad, 2006)

The human body is a good electrical conductor, but unfortunately the electrical conductivity varies with tissue type, thickness, physiological changes and temperature (Konrad, 2006).

### 3.3. EMG Measurement and Data Acquisition

Methods used to acquire data are heavily dependent on the nature of signals to be acquired. EMG signals are complex signals, controlled by the nervous system and are dependent on the anatomical and physiological properties of muscles. Also, it is important to realize that just like any other signals in transit, the EMG signal gets contaminated with undesirable signals (noise) as it traverses from its source to the recording apparatus, making it very difficult to detect. Fortunately, there are

techniques that can be used to minimize noise embedded in signals. One such technique is through the process of differential amplification. As a result, the recording of small signals buried in larger common signals is possible. Employing similar techniques, small EMG signals can reliably (high signal to noise ratio) be detected and recorded. Care should be taken when selecting electrodes and type of amplifiers. Electrode and internal amplifier noise may distort the recording of the EMG signal. Filtering is normally performed so that unwanted signals such as low frequency motion artifacts are removed from the EMG signal (Kasi, 2009).

The objective of the acquisition system and signal processing is to provide a high quality sEMG signals where the posture or muscle contraction specific information can be extracted and associated with the desired control command using classifiers, proportional or threshold algorithms, onset analysis, or finite state machines. The acquisition electronics of the sEMG interface consists of sEMG channels, filters, amplifiers, and an A/D converter. This section concentrates on the most essential issues in the design of an acquisition system: sEMG electrodes, cut-off frequencies of filters, sampling rate, and preprocessing algorithms.

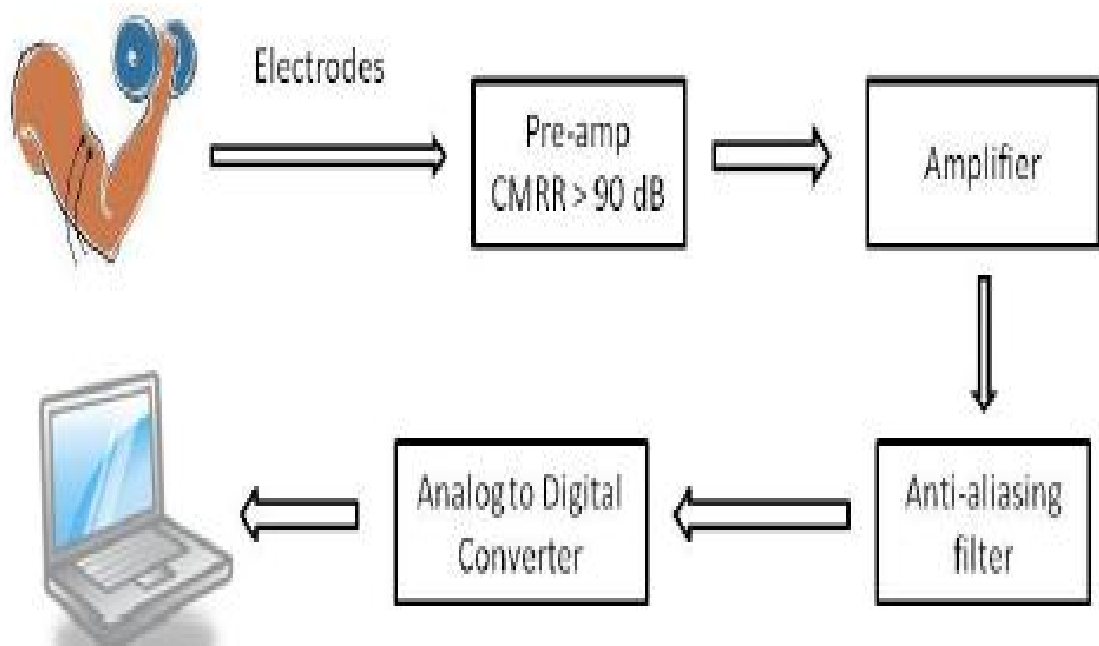


Figure 3.3. EMG Data Acquisition System (Fraser, 2012)

### 3.3.1. Electrodes

sEMG signals can be measured both with wet and dry electrodes. Commonly it is used wet electrodes require conductive electrolyte gel or sponge between the electrode and the skin, but it can provide high quality sEMG signals. The wet electrodes often require skin preparation (e.g. shaving and skin abrasion), which can reduce skin–electrode impedance and motion artifacts (Tam and Webster, 1977). Modern dry electrodes do not require conductive gel and skin preparation, and still can reach signal quality comparable to wet electrodes (Laferriere et al., 2010).

For surface electrodes, silver/ silver chloride pre-gelled electrodes are the most often used electrodes and recommended for the general use (SENIAM). Besides easy and quick handling, hygienic aspects are not a problem when using this disposable electrode type. The electrode diameter (conductive area) should be sized to 1cm or smaller.

Commercial disposable electrodes are manufactured as wet-gel electrodes or adhesive gel electrodes. Generally wet-gel electrodes have better conduction and impedance conditions (=lower impedance) than adhesive gel electrodes (Konrad, 2006).

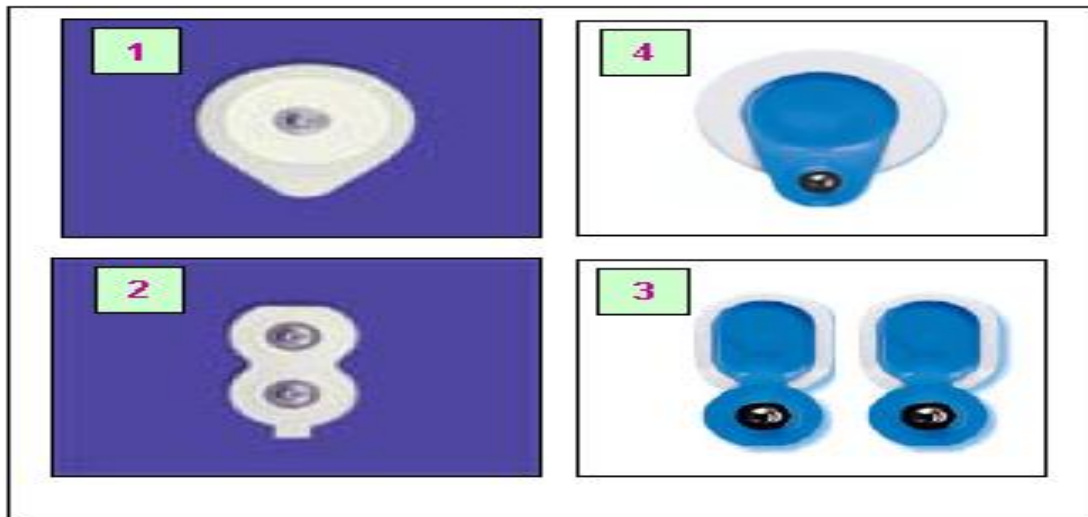


Figure 3.4. Types of Special EMG Electrodes (1,2 NORAXON INC. USA) and ECG Electrodes (3,4 AMBU-Blue Sensor) (Konrad, 2006)

### 3.3.2. Skin Preparation

The quality of an EMG measurement largely depends on a proper skin preparation and electrode positioning. The main strategy of skin preparation is stable electrode contact and low skin impedance. Most modern EMG-amplifiers are designed for skin impedance levels between 5 and 50 kOhm between pairs of electrodes. It is necessary to perform some skin preparation before the electrodes can be applied. There are no general rules for it and several possibilities to reach a good skin condition for EMG measurements exist (Konrad, 2006).

#### **Skin preparation procedures;**

The following procedures may be considered as steps to prepare the electrode application:

#### **Removing the hair;**

This is needed to improve the adhesion of the electrodes, especially under humid conditions or for sweaty skin types and/or dynamic movement conditions.

#### **Cleaning of the skin;**

Special abrasive and conductive cleaning pastes are available which remove dead skin cells because they produce high impedance and clean the skin from dirt and sweat.

Alternatively, a very fine sand paper can be used: A soft and controlled pressure in 3 or 4 sweeps usually is enough to get a good result. The use of sandpaper should be combined with an alcohol pad cleaning.

The pure use of alcohol may be another alternative if used with a textile towel that allows soft rubbing. This latter method may be sufficient for static muscle function tests in uncompromised conditions.

Whichever skin preparation method and electrode application technique is used, when done properly, the skin typically receives a light red color. This indicates good skin impedance condition (Konrad, 2006).

### 3.3.3. Amplifiers

Amplification is essential in EMG signal acquisition to improve the signal-to-noise ratio (SNR). A significant advantage to using a differential (bipolar) or double differential electrode configuration is to leverage the common mode rejection capability of the differential amplifier. Common signals to both electrodes such as those due to noise or deep muscle fibres are rejected (Day, 2002). The common mode rejection ratio (CMRR) for reliable EMG acquisition should be at least 95 dB (Konrad, 2006).

An amplifier is often separated into two components: a pre-amplifier and an amplifier. The pre-amplifier is often as close to the electrodes as possible to ensure minimal contamination. The preamplifier will provide a small amount of voltage amplification and pass the signal to the amplifier which provides more substantial amplification (Fraser, 2012).

EMG is typically in the range of 6 mV peak to peak (Day, 2002); therefore, a gain of at least 1000 is recommended, although a higher gain may be needed for low amplitude signals. The majority of the EMG bandwidth occurs between 10 Hz and 500 Hz. Other frequencies can be filtered out using amplifier settings although, notch filtering (e.g., for 50 Hz power line interference) is not recommended as it can cause loss of useful EMG signal information (Konrad, 2006).

The input impedance of the amplifier needs to be considerably higher than the skin impedance to avoid distortion due to input loading. For Ag-AgCl electrodes, an input of 15 at least 10 MW is recommended. Dry electrodes will result in much larger skin impedance and can require an amplifier input impedance as high as 1 GW (Day, 2002).

### 3.3.4. Filtering

Most EMG filtering is performed digitally; however analog filters are usually applied to the EMG signal during acquisition. The EMG signal passes through high and low pass filters (band filtered) to remove noise such as low frequency noise

introduced by motion artifacts as well as high frequency noise. In addition, low pass filtering prevents aliasing. Low pass filters exclude signals above a set frequency whereas high pass filters eliminate signals below a set frequency. Indwelling EMG signals are usually band filtered between 10 Hz (remove low frequency artifacts such as baseline wonder) and 10 kHz.

### **3.3.5. AD Converter**

An analog-to-digital converter (ADC) is required to sample and quantize the analog input from the amplifier. The ADC should have sufficient bit resolution to accurately represent the signal, and it should have a sufficient sampling rate to represent the entire signal bandwidth. A resolution of 12 bits is adequate for most applications (Konrad, 2006). The sampling rate should be set to at least twice the bandwidth of the signal as given by the Nyquist sampling theorem (Landau, 1967). For EMG this is at least 1000 Hz but often higher sampling rates are used to account for the finite roll-off of the anti-aliasing filter and avoid signal loss (Konrad, 2006).

#### **3.3.5.1. A/D Resolution**

The resolution of an ADC converter is the number of discrete values that it can produce over the range of analog input values. ADC resolution limits the accuracy of a measurement. The higher the resolution (number of bits), the more accurate the measurement.

An ADC converter of  $n$  bits will have  $2^n$  different discrete levels to represent the analog signal, and because of that, for a given dynamic range of the input signal, more bits make higher the system accuracy. For example, an 8 bit ADC converter will be able to produce 256 discrete levels, while a 12 bit converter will produce 4096 levels. For an input with a dynamic range of 10V (from 0 to 10 volts), the 8bit ADC converter would not be capable of resolving voltage differences smaller than 39mV while the 12bit converter could resolve voltage differences as small as 2.4mV

Resolution can also be defined as the minimum change in voltage input in order to make the output LSB change.

### **3.3.5.2. A/D Sample Rate**

The rate at which new single discrete values, representing the continuous signal being sampled, are created is called sampling rate or sampling frequency. This parameter express how many discrete values are created in a given time period by an ADC converter. Higher sampling rates means more samples per time per period, and more samples per period means major capability of capturing faster changes in given signal.

The sampling rate has to be selected taking into account the fulfillment of the Nyquist-Shannon sampling theorem, which basically says that the sample frequency must be at least two times higher than the highest frequency sampled. If this theorem is not respected, aliasing will occur.

## **3.4. Review of Feature Extraction Methods**

The feature extraction mentions about the transformation of the raw signal to relevant data structure which is called feature vector by deleting noise and keeping important data. It could also mean dimensionality reduction which removes redundant data from the feature vector in order to simplify the process of classification.

There are three types of features in EMG control systems: time domain, frequency domain and time-frequency domain (Zecca et al., 2002).

### **3.4.1. Time Domain**

Feature extraction in the time domain is the most popular in EMG classification due to easy and quick to compute. It does not also need a transformation. It is made calculation on the principle of signal amplitude in this

feature extraction. Outcomes of features give some information about amplitude, frequency and duration of signal within some limited parameters (Oskoei and Hu, 2006).

#### 3.4.1.1. Integrated Absolute Value (IAV)

According to Huang and Chen (1999), this parameter is found by calculating the summation of the absolute values of EMG signals. It can be treated as a signal power estimator. It is normally used as an onset detection index in EMG non-pattern recognition and in clinical application. It is defined as:

$$IAV_k = \sum_{i=1}^N |x_i| \quad (3.1)$$

where  $x_i$  is the value of each part of the segment  $k$ , and  $N$  is the length of the segment.

#### 3.4.1.2. Mean Absolute Value (MAV)

The mean absolute value of a signal  $MAV_k$ , calculates by adding the absolute value of all of the values  $x_i$  in a segment  $k$  and dividing it by the length of the segment  $N$  (Englehart and Hudgins, 2003). It is an easy way for detection of muscle contraction levels and it is a popular feature used in myoelectric control (Phinyomark et al., 2009).

$$MAV_k = \frac{1}{N} \sum_{i=1}^N |x_i| \quad (3.2)$$

**3.4.1.3. Mean Absolute Value Slope (MAVS)**

It estimates the difference between mean absolute values of the adjacent segments  $k + 1$  and  $k$  (Proakis and Manolakis, 1996).

$$MAVS_k = MAV_{k+1} - MAV_k \quad (3.3)$$

**3.4.1.4. Root Mean Square (RMS)**

Root mean square value is calculated by squaring each data point, summing the squares, then dividing the sum by the number of observations, and finally taking the square root (Hudgins et al., 1993)

$$RMS_k = \sqrt{\frac{1}{N} \sum_{i=1}^N x_i^2} \quad (3.4)$$

where  $x_i$  is the value of each part of the segment  $k$ , and  $N$  is the length of the segment. It is related to constant force and non-fatiguing contraction (Phinyomark et al., 2009).

**3.4.1.5. Variance (VAR)**

The variance of the signal gives a measure of how much the samples differ from each other (Joshi et al., 2008)

$$VAR_k = \frac{1}{N} \sum_{i=1}^N (x_i - \bar{x})^2 \quad (3.5)$$

where  $\bar{x}$  is the mean value of the segment  $k$ . It uses the power of the sEMG signal as a feature (Phinyomark et al., 2009).

#### 3.4.1.6. Waveform Length (WL)

It is the cumulative length of the waveform over the segment. The resultant values show a measurement of amplitude, frequency and duration of waveform within a single parameter (Englehart and Hudgins, 2003). It is related to the amplitude, frequency and time of waveform (Phinyomark et al., 2009).

$$WL_k = \sum_{i=1}^{N-1} |x_{i+1} - x_i| \quad (3.6)$$

#### 3.4.1.7. Zero Crossing (ZC)

This feature measures the amount of times the signal crosses zero. A zero crossing is only registered if the difference between the two samples  $x_i$  and  $x_{i+1}$  exceeds a pre-defined threshold  $\epsilon$  to avoid interference from noise (Hudgins et al., 1993). This feature provides an approximate estimation of frequency domain properties (Phinyomark et al., 2009).

$$ZC_k = \sum_{i=1}^{N-1} f(x) \quad (3.7)$$

$$f(x) = \begin{cases} 1 & \text{if } \{x_i > 0 \text{ and } x_{i+1} < 0\} \text{ or } \{x_i < 0 \text{ and } x_{i+1} > 0\} \text{ and } |x_i - x_{i+1}| \geq \epsilon \\ 0 & \text{otherwise} \end{cases} \quad (3.8)$$

#### 3.4.1.8. Slope Sign Changes (SSC)

This feature counts the number of times the sign of the slope of the signal change. A suitable threshold  $\epsilon$  must be chosen to reduce noise induced slope sign changes (Englehart and Hudgins, 2003). It is another method to represent the frequency information of sEMG signal (Phinyomark et al., 2009).

$$SSC_k = \sum_{i=1}^N f(x) \quad (3.9)$$

$$f(x) = \begin{cases} 1 & \text{if } \{x_i > x_{i-1} \text{ and } x_i > x_{i+1}\} \text{ or } \{x_i < x_{i-1} \text{ and } x_i < x_{i+1}\} \\ & \text{and} \\ & |x_i - x_{i+1}|^3 e \text{ or } |x_i - x_{i-1}|^3 e \\ 0 & \text{otherwise} \end{cases} \quad (3.10)$$

#### 3.4.1.9. Willison Amplitude (WAMP)

It calculates the number of times that the absolute value of the difference between amplitude of two consecutive samples ( $x_i$  and  $x_{i+1}$ ) exceeds a predetermined threshold  $e$  (Proakis and Manolakis, 1996). WAMP is related to firing of motor unit action potentials (MUAP) and the level of muscle contraction (Phinyomark et al., 2009).

$$WAMP_k = \sum_{i=1}^{N-1} f(|x_i - x_{i+1}|) \quad (3.11)$$

$$f(x) = \begin{cases} 1 & x > e \\ 0 & \text{otherwise} \end{cases} \quad (3.12)$$

#### 3.4.2. Frequency Domain

Feature extraction in the frequency domain is based on power spectrum density of signal and is computed by parametric methods, but it requires more calculation and time to be computed in this domain although feature extraction in the time domain (Oskoei and Hu, 2006).

**3.4.2.1. Auto-Regressive Coefficients (AR)**

It describes each sample of EMG signal as a linear combination of previous samples with a white noise error term. AR coefficients are used as features in EMG pattern recognition (Proakis and Manolakis, 1996).

$$x_k = - \sum_{i=1}^N a_i x_{k-i} + e_k \quad (3.13)$$

where  $a_i$  is AR coefficients,  $e_k$  is white noise or error sequence, and  $N$  is order of AR model.

**3.4.2.2. Frequency Median (FMD)**

The frequency median splits the power spectrum density into two equal parts. It is given by (Oskoei and Hu, 2006):

$$FMD = \frac{1}{2} \sum_{i=1}^M PSD_i \quad (3.14)$$

where  $M$  is the length of the power spectrum density, and  $PSD_i$  is the  $i$ th line of the power spectrum density.

**3.4.2.3. Frequency Mean (FMN)**

The frequency mean is given by (Oskoei and Hu, 2006):

$$FMN = \frac{\sum_{i=1}^M f_i PSD_i}{\sum_{i=1}^M PSD_i} \quad (3.15)$$

$$f_i = (i \cdot \text{sampling rate}) / (2 \cdot M) \quad (3.16)$$

where  $M$  is the length of the power spectrum density, and  $PSD_i$  is the  $i$ th line of the power spectrum density.

#### 3.4.2.4. Frequency Ratio (FR)

It is proposed in order to distinguish the difference between contraction and relaxation of a muscle in frequency domain by applying Fast Fourier transform to signals in time domain (Han et al., 2000).

$$FR_j = \frac{|F(\cdot)|_{j \text{ low freq}}}{|F(\cdot)|_{j \text{ high freq}}} \quad (3.17)$$

where  $|F(\cdot)|_j$  is the fast Fourier transform of EMG signal in channel  $j$ , *low freq* is the low frequency band and *high freq* is the high frequency band. The threshold for dividing a low frequency band and a high frequency band is decided through experiments.

#### 3.4.3. Time – Frequency Domain

According to Englehart (1998), time-frequency representation refers the energy of the signal both in time and in frequency, but these features generally requires a transformation that could be difficult computationally.

### 3.4.3.1. Short Time Fourier Transform (STFT)

Gabor (1946) expanded the applicability of Fourier transform method by dividing the input signal into segments thus the signal in each window can be assumed to be stationary. The STFT for a given signal  $x(t)$  can be expressed as:

$$STFT_x(t, w) = \int_{-\infty}^{\infty} W^*(t - \tau) x(\tau) e^{-jw\tau} d\tau \quad (3.18)$$

where  $W(t)$  is the window function,  $*$  is the complex conjugate,  $t$  represents time and  $w$  means frequency.

### 3.4.3.2. Wavelet Transform (WT)

A signal is integrated with a shifted and scaled mother wavelet function in wavelet transform. The continuous wavelet transform is represented by (Weeks, 2011):

$$W_x(a, b) = \int_{-\infty}^{\infty} x(t) \frac{1}{\sqrt{a}} \psi^* \left( \frac{t - b}{a} \right) dt \quad (3.19)$$

where  $x(t)$  is the function which shows the input signal,  $\psi^*$  is the complex conjugate of the mother wavelet function and  $\psi((t - b)/a)$  is the shifted and scaled version of the wavelet at time  $b$  and scale  $a$ .

### 3.4.3.3. Wavelet Packet Transform (WPT)

WPT is a generalized version of the continuous wavelet transform and the discrete wavelet transform (Zecca, 2002).

The STFT has a tile with constant shape, its each cell has an identical aspect ratio; while the WT has a tile with changing shape and the its aspect ratio of the cells varies in a form. Finally, the WPT has a tile with adaptive shape which provides several alternatives of tile (Englehart et al., 1999), as shown in Figure 3.5.

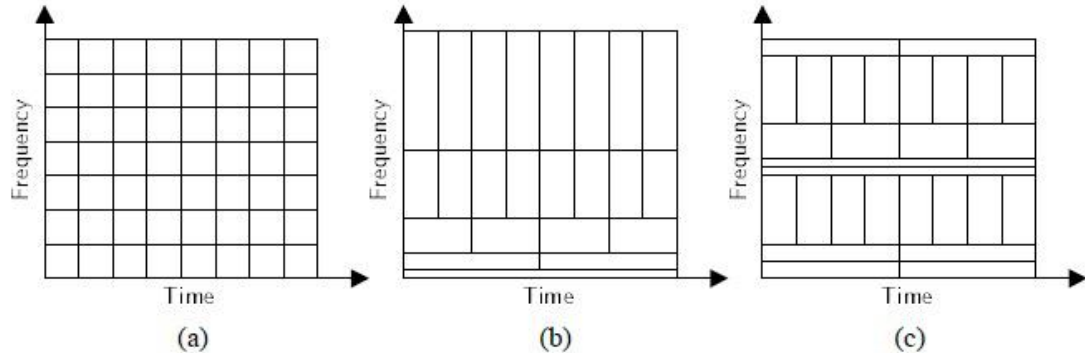


Figure 3.5. The Time-Frequency Tile of a) the STFT, b) the WT and c) the WPT (Englehart et al., 1999)

### 3.5. A Brief Overview of Neural Networks Used For Classification

A neuron is a cell in the brain whose principal function is the collection, processing and dissemination of electrical signals (Russell and Norvig, 2003); while an artificial neuron is an information-processing unit that is fundamental to the operation of a neural network (Haykin, 2009). This artificial neuron receives inputs  $x$  and weights  $w$ ; inside the neuron is performing an arithmetic summing which constitutes a linear combiner (Haykin, 2009) followed by an activation function (Kil and Shin, 1996). The arithmetic summing  $net$  consists in:

$$net = \sum_{i=0}^n w_i x_i \quad (3.20)$$

where  $x_i$  is the input to the neuron, and  $w_i$  is the weight associated to  $x_i$ .

An activation function fact is applied to  $net$ , giving as a result the output of the neuron  $O$ . This activation function limits the amplitude of the output of a neuron

(Haykin, 2009); it needs to meet two conditions: 1) “activate” the neuron (near +1) when the “right” inputs are given and “inactive” it (near 0) when the “wrong” inputs are given; and 2) the activation needs to be nonlinear (Russell and Norvig, 2003). According to Kil and Shin (1996), there are several activation functions, such as, threshold linear, step, arbitrary step, exponential and sigmoid which is the most common form of activation function used in the construction of neural networks (Haykin, 2009).

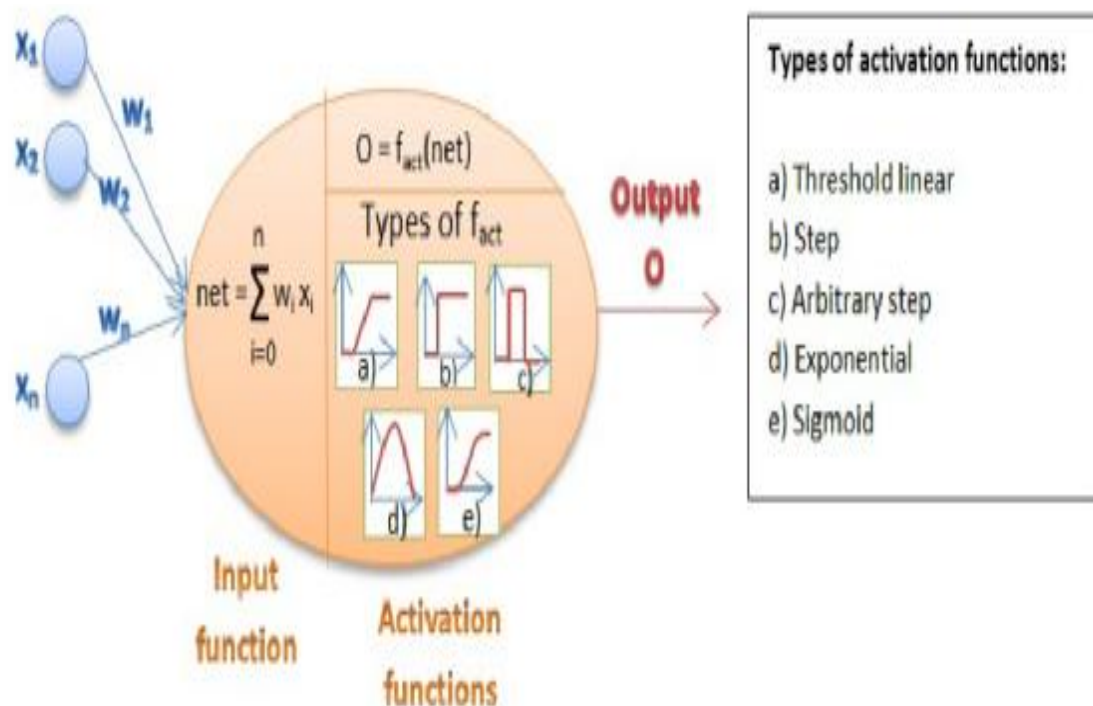


Figure 3.6. An Artificial Neuron (Rechy-Ramirez and Hu, 2011)

Feed forward networks are usually arranged in layers, such that each unit receives input only from units in the immediately preceding layer (feed forward type) (Russell and Norvig, 2003). In a multilayer feed forward network, there is one input layer, one or more hidden layers which is by adding one or more hidden layers, the network is enabled to extract higher-order statistics from its input (Haykin, 2009) and one output layer.

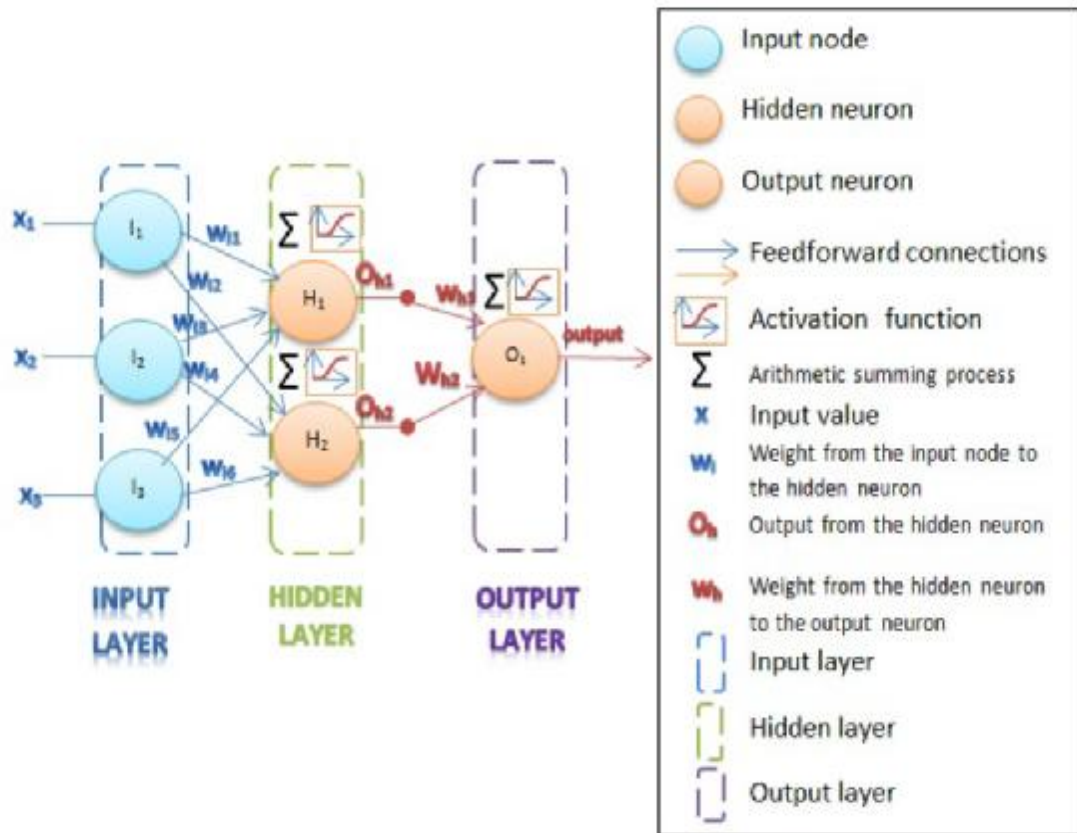


Figure 3.7. Feed Forward Network with One Input Layer, One Hidden Layer and One Output Layer (Rechy-Ramirez and Hu, 2011)

Haykin (2009) explains that the input nodes in the input layer of the network supply respective elements of the activation pattern (input vector), which constitute the input signals applied to the neurons (computation nodes) in the second layer (i.e., the first hidden layer). The output signals of the second layer are used as inputs to the third layer (i.e., the second hidden layer or the output layer) and so on for the rest of the network. The set of output signals of the neurons in the output layer of the network constitutes the overall response of the network to the activation pattern supplied by the input nodes in the input layer. In a fully connected network, every node in each layer is connected to every other node in the adjacent forward layer; if some of the communication links are missing from the network, then the network is partially connected.

### 3.5.1. Back Propagation Network

Kil and Shin (1996) define a back-propagation neural network (BPNN) as a feed forward network with at least one hidden layer. Each neuron performs arithmetic summing followed by the sigmoid activation. The back-propagation algorithm is an iterative gradient descent algorithm to minimize the mean-squared error between the desired output and the actual network output.

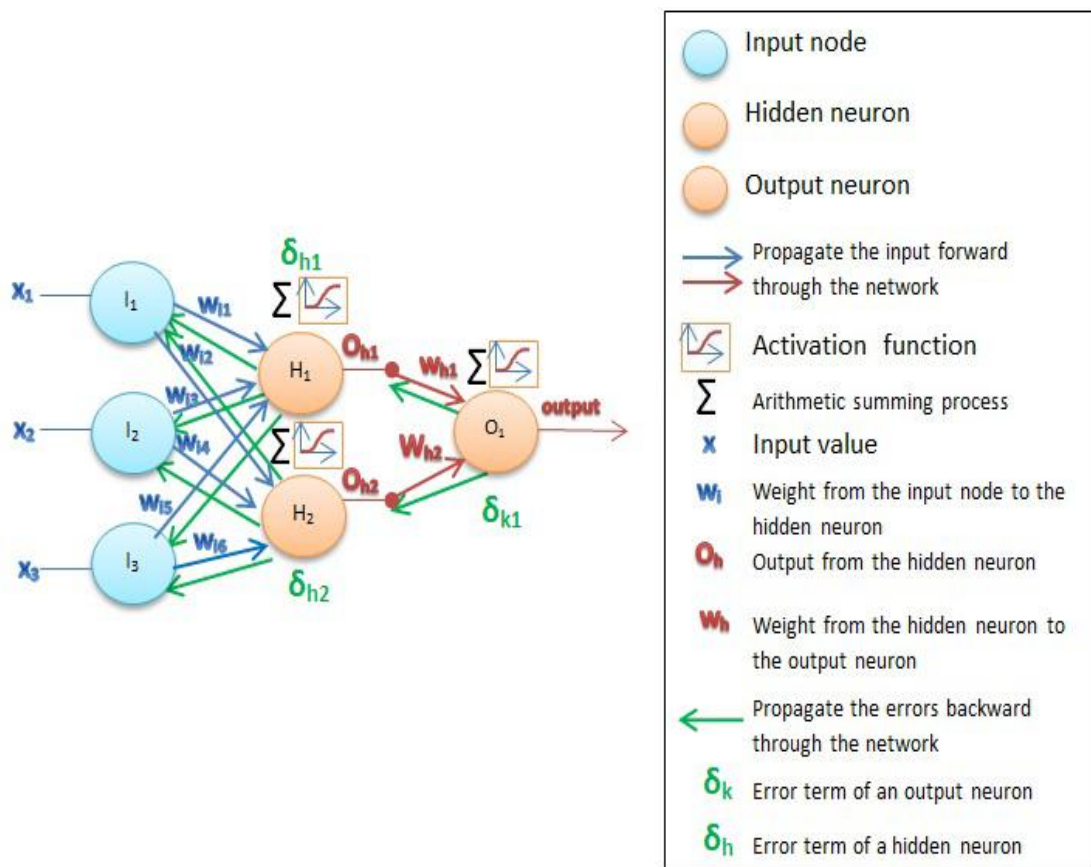


Figure 3.8. A Back-Propagation Neural Network (Rechy-Ramirez and Hu, 2011)

The steps for applying the back propagation algorithm are the following (Mitchell, 1997):

1. Create a feed forward network with  $n_{in}$  input nodes,  $n_{hidden}$  hidden neurons and  $n_{out}$  output neurons.
2. Initialize all network weights to small random numbers.

3. Until the termination condition which is to halt the procedure could be after a fixed number of iterations through the loop, once the error on the training examples falls below some threshold or once the error on a separate validation set of examples meets some criterion is met, do:

For each  $\langle X, T \rangle$  in training examples, do: Propagate the input forward through the network:

(a) Input the instance  $X$  to the network and compute the output  $o_u$  of every unit  $u$  in the network.

Propagate the errors backward through the network:

(b) For each output neuron  $k$ , calculate its error term  $d_k$

$$d_k \leftarrow o_k(1 - o_k)(t_k - o_k) \quad (3.21)$$

(c) For each hidden neuron  $h$ , calculate its error term  $d_h$

$$d_h \leftarrow o_h(1 - o_h) \sum_{k \in \text{outputs}} w_{kh} d_k \quad (3.22)$$

(d) Update each network weight  $w_{ji}$

$$w_{ji} \leftarrow w_{ji} + (n d_j x_{ji}) \quad (3.23)$$

where  $n_{in}$  is the number of input nodes;  $n_{hidden}$  is the number of hidden neurons;  $n_{out}$  is the number of output neurons;  $\langle X, T \rangle$  is a training example;  $X$  is the vector of network input values;  $T$  is the vector of target network output values;  $t_k$  is the target value associated with the  $k$ th output neuron; output is the set of output neurons in the network;  $w_{kh}$  is the weight from hidden neuron  $h$  to output neuron  $k$ ;  $n$  is the

learning rate;  $x_{ji}$  is the input from node  $i$  to unit  $j$ ; and  $w_{ji}$  is the weight from node  $i$  to unit  $j$ .

### 3.5.2. General Regression Neural Network (GRNN)

A GRNN is a variation of the radial basis neural networks, which is based on kernel regression networks. A GRNN does not require an iterative training procedure as back propagation networks. It approximates any arbitrary function between input and output vectors, drawing the function estimate directly from the training data. In addition, it is consistent that as the training set size becomes large, the estimation error approaches zero, with only mild restrictions on the function (Specht, 1991).

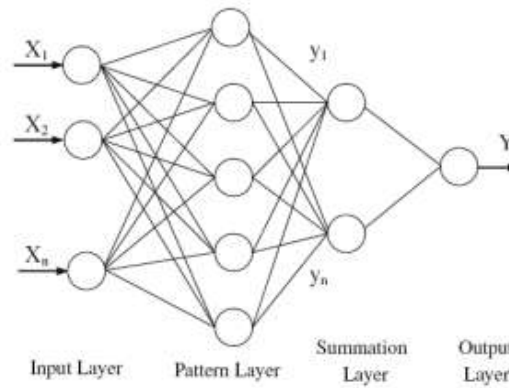


Figure 3.9. General Structure of GRNN (Hannan et al., 2010)

A GRNN consists of four layers: input layer, pattern layer, summation layer and output layer as shown in Figure 3.9. The number of input units in input layer depends on the total number of the observation parameters. The first layer is connected to the pattern layer and in this layer each neuron presents a training pattern and its output. The pattern layer is connected to the summation layer. The summation layer has two different types of summation, which are a single division unit and summation units. The summation and output layer together perform a normalization of output set. In training of network, radial basis and linear activation functions are used in hidden and output layers. Each pattern layer unit is connected to the two neurons in the summation layer,  $S$  and  $D$  summation neurons.  $S$  summation neuron

computes the sum of weighted responses of the pattern layer. On the other hand,  $D$  summation neuron is used to calculate un-weighted outputs of pattern neurons. The output layer merely divides the output of each  $S$ -summation neuron by that of each  $D$ -summation neuron, yielding the predicted value  $Y_i'$  to an unknown input vector  $x$  as (Jang et al., 1997):

$$Y_i' = \frac{\sum_{i=1}^n y_i e^{-D(x, x_i)}}{\sum_{i=1}^n e^{-D(x, x_i)}} \quad (3.24)$$

$$D(x, x_i) = \sum_{k=1}^m \left( \frac{x_k - x_{ik}}{s} \right)^2 \quad (3.25)$$

where  $Y_i'$  is the weight connection between the  $i$ th neuron in the pattern layer and the  $S$ -summation neuron,  $n$  is the number of the training patterns,  $D$  is the Gaussian function,  $m$  is the number of elements of an input vector,  $x_k$  and  $x_{ik}$  are the  $j$ th element of  $x$  and  $x_i$ .

### 3.6. The Experimental Setup for Measurement and Data Acquisition

#### 3.6.1. Biopac MP36 Data Acquisition Unit

The MP36 data acquisition unit has an internal microprocessor to control data acquisition and communication with the computer. The MP36 Unit takes incoming signals and converts them into digital signals that can be processed with the computer. There are four analog input channels, one of which can be used as a trigger input. The MP36 Unit must be connected to the computer and electrodes, transducers, and/or I/O devices must be connected to the MP36 Unit.

It has four analog channels with isolated human-safe universal input amplifiers. A/D sampling resolution is 24 bits. Its gain ranges are between 5 and

50000 in 13 steps. Input voltage range is adjustable from  $\pm 200 \mu\text{V}$  to  $\pm 2 \text{ V}$  and CMRR is 85 dB. It has software filters which are three programmable digital IIR automatic or user-adjustable filters and hardware filters which are 20 KHz lowpass, 0.05 Hz, 0.5 Hz, 5 Hz and DC highpass filters.

In this thesis, BIOPAC MP36 system for EMG signals acquisition and an electrogoniometer for measuring the arm joint angle. The system uses amplifiers with minimum 85 dB CMRR. Two channels of the amplified EMG signal and the angle displacement signal from the electrogoniometer are analogically multiplexed and sampled 24 bit analog-to-digital (ADC) converter at a sampling rate of 2 KHz for each channel.

The system implements real-time analog filters which limit the EMG signals to the 30–250Hz and a real-time adaptive notch filter which maintains a running estimate of the 50 Hz power-line interference (Delis *et al* 2008). The filtered EMG signals and the arm joint angle measurements are transferred to a personal computer through a serial interface (RS-232 C or USB).



Figure 3.10. BIOPAC MP36 Data Acquisition System

### 3.6.2. Muscles, Electrodes and Goniometer

Two pairs of 10 mm Ag/AgCl surface electrodes with conductive gel were placed in bipolar configuration over a pair of biceps and triceps muscles of the same

arm, corresponding to the flexion and extension movements of the arm joint, respectively (Figures 3.11(a) and (b)). The distance between the centers of the electrodes of each pair was 3–5 cm. Each pair of electrodes was associated with a different EMG acquisition channel. Reference electrodes were placed over the lateral and medial epicondyle bones.

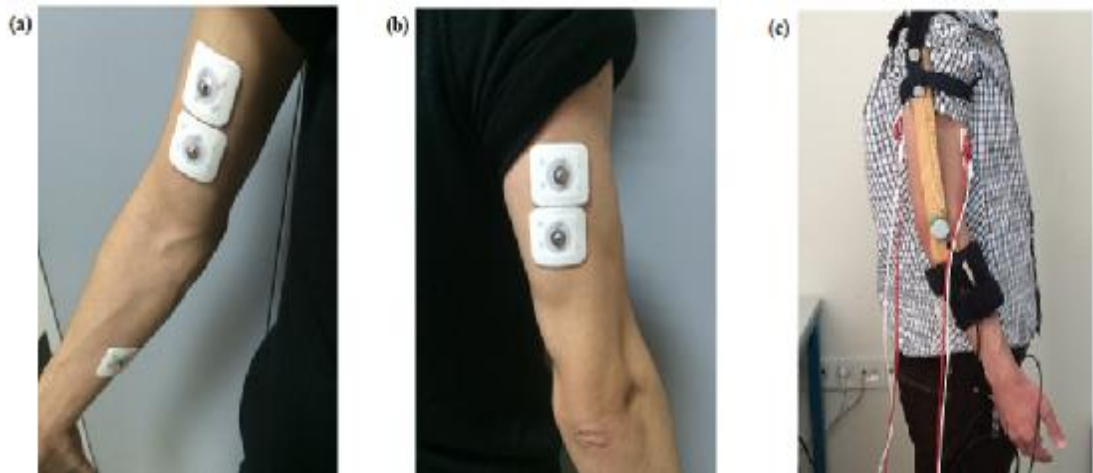


Figure 3.11. Placement of Electrodes (a), (b) and Electrogoniometer (c)

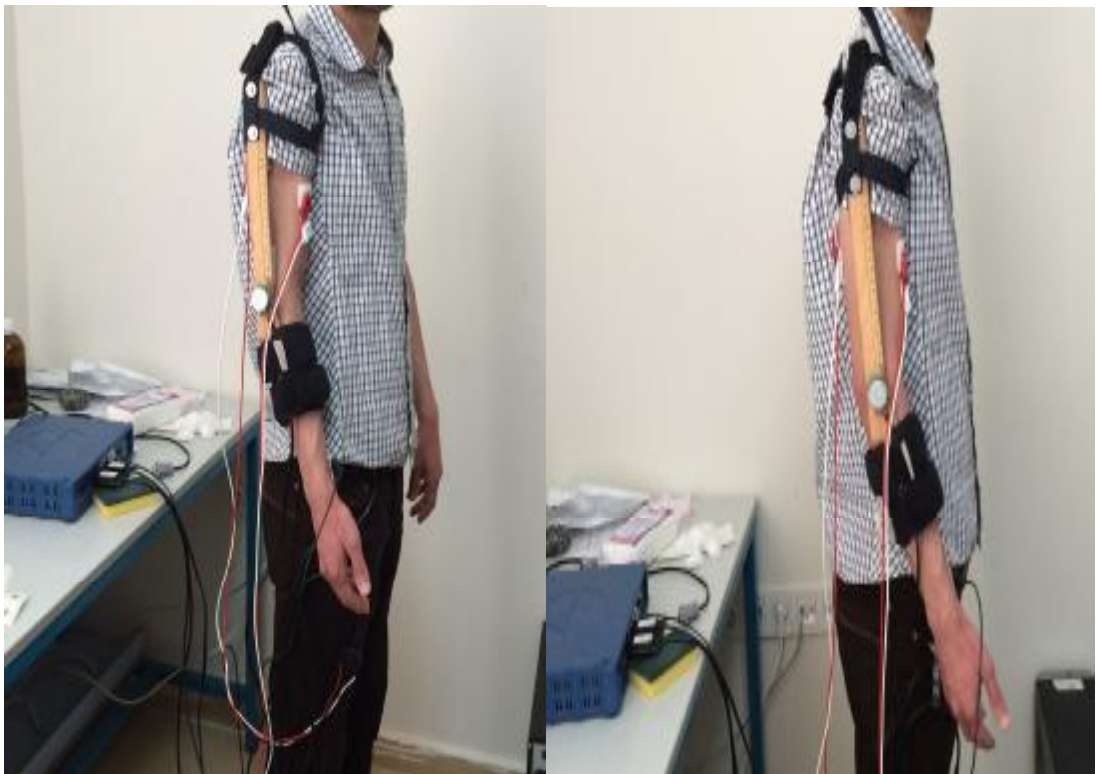


Figure 3.12. Setup for Measurement and Data Acquisition

An electrogoniometer was placed and strapped over the external side of the same arm, so that it would measure the angular displacement of the arm in sagittal plane (Figure 3.11(c)). The two channels of EMG data and the arm joint angle information were acquired using the BIOPAC MP36 data acquisition system described above (Figure 3.12).

### 3.7. Data Collection and Formation

For data collection, one able-bodied volunteer was studied and provided informed consent in accordance with institutional policy. The collected data is put into formation, using speed and weight criteria, into categories given in Table 3.1.

Table 3.1. Experiments and Corresponding Experimental Configurations

| Experiments | Speed of Arm | Weight |
|-------------|--------------|--------|
| A1B1        | Low          | 0 kg   |
| A1B2        | Low          | 0.5 kg |
| A1B3        | Low          | 1 kg   |
| A2B1        | Medium       | 0 kg   |
| A2B2        | Medium       | 0.5 kg |
| A2B3        | Medium       | 1 kg   |
| A3B1        | High         | 0 kg   |
| A3B2        | High         | 0.5 kg |
| A3B3        | High         | 1 kg   |

A1: Low Speed A2: Medium Speed A3: High Speed

B1: No weight B2: 0.5 kg B3: 1 kg

Five 20 seconds measurements were performed on each experiment. For each measurement, the subject was asked to stand. Thus, a total of 45 measurements were obtained. While the speed of arm was low, it was not got the volunteer any weights to hand in five measurements of experiments (A1B1). When the speed of arm was also low, it was got the volunteer 0.5 kg to hand in other five measurements. It was recorded by continuing in this way. It is shown some sets of experiments which occur EMG signals and their measured elbow joint angles in Figure 3.13.

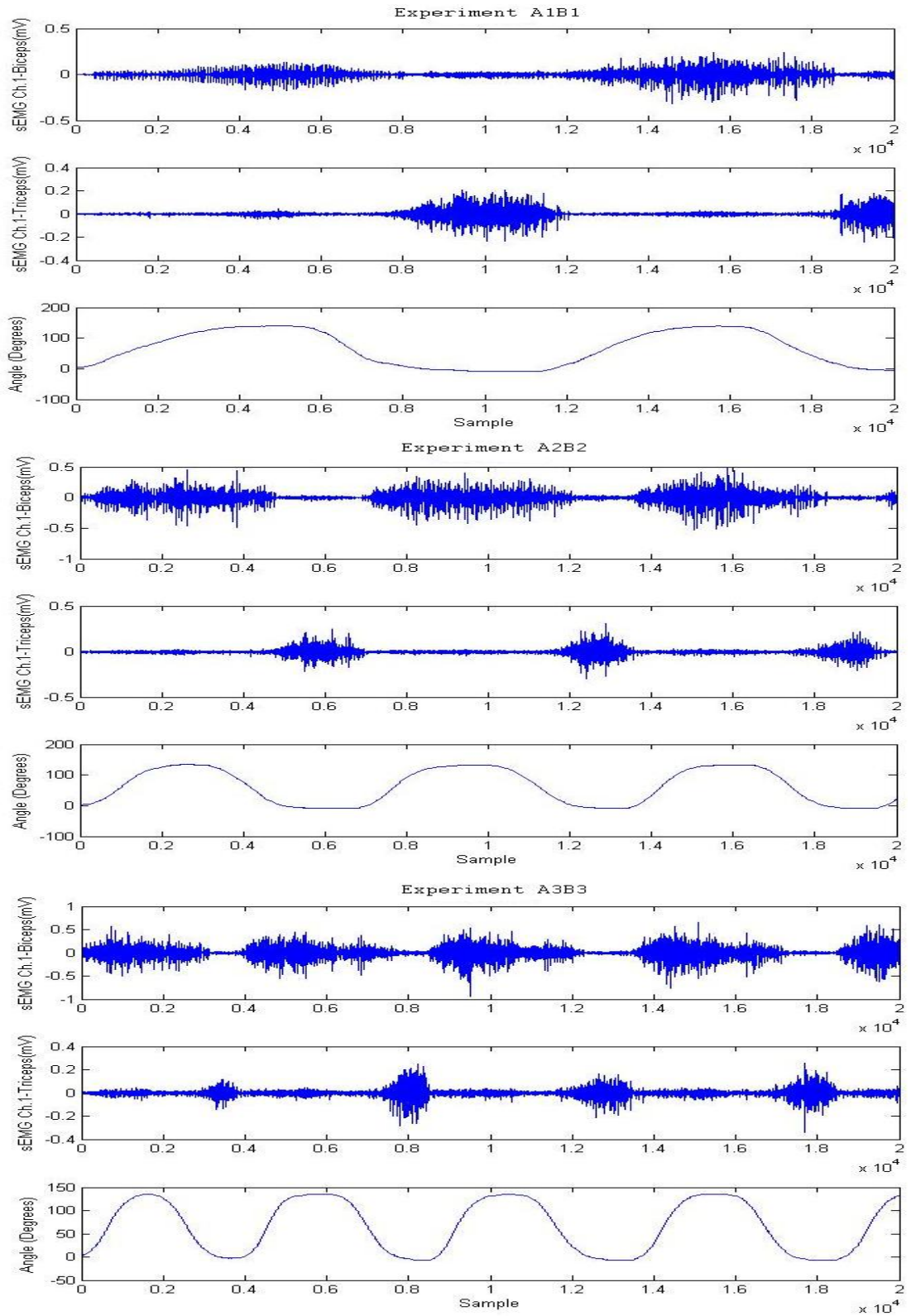


Figure 3.13. Some Sets of Recorded EMG Signals and Measured Elbow Joint Angles from Experiments in Categories A1B1, A2B2, A3B3

### 3.8. User Interface for Real Time Data Acquisition

A user interface is prepared to estimate real time elbow joint angle using Matlab GUI software. In interface, there are sections of channels check boxes, button of Biopac Data Acquisition unit connection, start, stop, clear and save button. There are also list boxes for data acquisition adjustment such as sample rate, gain and time.

In section channel check box, the more channels a user will use, the more channels he or she can activate check boxes. It is added four check boxes because Biopac Data Acquisition Unit has four analog channels. It is also added four axes to plot four different data to interface.

It is connected to Biopac Data Acquisition Unit with connect button as real time, started to data acquisition with start button, finished to data acquisition with stop button, deleted data which is plotted with clear button and recorded data which is plotted with save button.

Finally, there is a section which shows movement of an arm. In this section, an arm is moved according to estimated elbow joint angle.

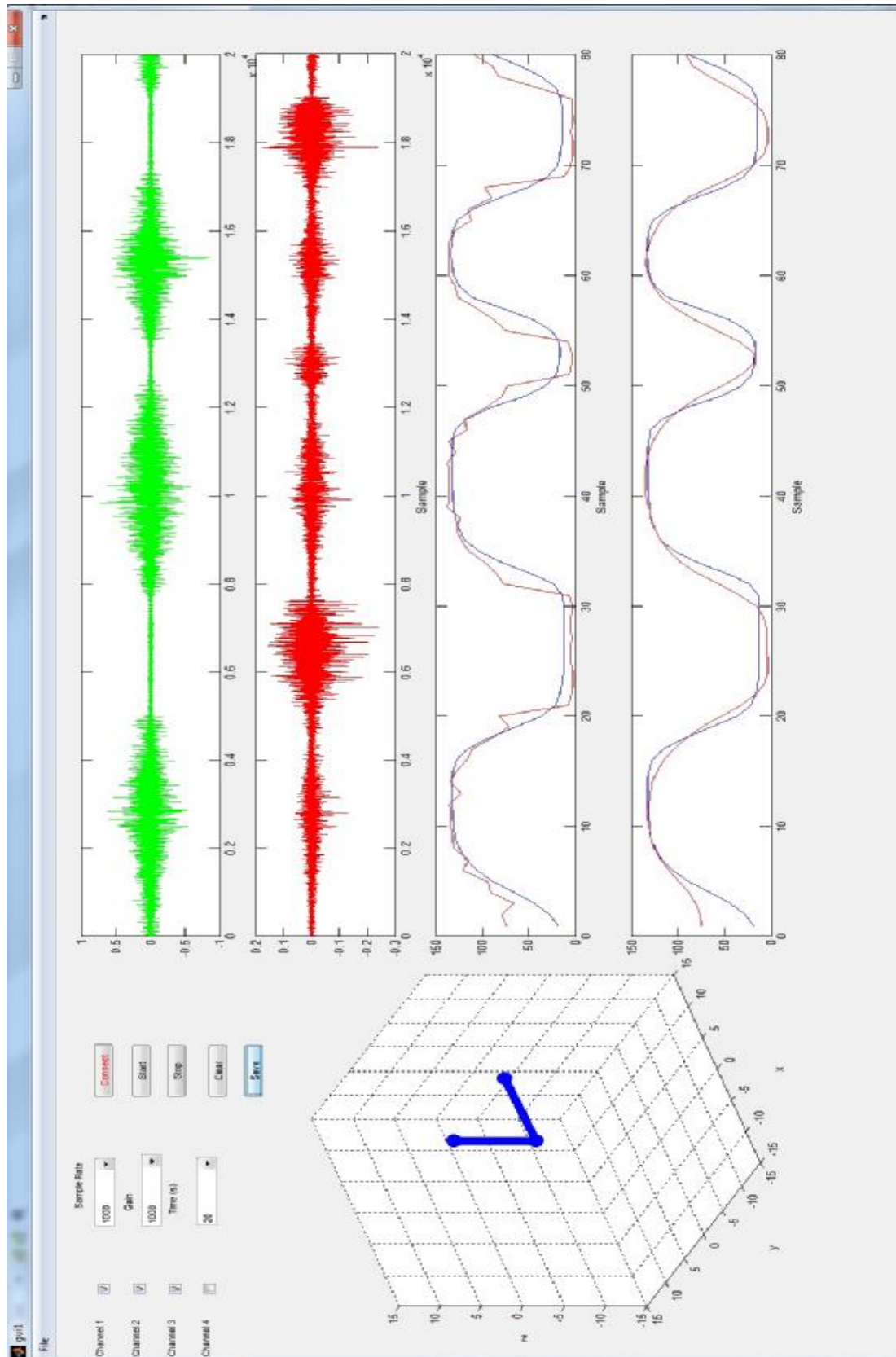


Figure 3.14. User Interface for Real Time Data Acquisition

### **3.9. Elbow Joint Angle Estimation System Algorithm and Neural Network Structure**

Figure 3.15 presents the main components of the proposed arm joint angle estimation system algorithm, which is based on myoelectric pattern recognition. The proposed algorithm is composed of two main stages: feature extraction, using time domain approaches such as mean absolute value (MAV), root mean square (RMS), waveform length (WL); and pattern classification, using the Multilayer Perceptron neural network. Feature extraction is performed independently for each EMG channel. Data from the electrogoniometer is used as reference during network training, and is not used by the network during testing. Each of these stages is discussed in detail below. All operations are performed by using the program developed in MATLAB software.

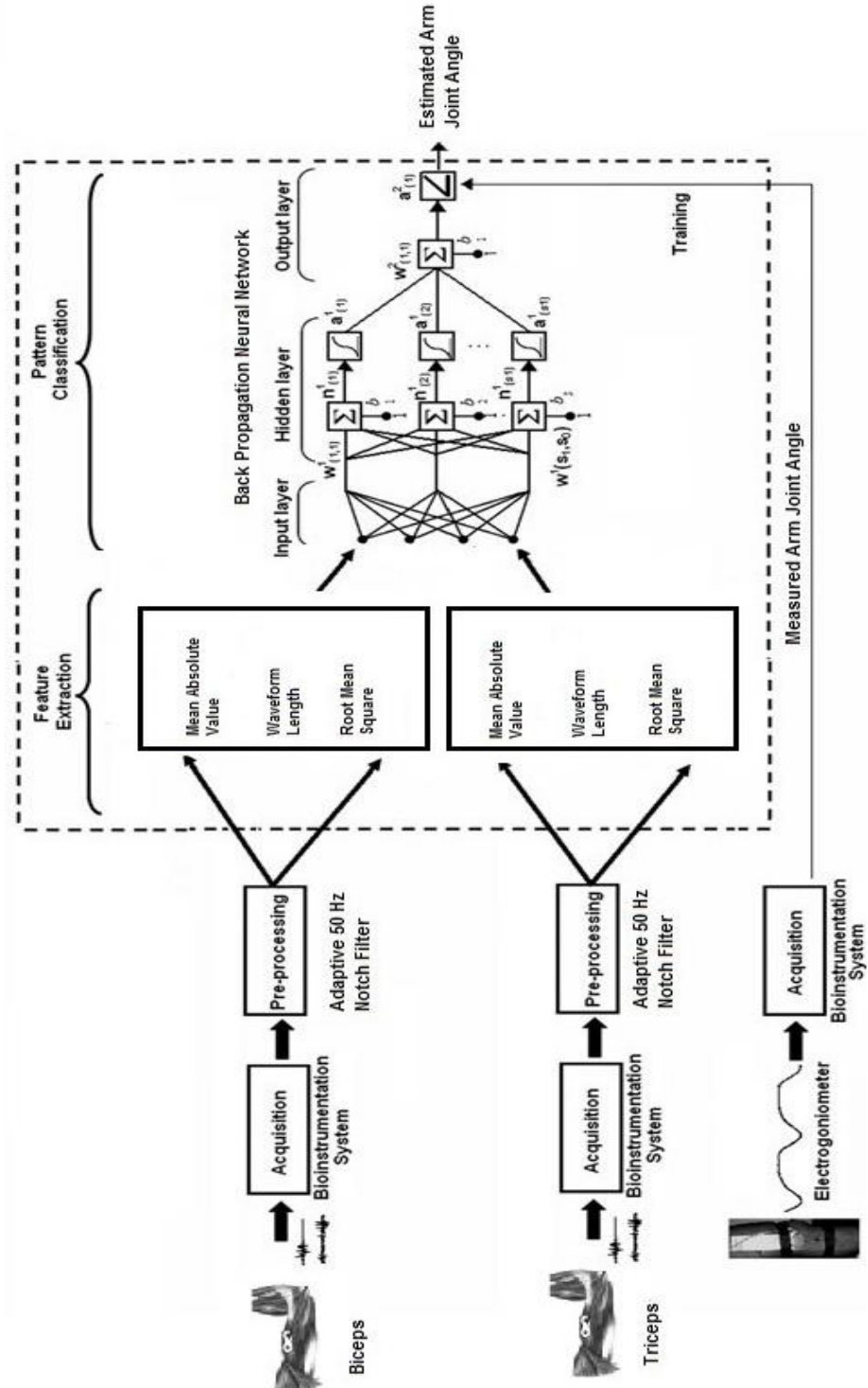


Figure 3.15. Block Diagram of Arm Joint Angle Estimation Algorithm (Delis et al., 2009)

### 3.9.1. Feature Extraction

Presenting the myoelectric signal directly to a neural classifier is impractical, because of the dimensionality and random characteristics of the signal. The signal needs to be represented by a vector of reduced dimensionality, capable of representing the information of signal in a more compact fashion. Such a vector is called a feature vector. In this thesis, it is chosen time domain feature extraction because of their computational simplicity. Thus, their calculations are quicker and it does not have a more delay for real time estimation of elbow arm joint.

The feature vector which occurs mean absolute value (MAV), waveform length (WL) and root mean square (RMS) representing the time-domain characteristics of the EMG signal is created in this thesis. MAV is an easy way for detection of muscle contraction levels and it is a popular feature used in myoelectric control application. WL is related to the amplitude, frequency, time of EMG signals. RMS is related to the constant force and non- fatiguing contraction. MAV is similar to RMS but RMS gives better results at high level contraction while MAV gives better for low contractions.

MAV, WL and RMS were explained in Section 3.6.1 before.

### 3.9.2. Neural Network Structure

The Neural Network stage is responsible for providing an estimate of the elbow joint angle from the set of six feature vectors obtained from the feature extraction stage. Pattern classification was performed using a Levenberg – Marquardt Multilayer Perceptron Neural Network (MLP) and General Regression Neural Network (GRNN).

The MLP network which is used in this thesis has three layers in its structure, with twelve input nodes that are output vectors of feature extraction in the first layer, four nodes in the second layer which is associated with tangential functions and one node in the output layer which is associated with a linear function. This structure was chosen empirically, based on experiments aimed at minimizing the mean square error

(MSE). The node in the output layer represents the estimated elbow joint angle (Figure 3.15).

The proposed algorithm was implemented and evaluated in Matlab (Mathworks, Inc., South Natick, MA). Firstly, MAV, WL, RMS associated with each sample of each of the two EMG signals were calculated. Then, these feature vectors were used in MLP in order to generate the estimated elbow joint angle.

During MLP network training, the outputs of feature extraction were used as inputs, and the corresponding angular displacement measurements from the electrogoniometer were used as the target outputs.

General Regression Neural Network (GRNN) was also used to train EMG data. Generalized Regression neural networks are a kind of radial basis network that is often used for function approximation. GRNNs can be designed very quickly so it is chosen as a neural network for these reasons.

“*newgrnn*” matlab code was used to train EMG data. *newgrnn*(X,T,SPREAD) takes RxQ matrix of column input vectors (X), SxQ matrix of column target vectors (T), and the SPREAD of the radial basis functions (default = 1.0), and returns a new generalized regression network. The larger SPREAD is, the smoother the function approximation occurs. To fit data closely, it should be used a SPREAD smaller than the typical distance between input vectors. To fit the data more smoothly, it should be used a larger SPREAD. It was chosen SPREAD as 0.1 to obtain angle estimation closely.

### 3.9.3. Formation of Training and Test Data

The collected and formatted data is used for Neural Network training, which is taken randomly from records of each experiment is combined as mixed and the experiments which are close each other in terms of speed and weight are not taken in a sequential manner. For example data which is taken some part of Experiment A3B3 was added back of data which is taken some part of Experiment A1B1. Training data is obtained by continuing in this way. It is shown training data which consists of biceps and triceps EMG Signals and measured elbow joint angle

in Figure 3.16. The table of training data which occurs from experiments is added in Appendix A.

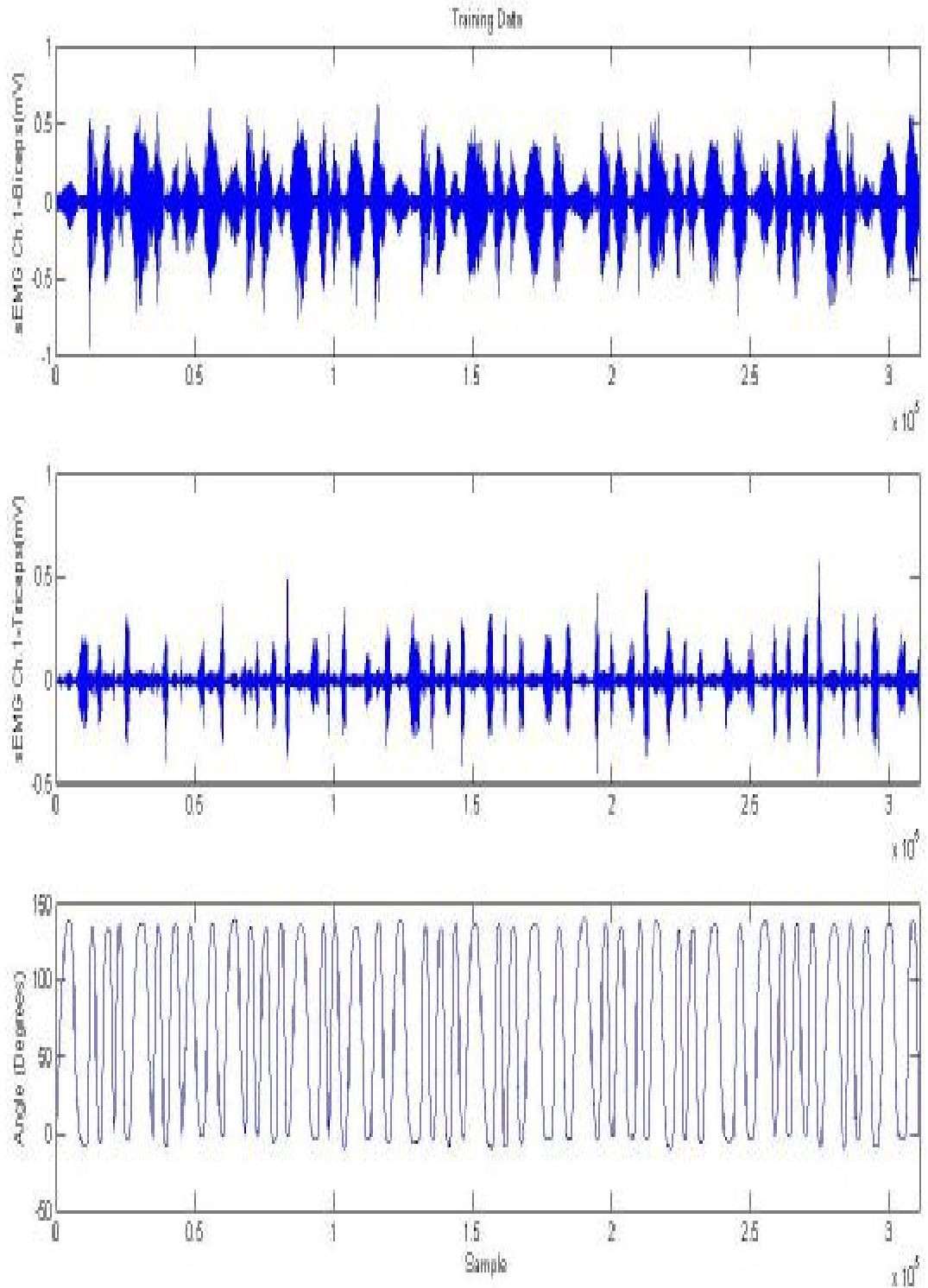


Figure 3.16. A Sample Training Data for Neural Network

The test data is obtained in a similar manner as of training data. Data is taken randomly from records of each experiment and not belonging to training data is combined as mixed. The experiments which are close each other in terms of speed and weight are not taken in a sequential manner, neither. It is shown test data which consists of biceps and triceps EMG Signals and measured elbow joint angle in Figure 3.17. The table of test data which occurs from experiments is added in Appendix B.

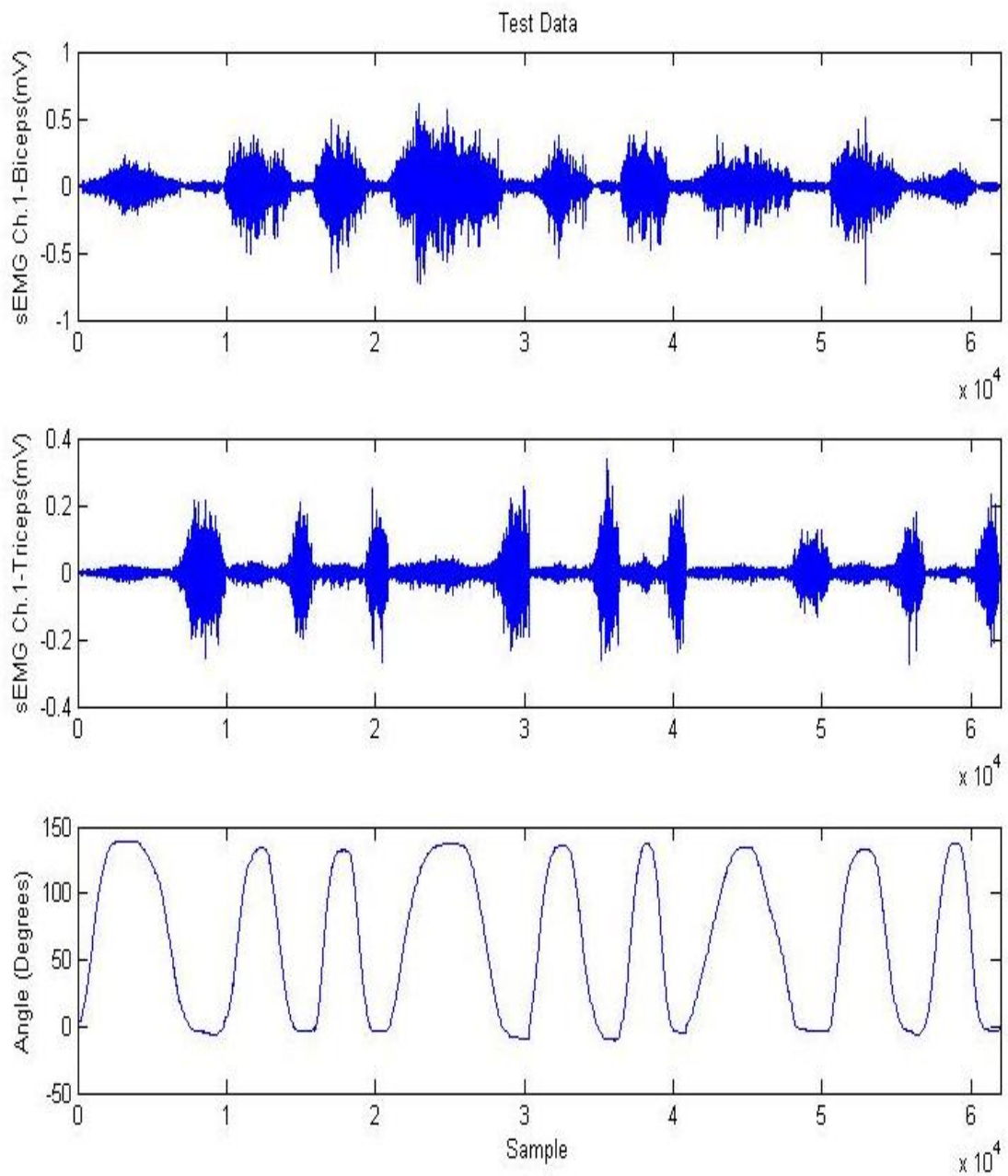


Figure 3.17. A Sample of Formed Test Data

### 3.10. Training Performance of Neural Networks

Figure 3.18 shows the performance of MLP in the course of 1000 training epochs for a representative experiment. The final mean square error after 1000 epochs was 0.025601.

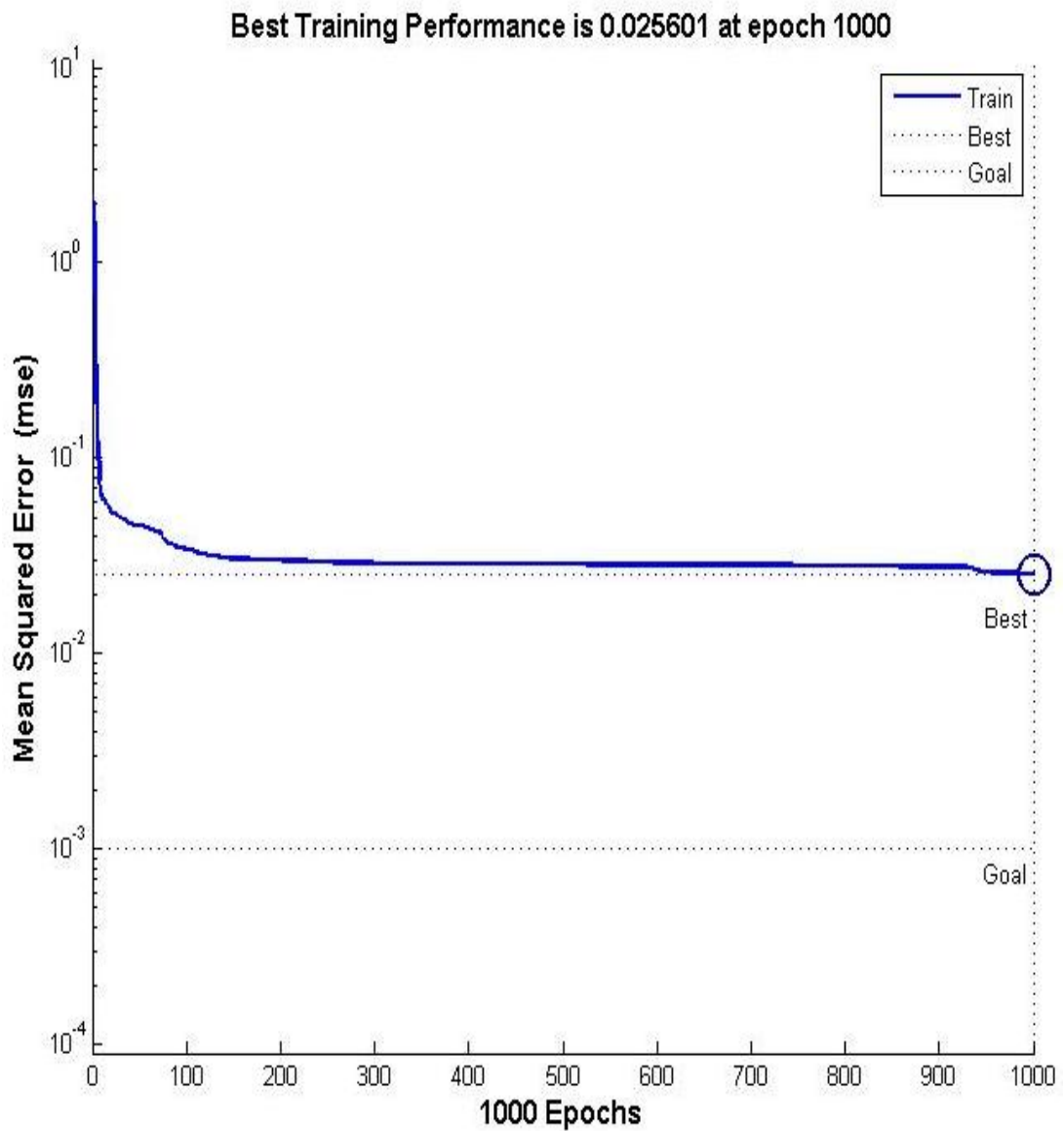


Figure 3.18. MLP Training Performance



#### 4. RESULTS AND DISCUSSION

In this section, the angle estimation results obtained during neural network training, neural network performance tests and the real-time estimation stages. Instead of giving all results, just a few samples of results representing each category is given. The results are obtained by performing experiments as stated in section 3.9.3. The detailed results are given in appendices C and D.

##### 4.1. Experimental Results for Joint Angle Estimation

First of all, it is given the angle estimation results obtained during neural network training process. A part of training data which was composed of measured EMG signal from biceps and triceps muscles as described at section 3.9.3 was plotted at Figure 4.1. Time domain based features such as Mean Absolute Value (MAV), Root Mean Square (RMS) and Waveform Length (WL) were also plotted respectively. They were calculated from EMG data which was plotted in the same figure segmenting into 250 samples. Feature vector which consisted from MAV, RMS and WL values were used as input to train MLP neural network and estimated elbow joint angle became as an output of MLP neural network.

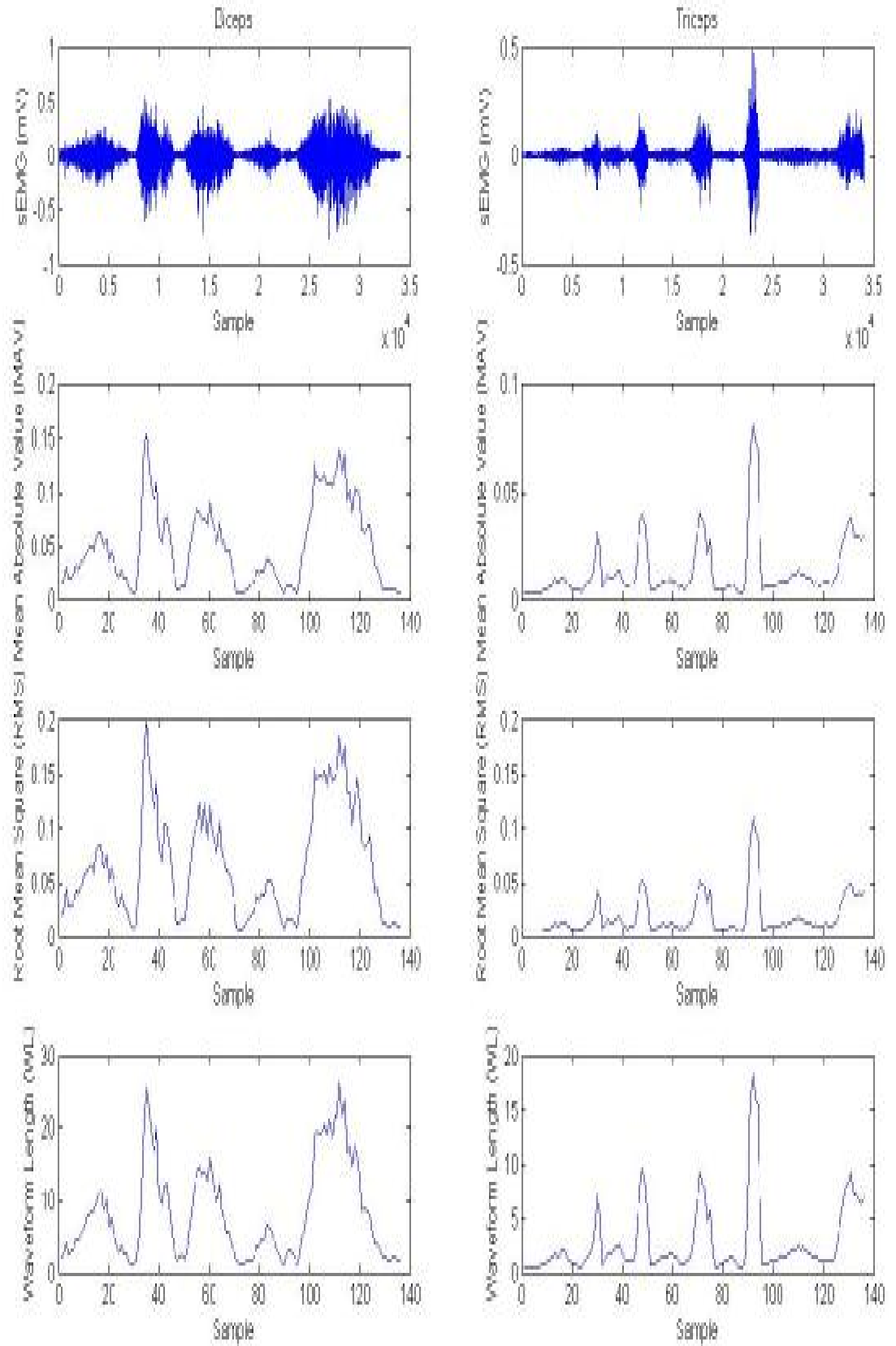


Figure 4.1. A Part of Training Data and its Feature Graphs for MLP

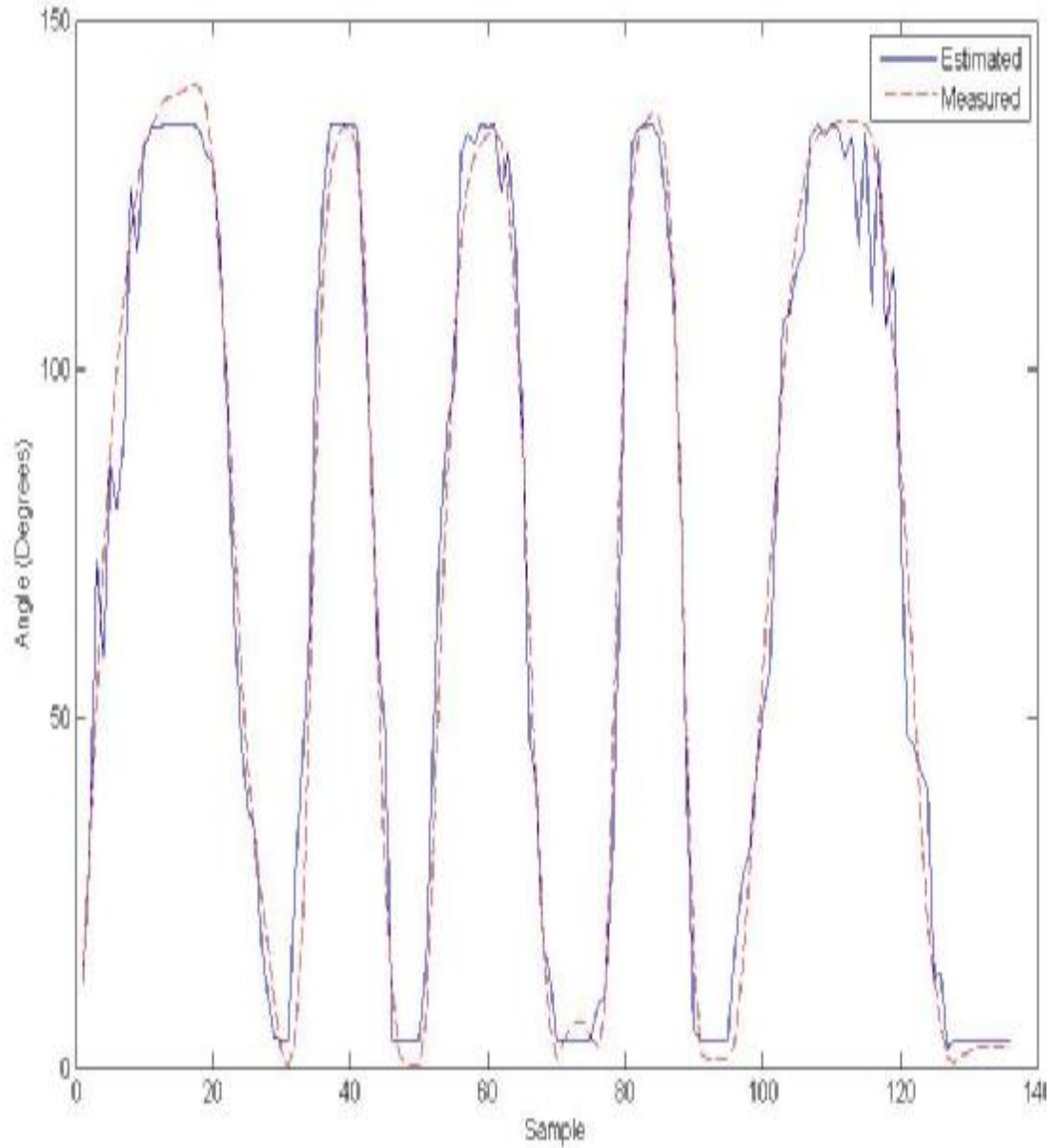


Figure 4.2. Estimated and Measured Arm Joint Angle during MLP Neural Network Training Process

The graph of estimated joint angle is given in Figure 4.2 during MLP training phase. The actual elbow joint angle was measured by a goniometer is also plotted in same figure and estimated elbow joint angle was compared with measured elbow joint angle.

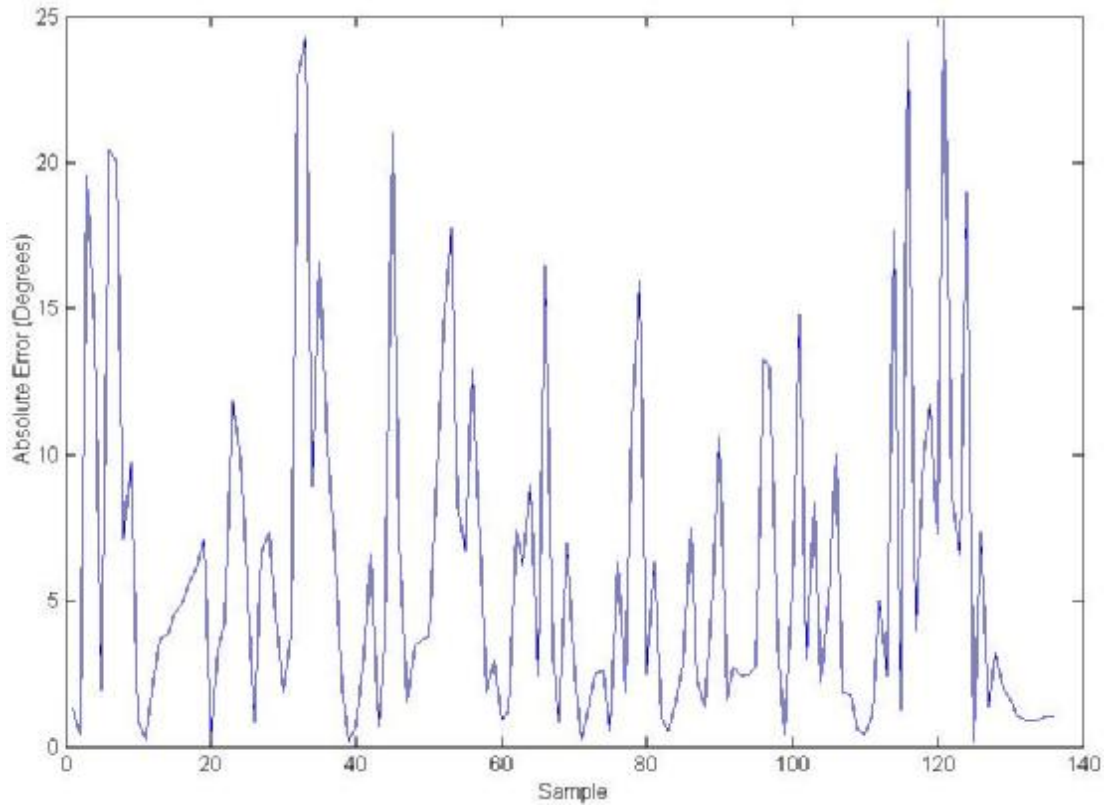


Figure 4.3. Absolute Error of Elbow Joint Angle Estimation during MLP Neural Network Training Stage

The absolute error value was calculated subtracting measured elbow joint angle values from estimated elbow joint angle values which were obtained during training phase of MLP neural network and plotted at Figure 4.3. It is also worthy to state here the range for elbow joint angle is approximately 140 degrees. Hence, average percentage error around 4.31 %.

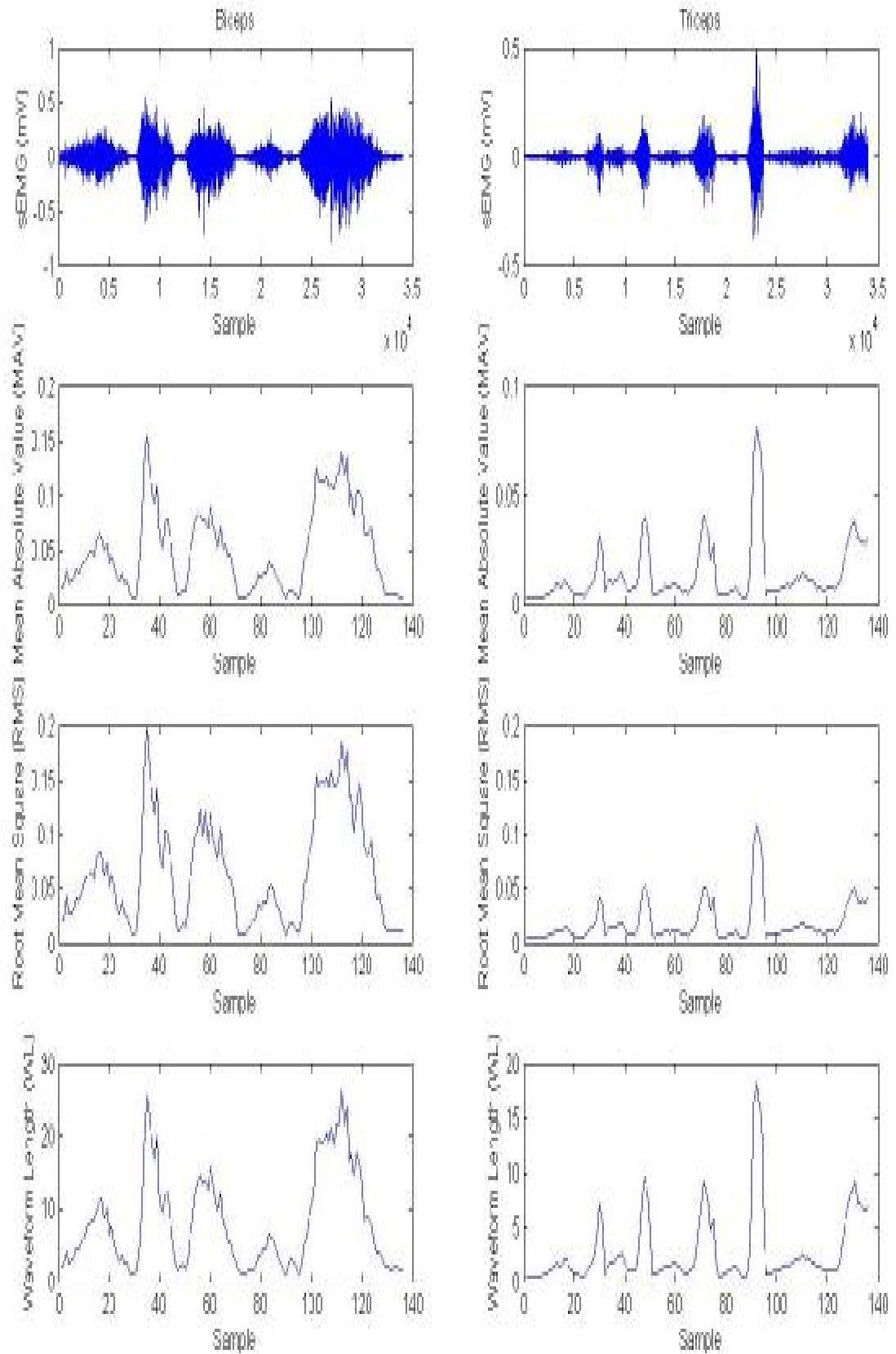


Figure 4.4. A Part of Test Data and Feature Graphs for MLP

A part of test data which was composed of measured EMG signal from biceps and triceps muscles as described at section 3.9.3 was plotted at Figure 4.4. Time domain based features such as Mean Absolute Value (MAV), Root Mean Square (RMS) and Waveform Length (WL) were also plotted respectively. They were calculated from EMG data which was plotted in the same figure segmenting into 250 samples. These features were used as input values to simulate multilayer perceptron neural network (MLP) which was trained before and it was obtained estimated elbow joint angle in the end.

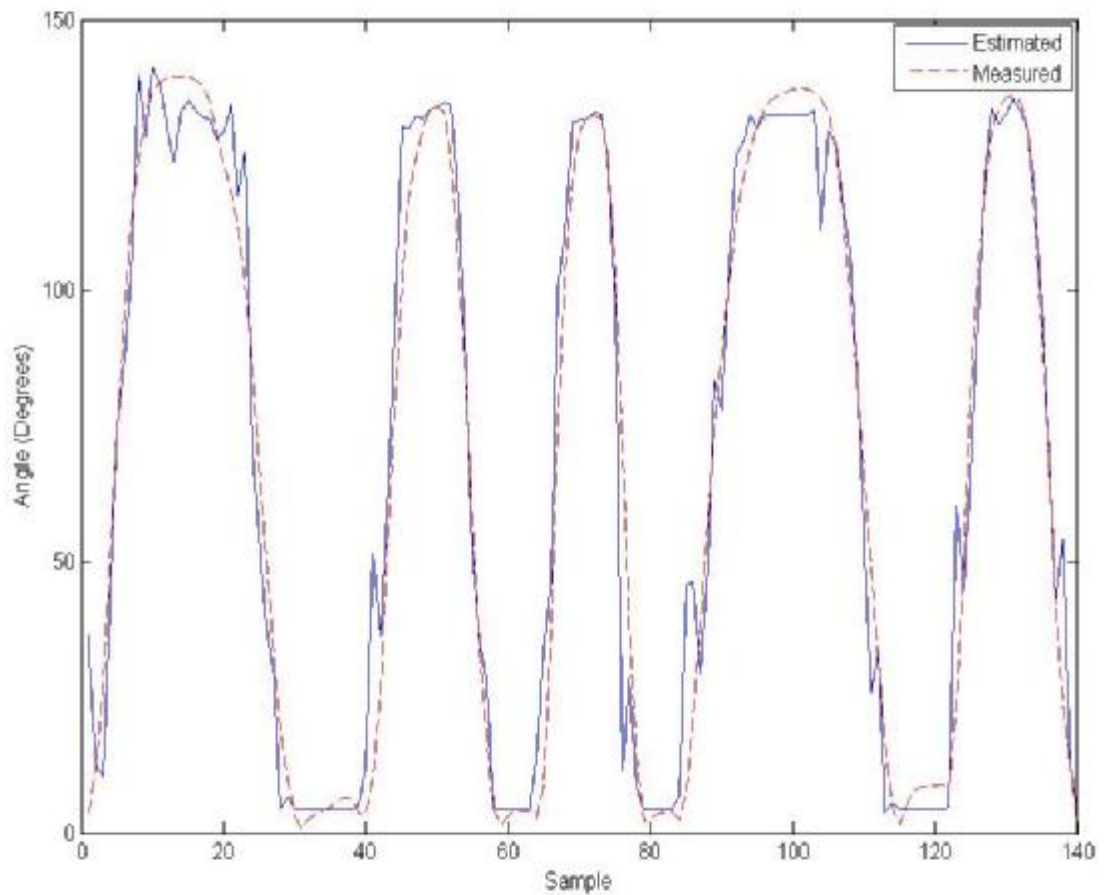


Figure 4.5. Estimated and Measured Arm Joint Angle during Test Phase of MLP Neural Network

Feature vector which consisted from MAV, RMS and WL features was as an input to test MLP neural network which was trained before and estimated elbow joint angle became as an output of MLP neural network. It was seen graph of estimated

joint angle at Figure 4.5. At the same time, measured elbow joint angle which was measured by goniometer was plotted in the same figure and estimated elbow joint angle was compared with measured elbow joint angle.

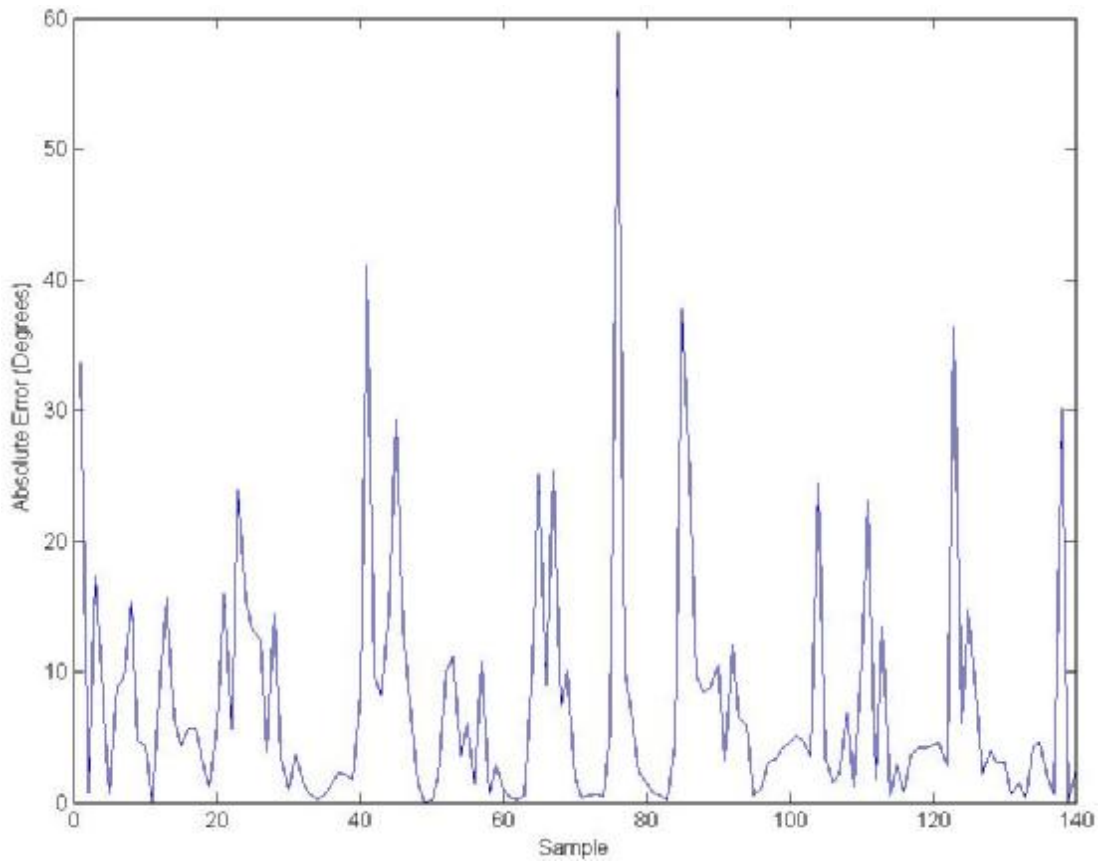


Figure 4.6. Absolute Error of Elbow Joint Angle Estimation in MLP Neural Network during Test Phase

The absolute error value was calculated subtracting measured elbow joint angle values from estimated elbow joint angle values which were obtained during test phase of MLP neural network and plotted at Figure 4.6. It is also worthy to state here the range for elbow joint angle is approximately 140 degrees. Hence, average percentage error around 5%.

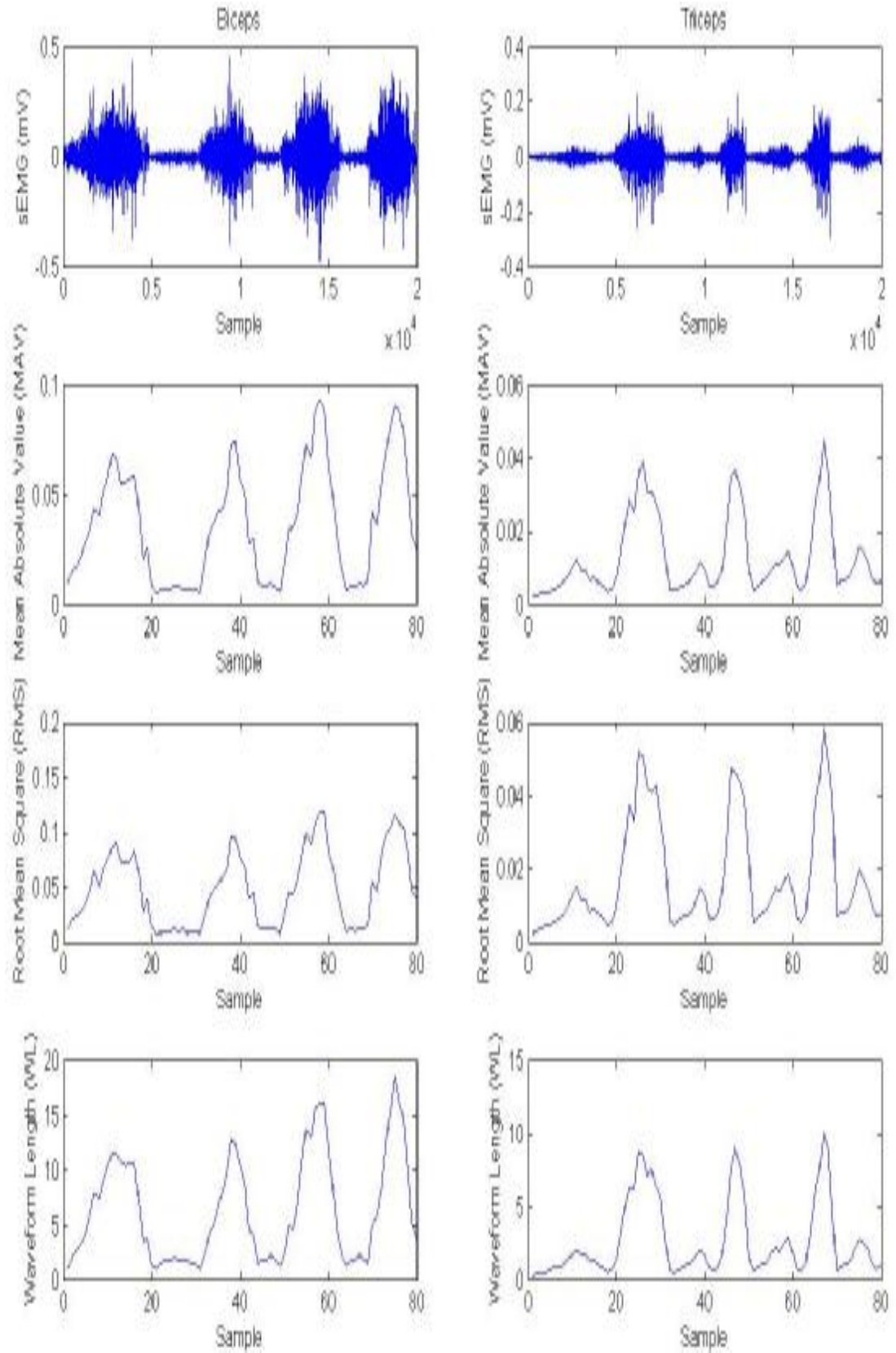


Figure 4.7. A Part of Real Time Data and Feature Graphs for MLP

A part of real time data which was composed of measured EMG signal from biceps and triceps muscles was plotted at Figure 4.7. Time domain based features such as Mean Absolute Value (MAV), Root Mean Square (RMS) and Waveform Length (WL) were also plotted respectively. They were calculated from EMG data which was plotted in the same figure segmenting into 250 samples. These features were used as input values to test multilayer perceptron neural network (MLP) which was trained before and it was obtained estimated elbow joint angle in the end.

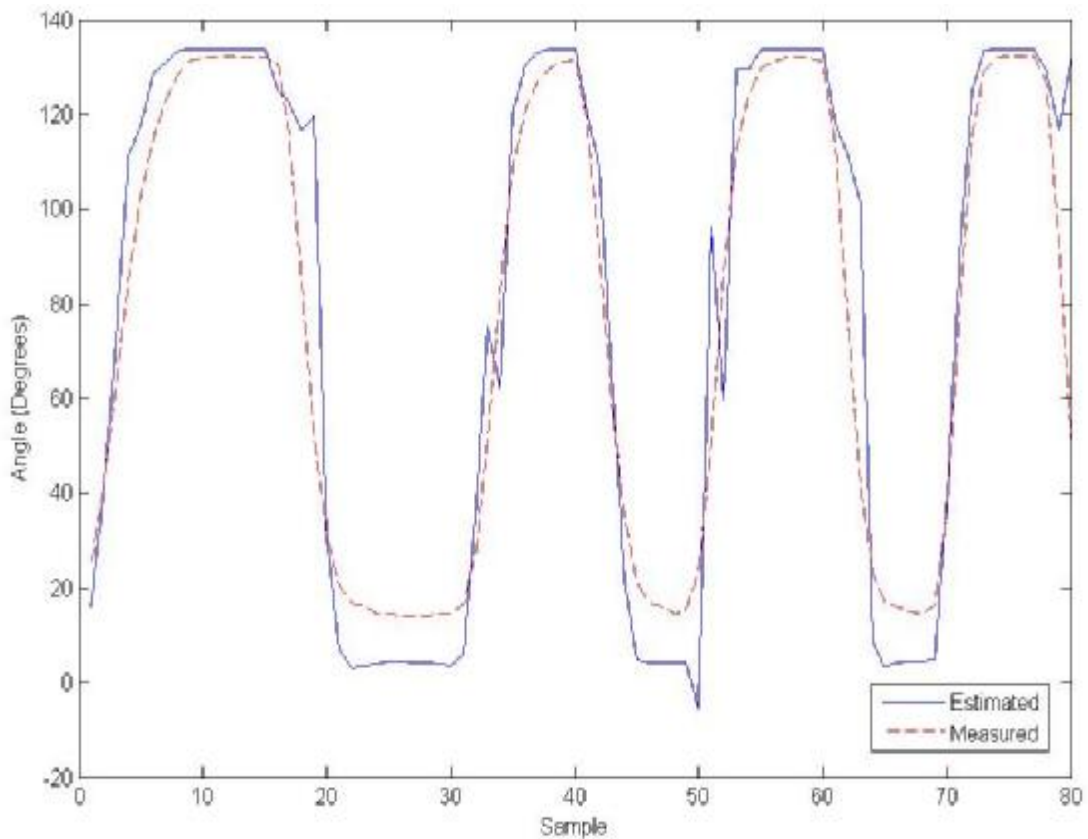


Figure 4.8. Real Time Estimated and Measured Arm Joint Angle using MLP Neural Network

Feature vector which consisted from MAV, RMS and WL features calculated from real time data was as an input to test MLP neural network which was trained before and real time estimated elbow joint angle became as an output of MLP neural network. It was seen graph of real time estimated joint angle at Figure 4.8. At the same time, measured elbow joint angle which was measured by goniometer was

plotted in the same figure and real time estimated elbow joint angle was compared with measured elbow joint angle.

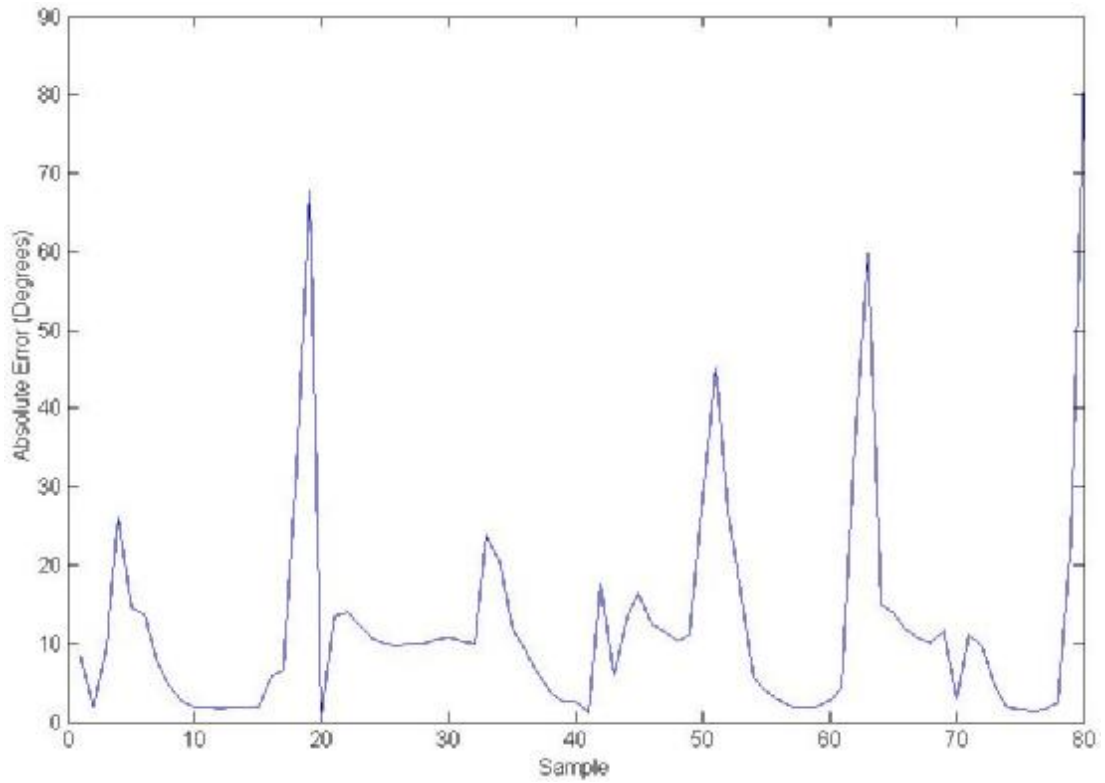


Figure 4.9. Absolute Error of Elbow Joint Angle Estimation in MLP Neural Network using Real Time Data

The absolute error value was calculated subtracting measured elbow joint angle values from estimated elbow joint angle values which were obtained during real time test phase of MLP neural network and plotted at Figure 4.9. It is also worthy to state here the range for elbow joint angle is approximately 130 degrees. Hence, average percentage error around 10 %.

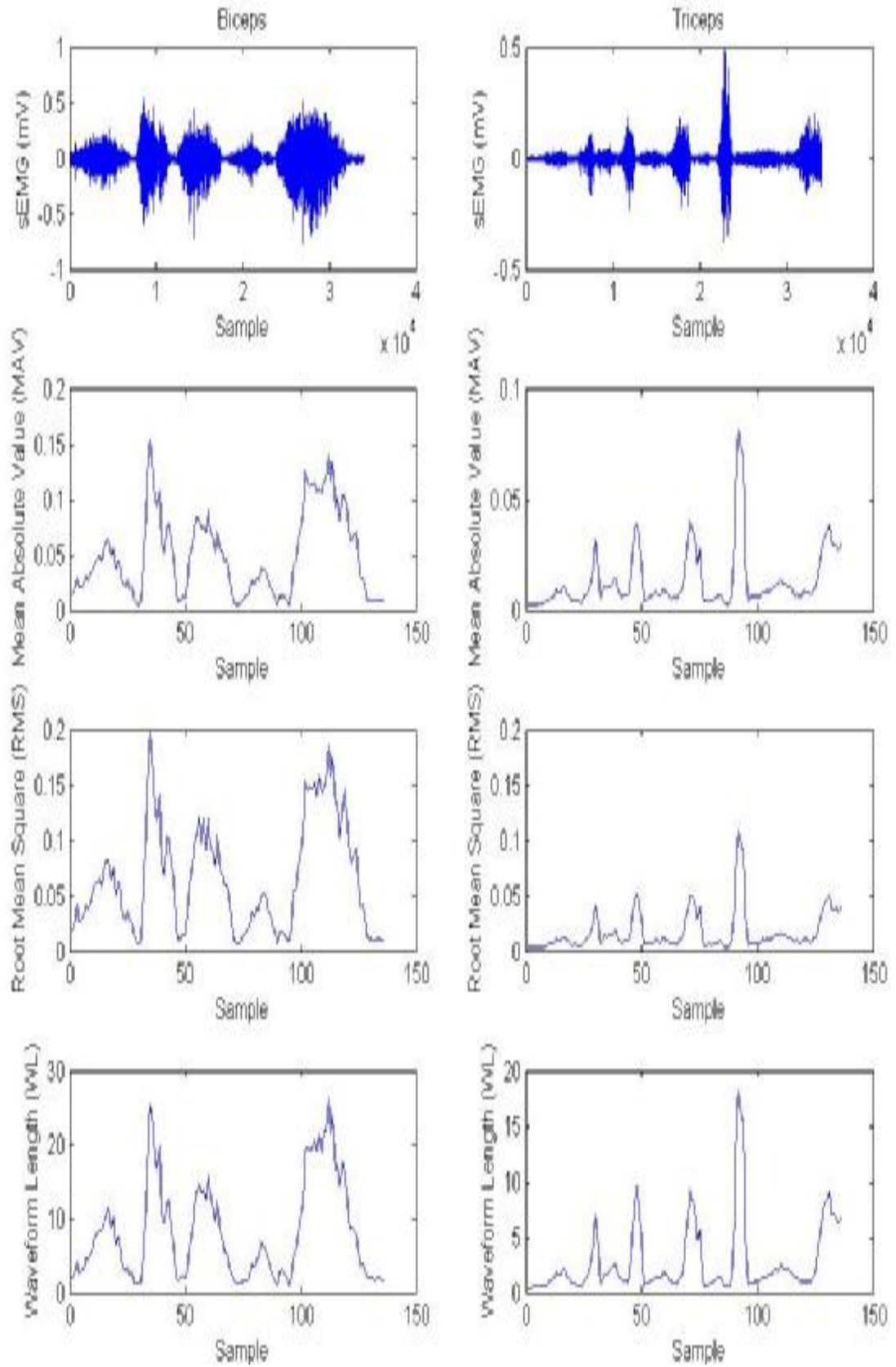


Figure 4.10. A Part of Training Data and Feature Graphs for GRNN

A part of training data which was composed of measured EMG signal from biceps and triceps muscles as described at section 3.9.3 was plotted at Figure 4.10. Time domain based features such as Mean Absolute Value (MAV), Root Mean Square (RMS) and Waveform Length (WL) were also plotted respectively. They were calculated from EMG data which was plotted in the same figure segmenting into 250 samples. These features were used as input values for General Regression neural network (GRNN) training and it was obtained estimated elbow joint angle in the end.

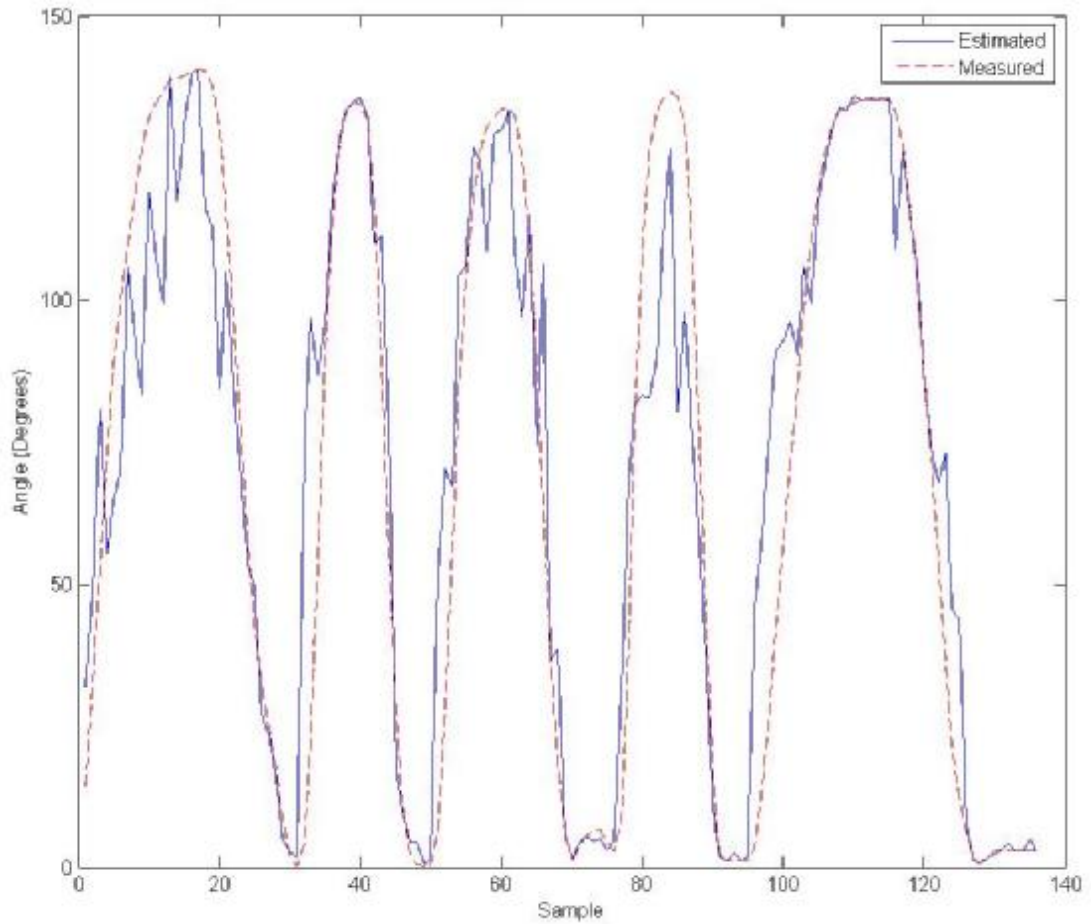


Figure 4.11. Estimated and Measured Arm Joint Angle during Training Phase of General Regression Neural Network

Feature vector which consisted from MAV, RMS and WL features was as an input to train general regression neural network and estimated elbow joint angle became as an output of general regression neural network. It was seen graph of

estimated joint angle at Figure 4.11. At the same time, measured elbow joint angle which was measured by goniometer was plotted in the same figure and estimated elbow joint angle was compared with measured elbow joint angle.

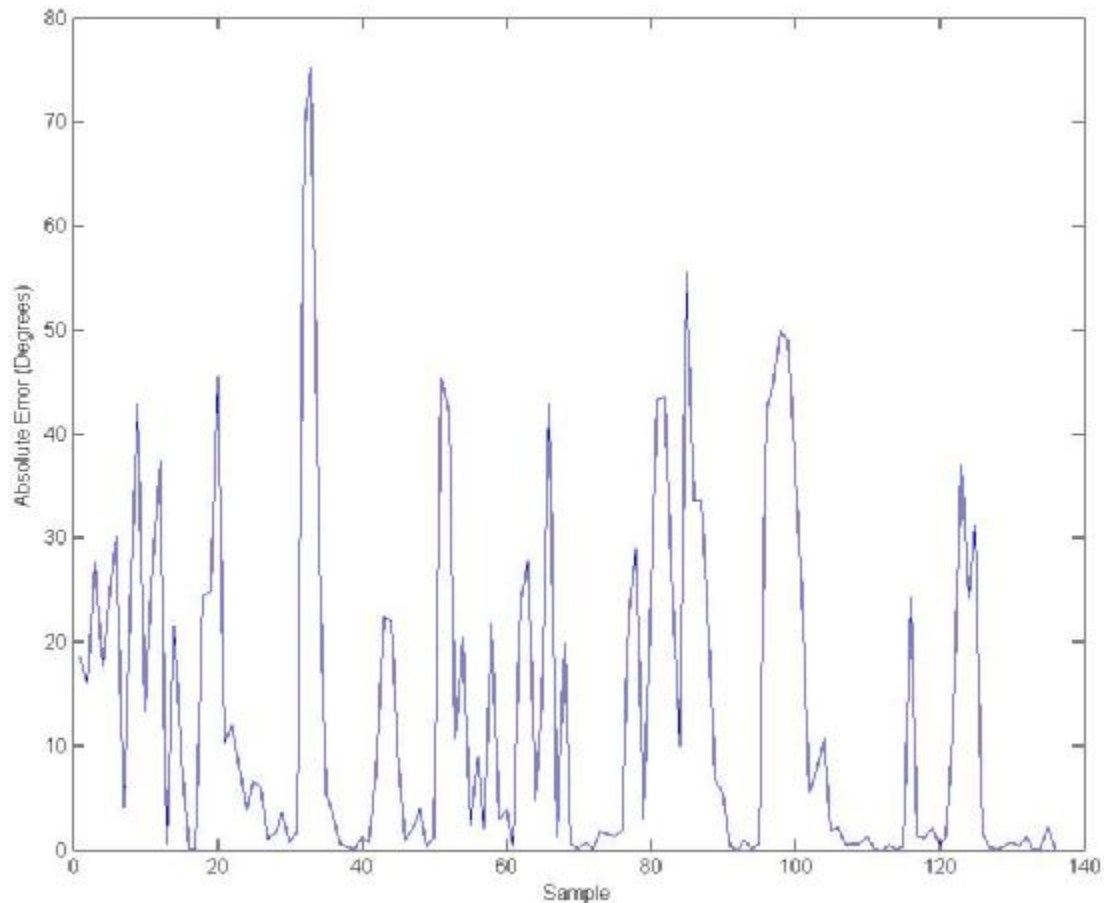


Figure 4.12. Absolute Error of Elbow Joint Angle Estimation in General Regression Neural Network during Training

The absolute error value was calculated subtracting measured elbow joint angle values from estimated elbow joint angle values which were obtained during training phase of General Regression Neural Network and plotted at Figure 4.12. It is also worthy to state here the range for elbow joint angle is approximately 140 degrees. Hence, average percentage error around 9%.

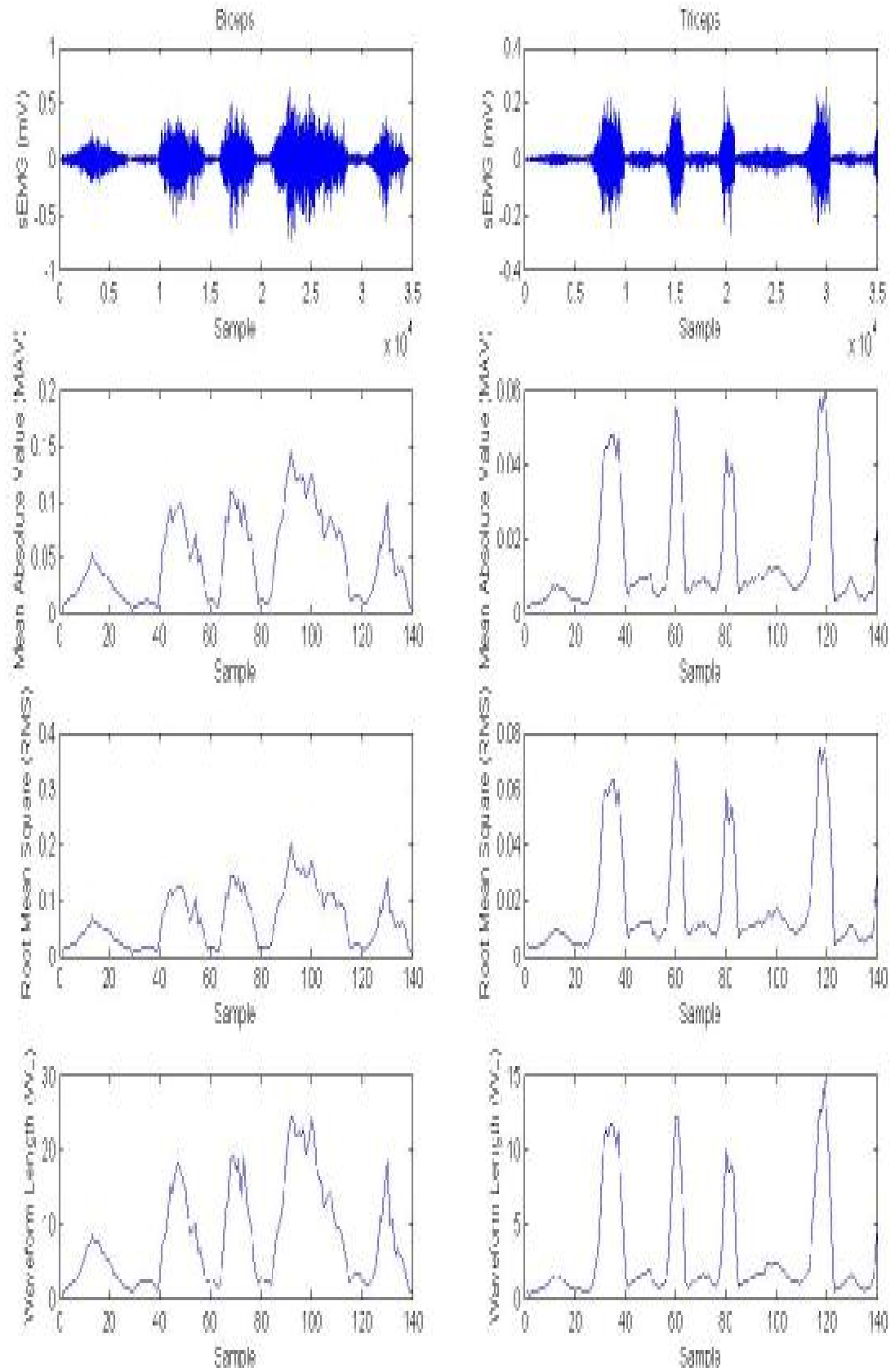


Figure 4.13. A Part of Test Data and Feature Graphs for GRNN

A part of test data which was consisted of measured EMG signal from biceps and triceps muscles as described at section 3.9.3 was plotted at Figure 4.13. Time domain based features such as Mean Absolute Value (MAV), Root Mean Square (RMS) and Waveform Length (WL) were also plotted respectively. They were calculated from EMG data which was plotted in the same figure segmenting into 250 samples. These features were used as input values to test general regression neural network (GRNN) which was trained before and it was obtained estimated elbow joint angle in the end.

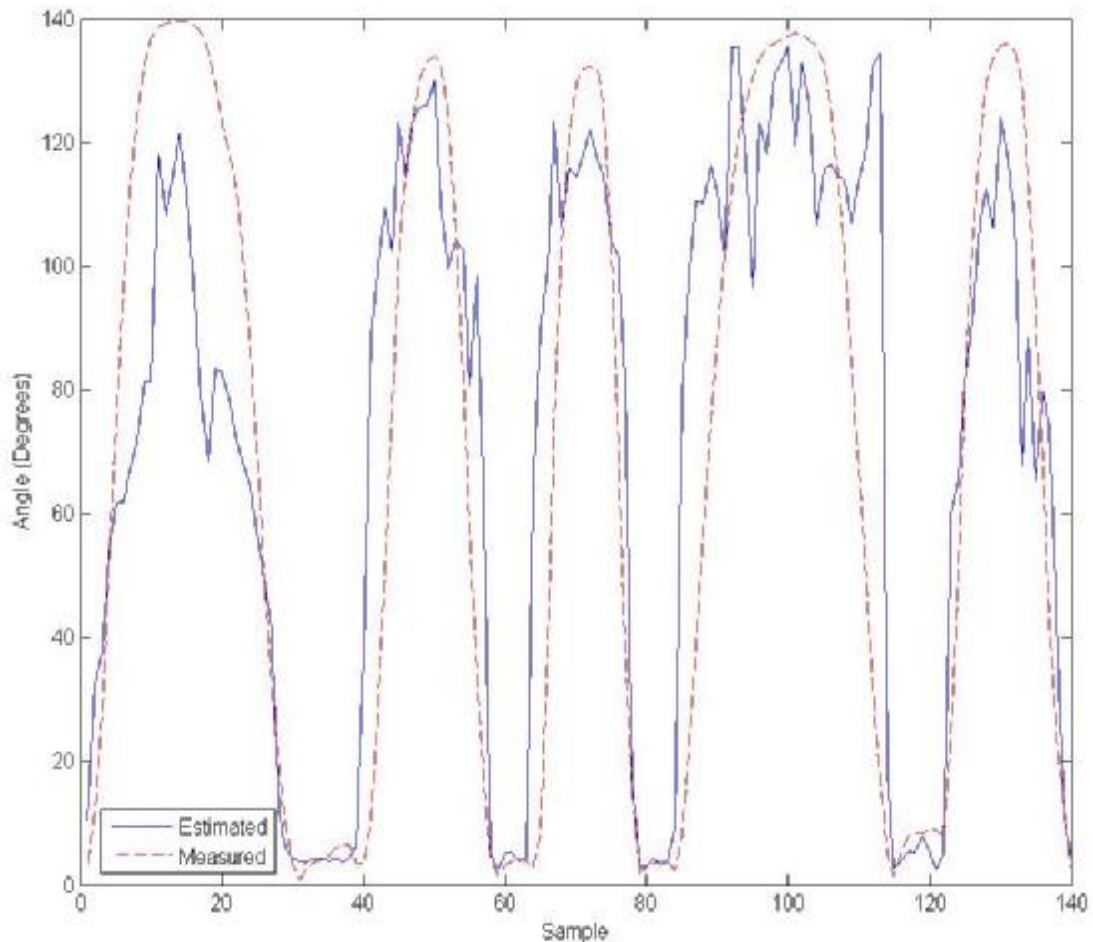


Figure 4.14. Estimated and Measured Arm Joint Angle during Test Phase of General Regression Neural Network

Feature vector which consisted from MAV, RMS and WL features was as an input to test general regression neural network which was trained before and estimated elbow joint angle became as an output of general regression neural

network. It was seen graph of estimated joint angle at Figure 4.14. At the same time, measured elbow joint angle which was measured by goniometer was plotted in the same figure and estimated elbow joint angle was compared with measured elbow joint angle.

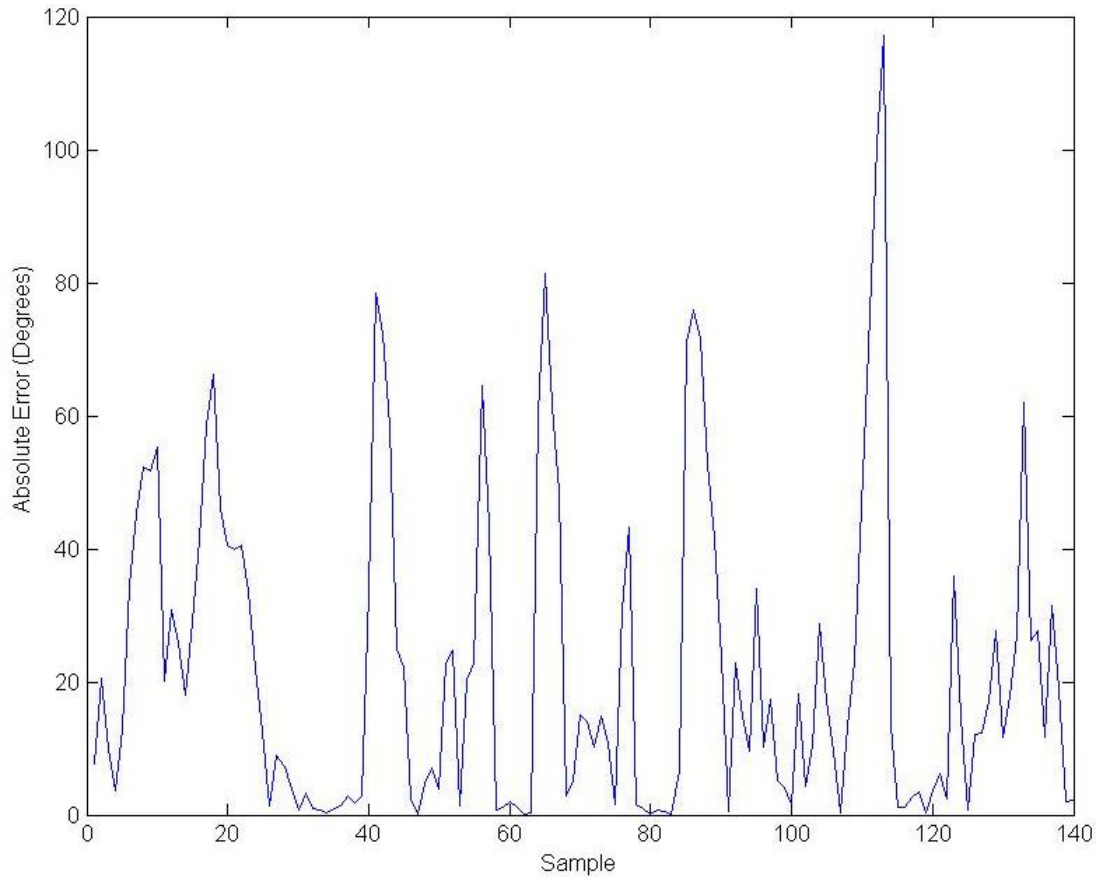


Figure 4.15. Absolute Error of Elbow Joint Angle Estimation in General Regression Neural Network using Test Data

The absolute error value was calculated subtracting measured elbow joint angle values from estimated elbow joint angle values which were obtained during test phase of General Regression Neural Network and plotted at Figure 4.15. It is also worthy to state here the range for elbow joint angle is approximately 140 degrees. Hence, average percentage error around 15%.

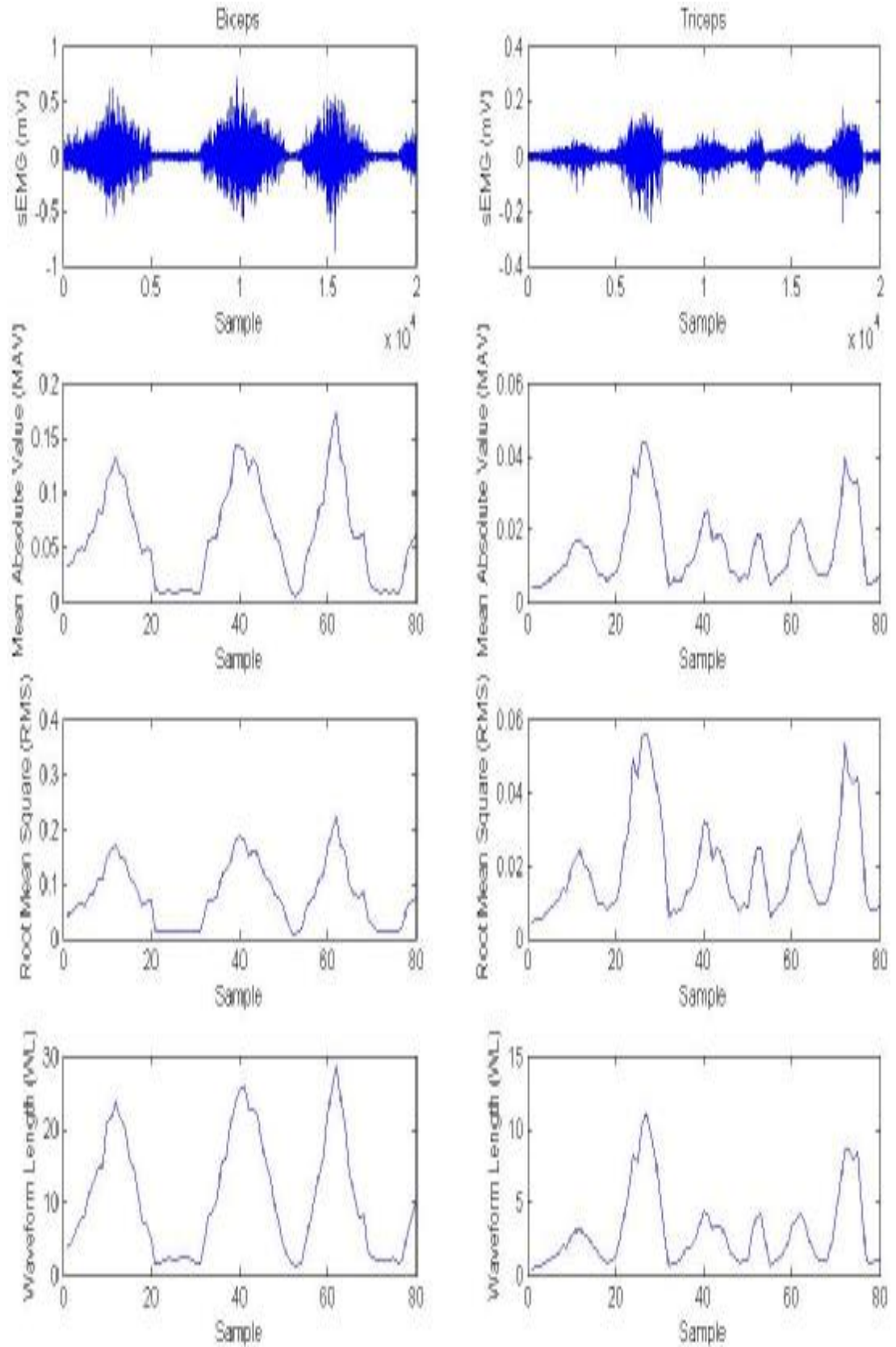


Figure 4.16. A Part of Real Time Data and Feature Graphs for GRNN

A part of real time data which was composed of measured EMG signal from biceps and triceps muscles was plotted at Figure 4.16. Time domain based features such as Mean Absolute Value (MAV), Root Mean Square (RMS) and Waveform Length (WL) were also plotted respectively. They were calculated from EMG data which was plotted in the same figure segmenting into 250 samples. These features were used as input values to test general regression neural network (GRNN) which was trained before and it was obtained estimated elbow joint angle in the end.

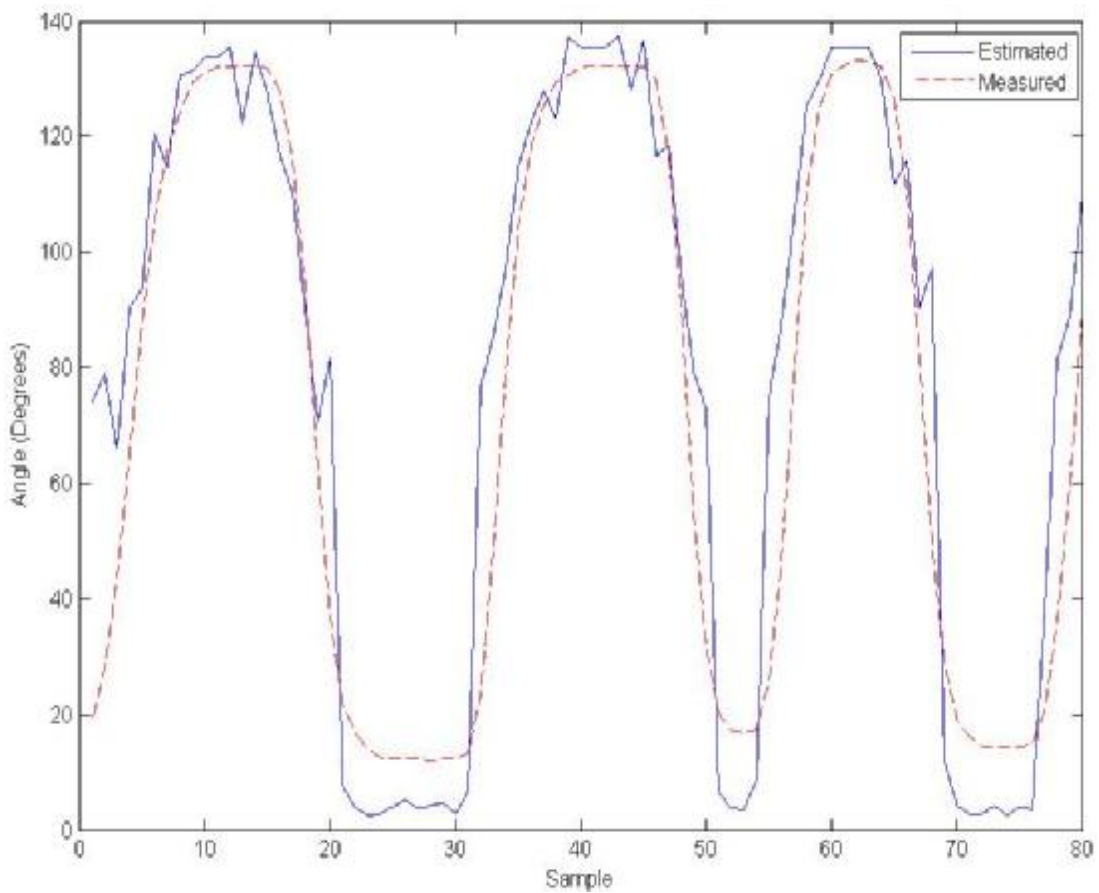


Figure 4.17. Real Time Estimated and Measured Arm Joint Angle using General Regression Neural Network

Feature vector which consisted from MAV, RMS and WL features calculated from real time data was as an input to test general regression neural network which was trained before and real time estimated elbow joint angle became as an output of general regression neural network. It was seen graph of real time estimated joint angle at Figure 4.17. At the same time, measured elbow joint angle which was

measured by goniometer was plotted in the same figure and real time estimated elbow joint angle was compared with measured elbow joint angle.

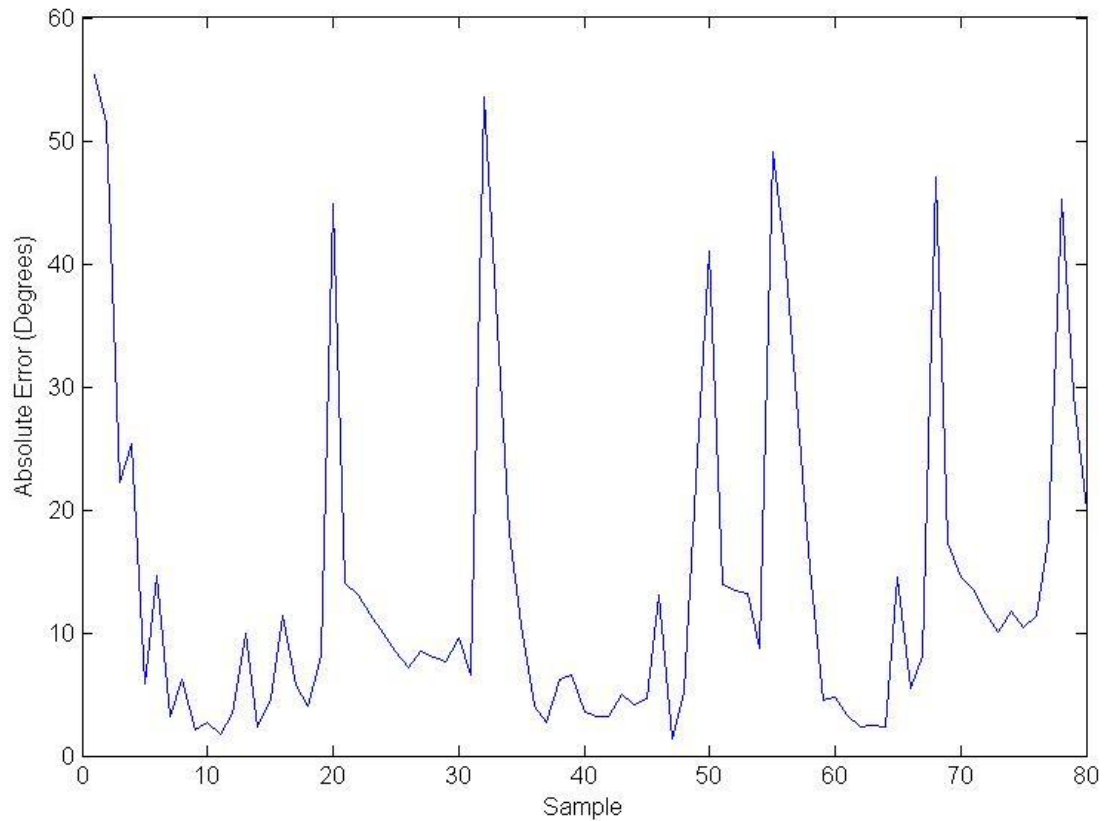


Figure 4.18. Absolute Error of Elbow Joint Angle Estimation in General Regression Neural Network during Real Time Phase

The absolute error value was calculated subtracting measured elbow joint angle values from estimated elbow joint angle values which were obtained during training phase of General Regression Neural Network and plotted at Figure 4.18. It is also worthy to state here the range for elbow joint angle is approximately 135 degrees. Hence, average percentage error around 11%.

Table 4.1. Overall Percentage Accuracy of MLP and GRNN

| Accuracy       | MLP % | GRNN % |
|----------------|-------|--------|
| Training Data  | 95.69 | 90.55  |
| Test Data      | 94.59 | 84.11  |
| Real Time Data | 89.63 | 88.35  |

Table 4.1 show that overall percentage accuracy values of estimated elbow joint angle which is obtained using training, test and real time EMG data in MLP and General Regression Neural Network.

#### 4.2. Discussion

Figures 4.2, 4.5, 4.8 and 4.11, 4.14, 4.17 present a qualitative comparison of estimated elbow joint angle between MLP neural network and GRNN for training data, test data and real time data respectively. Measured and estimated angle are shown using MLP algorithm at Figures 4.2, 4.5, 4.8 and using GRNN algorithm at Figures 4.11, 4.14, 4.17.

It is seen that MLP method provides less error values than GRNN algorithm for training data, test data and real time data. Accuracy of elbow joint angle estimation using MLP algorithm is higher than GRNN algorithm in three kinds of data. Training data produces less error according to test data and real time at MLP. Test data produces less error according to real time data at MLP, too. Accuracy values of estimated elbow joint angle at MLP are 95.69%, 94.59% and 89.63% for training data, test data and real time data respectively.

At GRNN algorithm, performance of elbow joint angle estimation is low in test data and real time data but it is seen that estimation of elbow joint angle in training data is more accurate than others. Accuracy values of estimated elbow joint angle at GRNN are 90.55%, 84.11% and 88.35% for training data, test data and real time data respectively.

Ahsan et al (2012) used 7 statistical time and time- frequency based features namely mean absolute value (MAV), root mean square (RMS), variance (VAR), standard deviation (SD), zero crossing (ZC), slope sign change (SSC) and waveform length (WL) as inputs to neural network. When neural network was trained with 15 hidden neurons, they found the value of MSE as 0.106199 with performance value of 89.2%.

Mean square error (MSE) of MLP with three layers after 1000 epochs is 0.025601 in this thesis study. When this value is compared with their studies, it is seen that the value of MSE in this study which has neural network structure with fewer neurons and fewer feature vectors is lower than their studies. It is also obtained higher performance than their studies.



## 5. CONCLUSION AND FUTURE WORKS

This thesis introduces an algorithm for real time elbow joint angle estimation from sEMG signals, which could be used for myoelectric control of prosthetic devices. The proposed method developed in the thesis is based on time domain feature extraction and a NN based pattern classification. Features in time domain are chosen since they are usually quick and easily implemented because they do not need any transformation (Phinyomark et al., 2012). It is an important point to estimate real time elbow joint angle so it is chosen time domain feature extraction. In the feature extraction, mean absolute value (MAV), root mean square (RMS) and waveform length (WL) was used. Pattern classification was performed using a Levenberg – Marquardt Multilayer Perceptron Neural Network (MLP) and General Regression Neural Network (GRNN).

As performance evaluation of the algorithm, the results obtained using MLP method was quantitatively compared with the results obtained using GRNN method. The results indicate that the MLP algorithm presented less error in estimations and performed better estimations than GRNN algorithm. However, all results are acceptable in terms of accuracy and response speed as compared to previous studies in literature.

In this work, it has been also shown that it is possible to continuously decode elbow joint angle from EMG signals collected from a generalized electrode placement in an able-bodied subject.

Future work could be aimed at reducing noise, evaluating the method in amputees, optimizing the code for its execution in real time and adding gyroscopic sensor to the system. It does not only improve the accuracy of the system in estimation of elbow joint angle, but it also allows to estimate the angular velocity of elbow joint. It is also possible to make a FPGA hardware application the algorithm which could be used in production of prosthesis and orthosis.



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## **CURRICULUM VITAE**

Durmuş Ali EROĞLU was born in Adana, Turkey in 1987. He received his B.S. degree in Electrical and Electronics Engineering Department from Anadolu University in 2010. He started MSc education in Electrical and Electronics Engineering Department in Çukurova University in 2012. He has been working as a Research Assistant in Biomedical Engineering Department of Çukurova University since 2012. His research areas are EMG Signals, Digital Signal Processing and Biosignal Processing.

# **APPENDIX**



## APPENDIX A

TABLE OF FORMED TRAINING DATA

| EXPERIMENT | SAMPLE RANGE |
|------------|--------------|
| A1B1_01    | 0-12070      |
| A3B3_01    | 8695-13517   |
| A2B2_01    | 13488-18200  |
| A3B1_01    | 0-5342       |
| A1B3_01    | 10932-19411  |
| A3B2_01    | 5251-10628   |
| A2B1_01    | 6835-11838   |
| A1B2_01    | 0-7807       |
| A2B3_01    | 6630-13738   |
| A1B1_02    | 9746-17429   |
| A3B3_02    | 9774-14780   |
| A2B2_02    | 6195-12683   |
| A3B1_02    | 13601-18302  |
| A1B3_02    | 9714-20000   |
| A3B2_02    | 16119-20000  |
| A2B1_02    | 6828-13059   |
| A1B2_02    | 8900-17699   |
| A2B3_02    | 6515-13662   |
| A1B1_03    | 9757-20000   |
| A3B3_03    | 9299-14769   |
| A2B2_03    | 11886-17494  |
| A3B1_03    | 14885-20000  |
| A1B3_03    | 0-10595      |
| A3B2_03    | 5079-9931    |
| A2B1_03    | 12150-18141  |
| A1B2_03    | 10726-20000  |
| A2B3_03    | 4992-12615   |
| A1B1_04    | 11307-20000  |

|         |             |
|---------|-------------|
| A3B3_04 | 8349-14947  |
| A2B2_04 | 7675-15267  |
| A3B1_04 | 13922-18800 |
| A1B3_04 | 10160-19376 |
| A3B2_04 | 0-4724      |
| A2B1_04 | 13287-19004 |
| A1B2_04 | 9773-20000  |
| A2B3_04 | 11787-20000 |
| A1B1_05 | 10466-17761 |
| A3B3_05 | 15132-19869 |
| A2B2_05 | 12881-20000 |
| A3B1_05 | 10803-15951 |
| A1B3_05 | 12663-20000 |
| A3B2_05 | 8215-14764  |
| A2B1_05 | 109-6806    |
| A1B2_05 | 0-9678      |
| A2B3_05 | 12789-17778 |

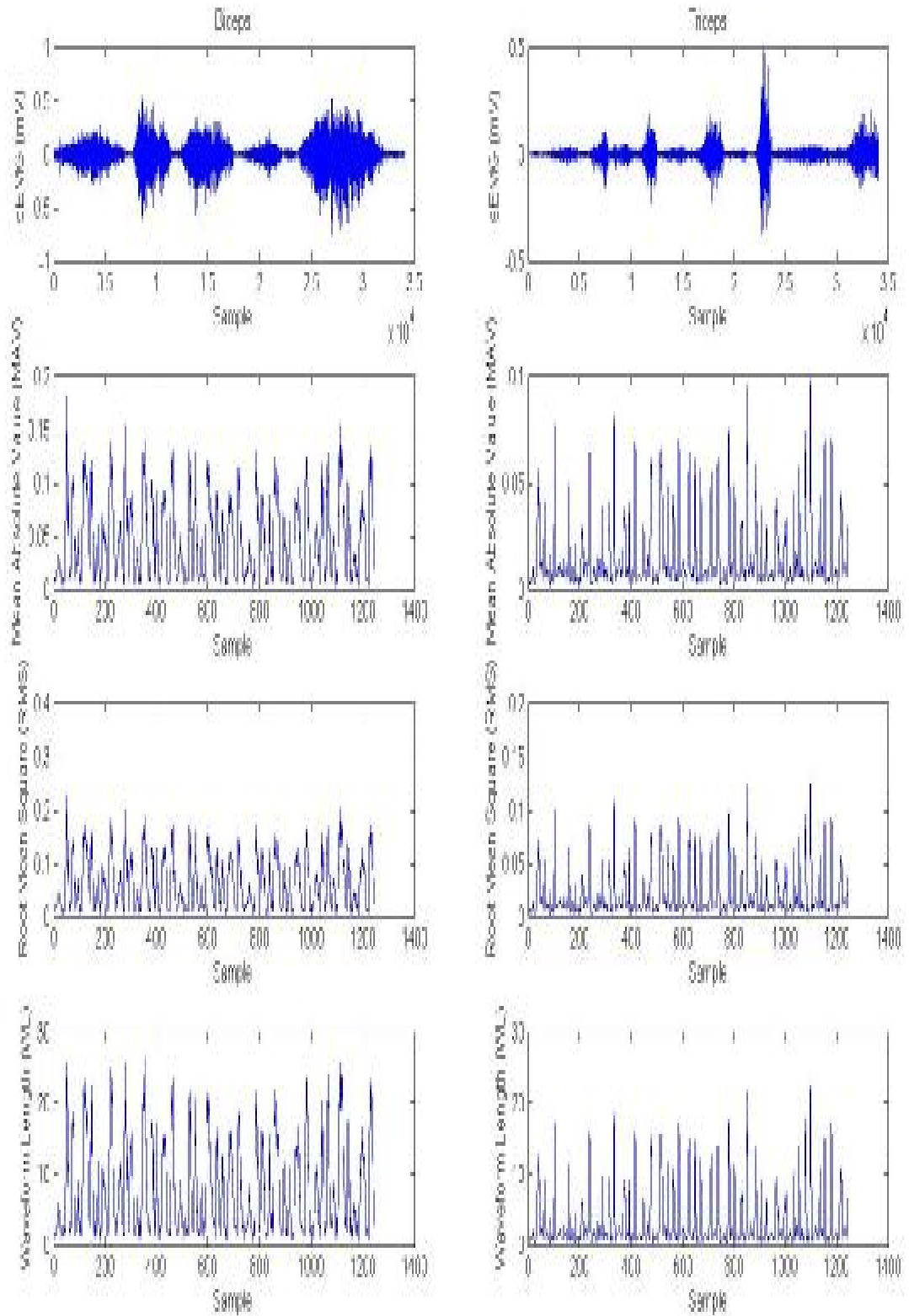
## **APPENDIX B**

**TABLE OF FORMED TEST DATA**

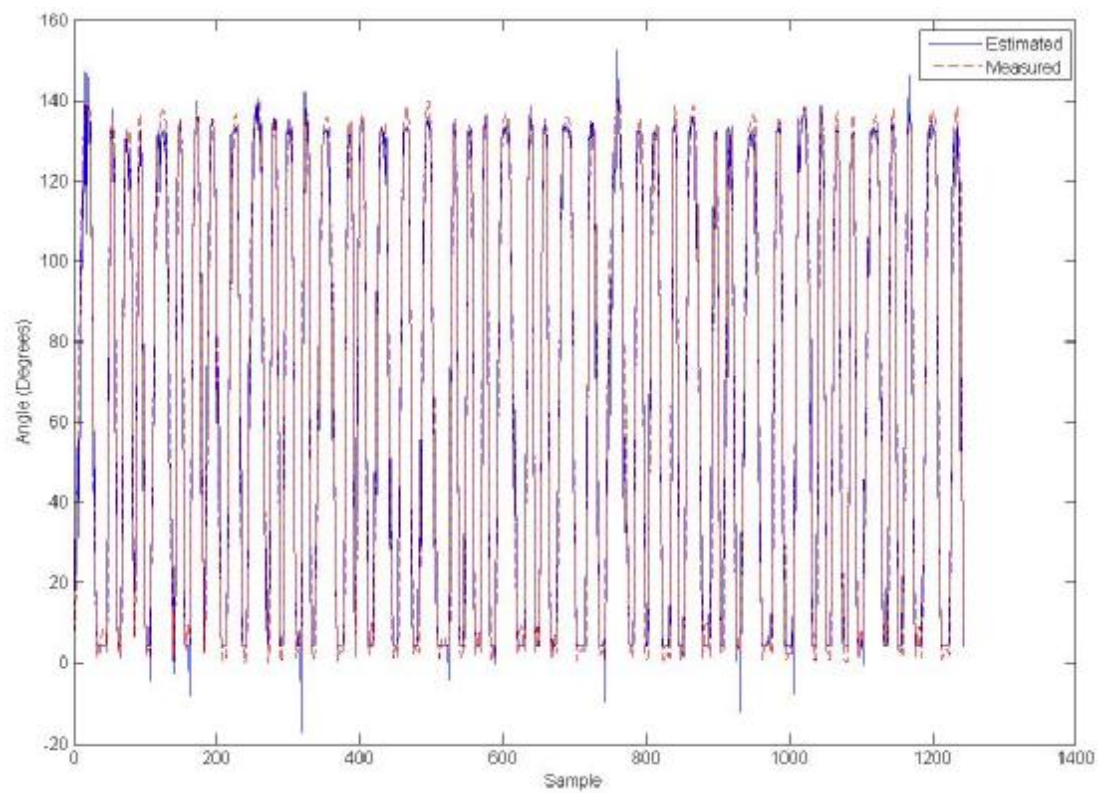
| <b>EXPERIMENT</b> | <b>SAMPLE RANGE</b> |
|-------------------|---------------------|
| A1B1_02           | 0-9915              |
| A1B2_04           | 0-9600              |
| A1B3_03           | 10500-20000         |
| A2B1_02           | 6900-12982          |
| A2B2_02           | 12600-18970         |
| A2B3_03           | 0-6010              |
| A3B1_05           | 0-5105              |
| A3B2_04           | 15065-20000         |
| A3B3_04           | 0-4448              |

## APPENDIX C

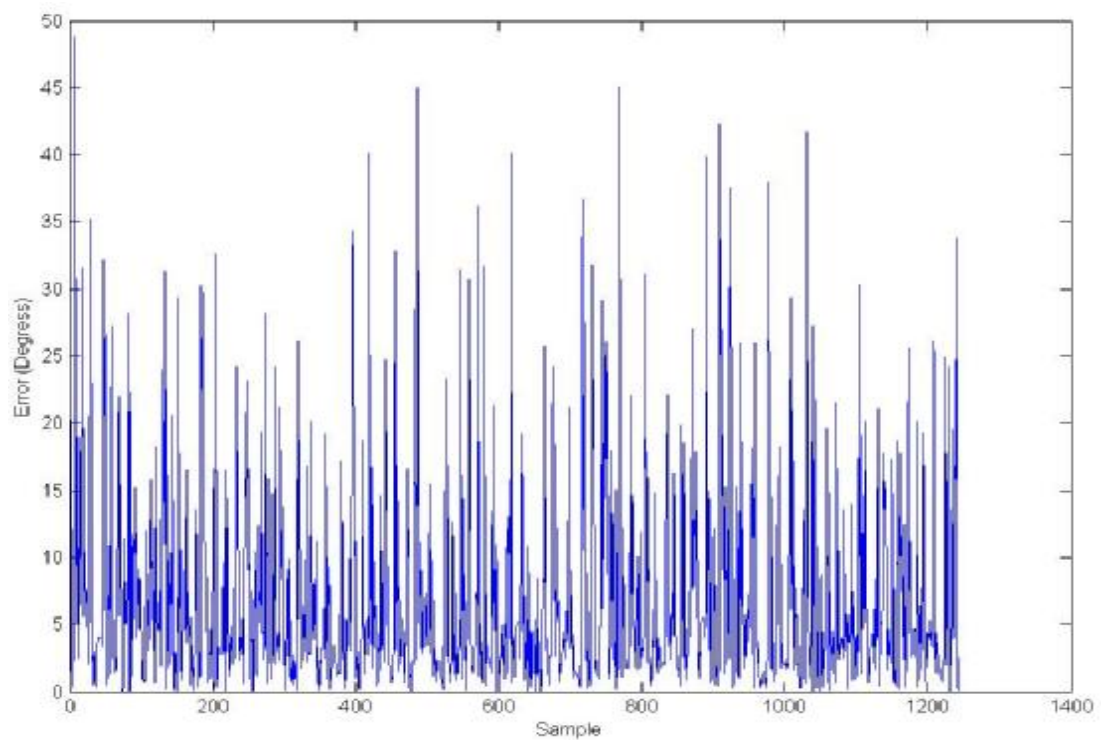
### TRAINING DATA AND FEATURE GRAPH FOR MLP



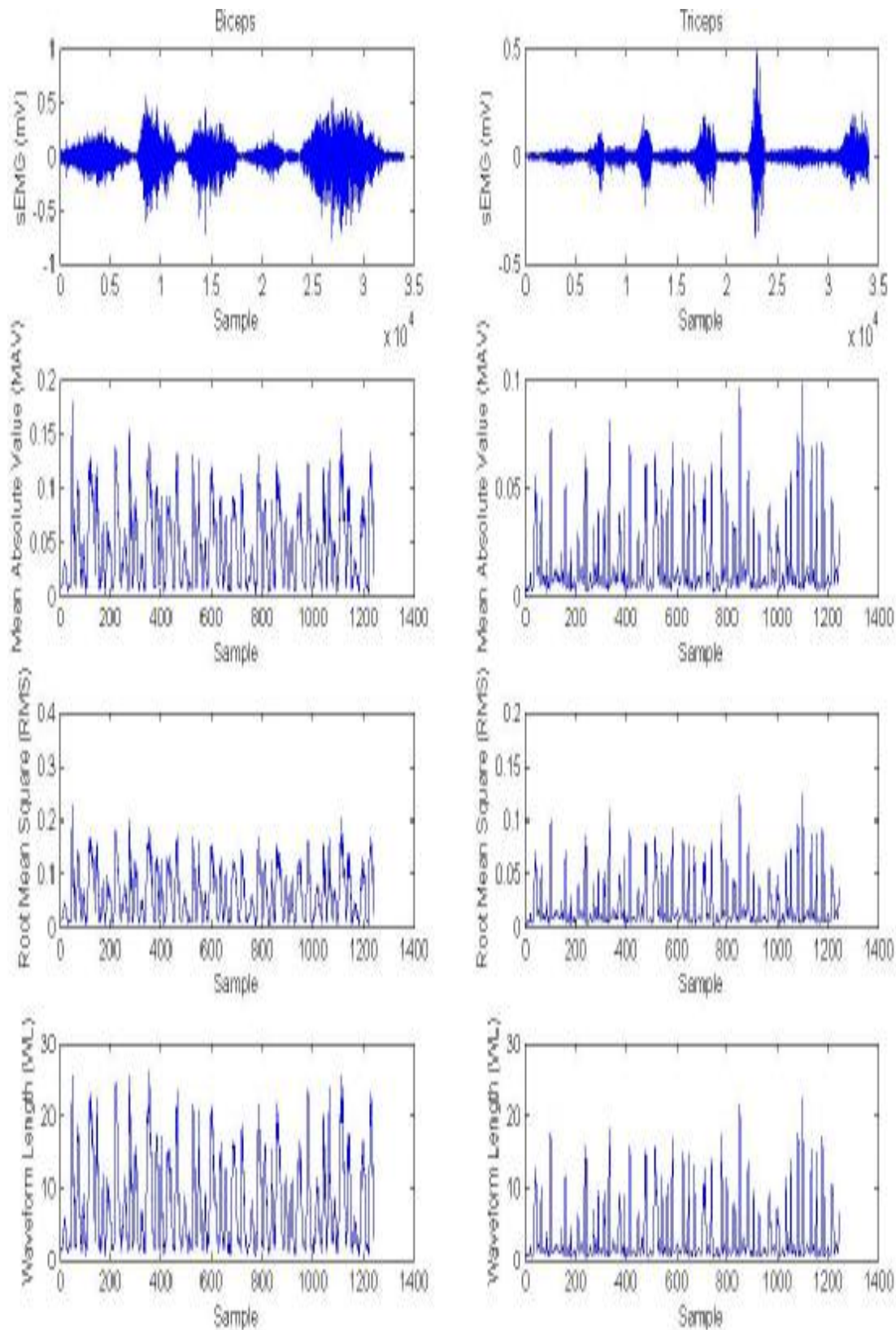
### MEASURED AND ESTIMATED ANGLE DURING MLP TRAINING STAGE



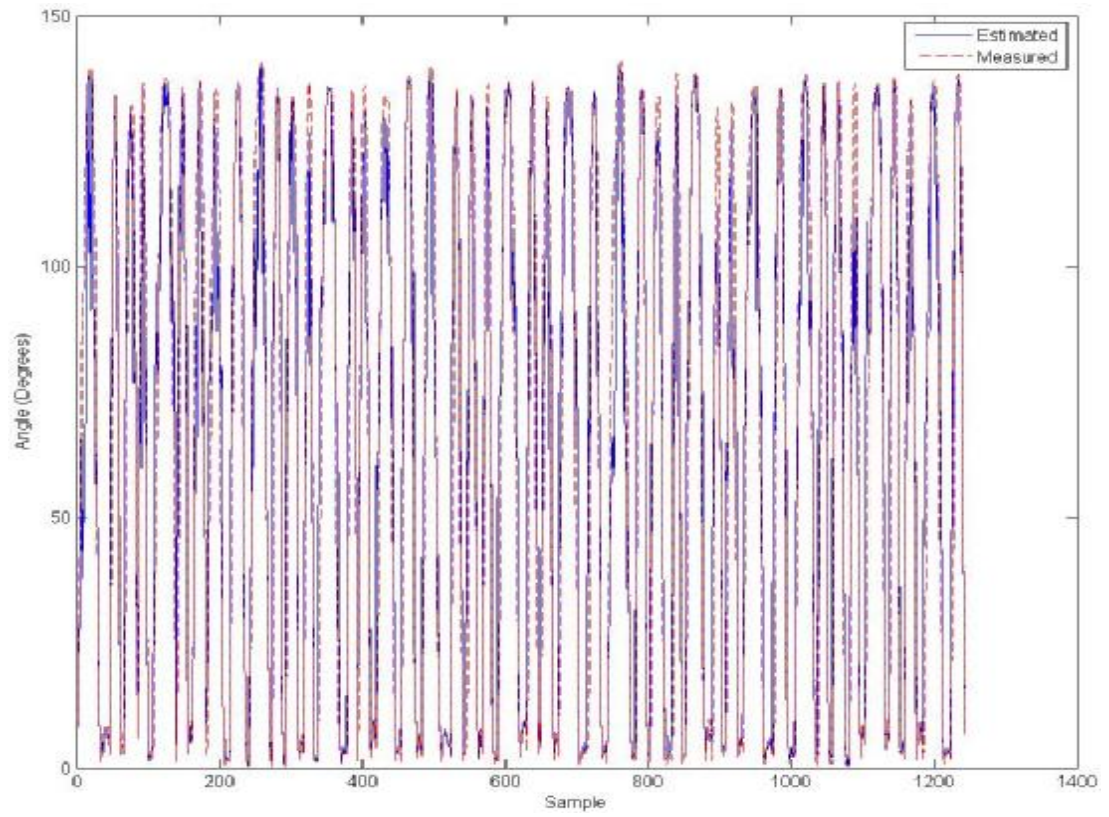
### ERROR OF ESTIMATED ANGLE DURING MLP TRAINING STAGE



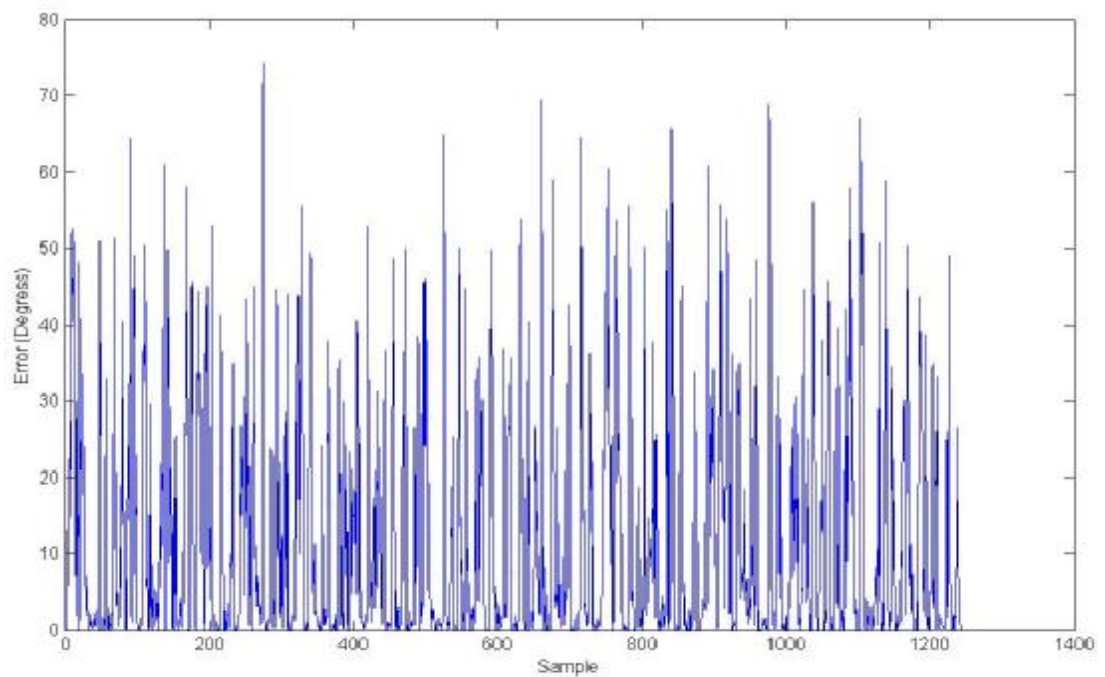
**TRAINING DATA AND FEATURE GRAPH FOR GRNN**



## MEASURED AND ESTIMATED ANGLE DURING GRNN TRAINING STAGE

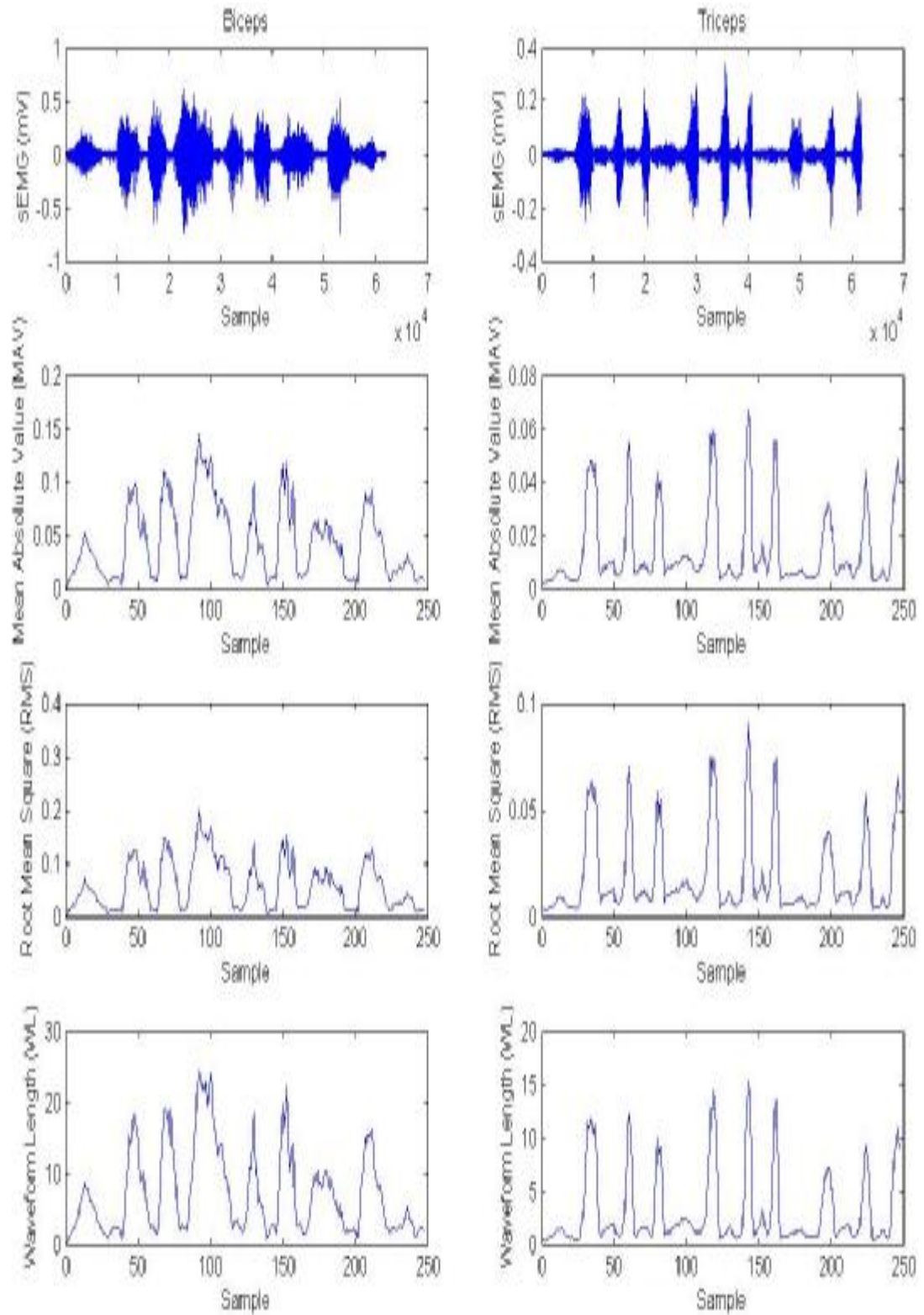


## ERROR OF ESTIMATED ANGLE DURING GRNN TRAINING STAGE

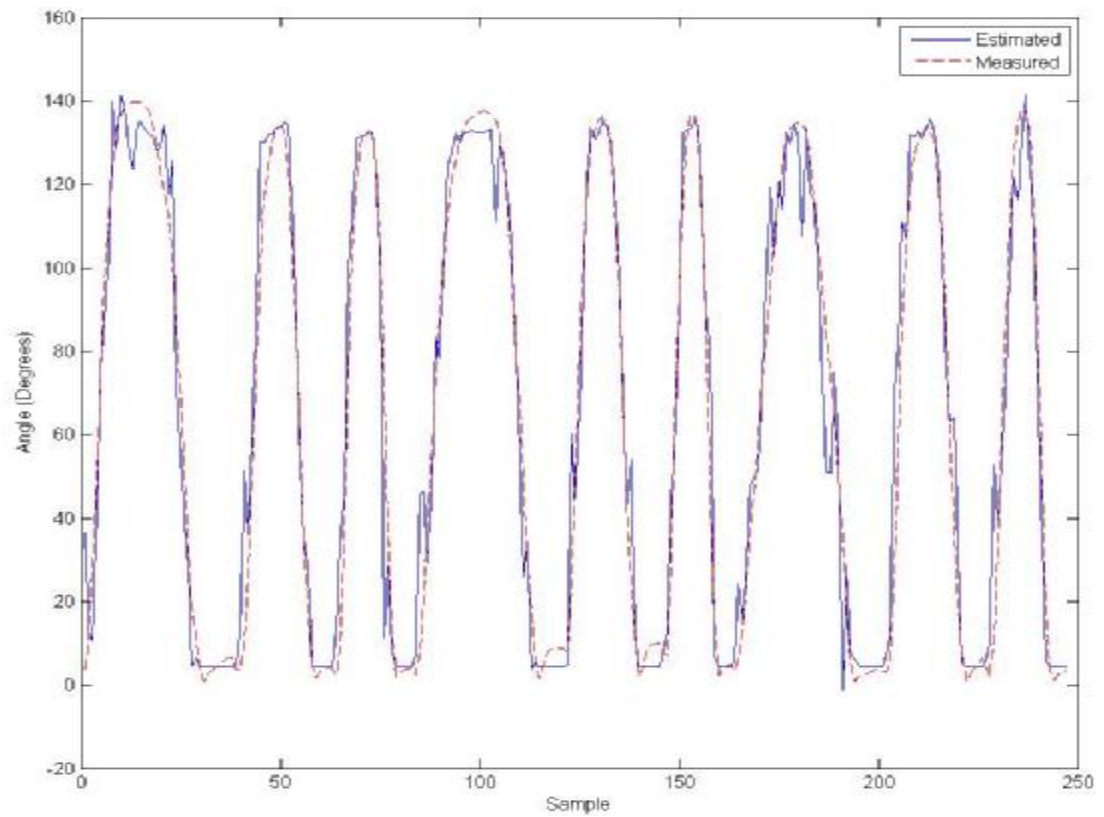


## APPENDIX D

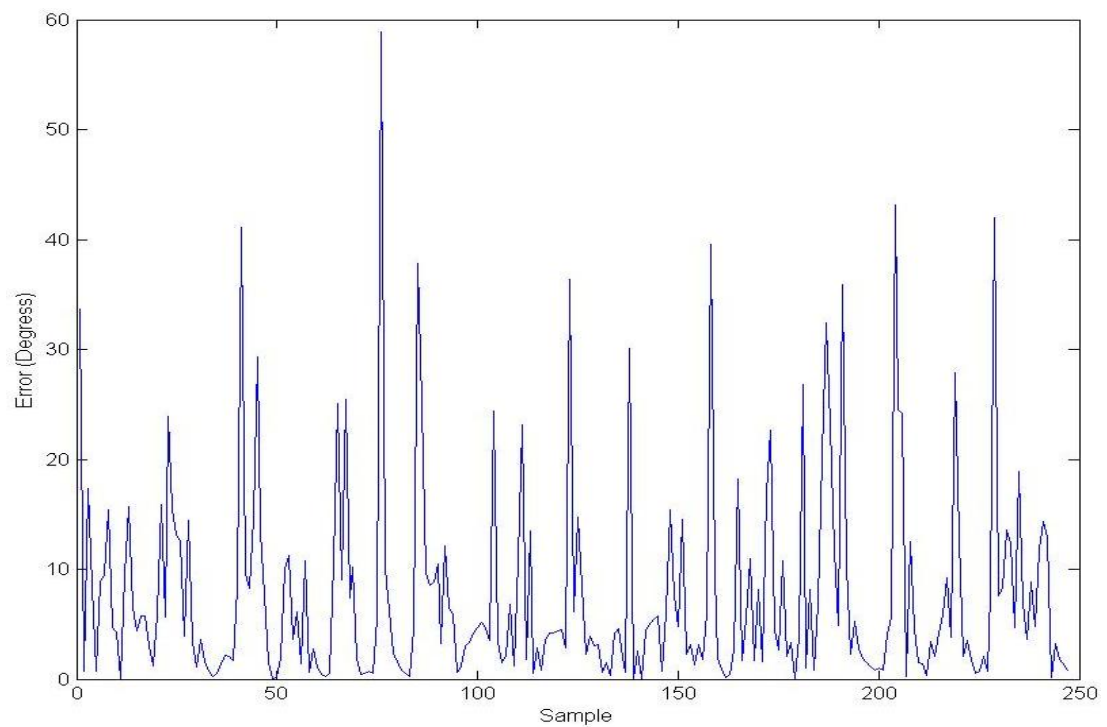
### TEST DATA AND FEATURE GRAPH FOR MLP



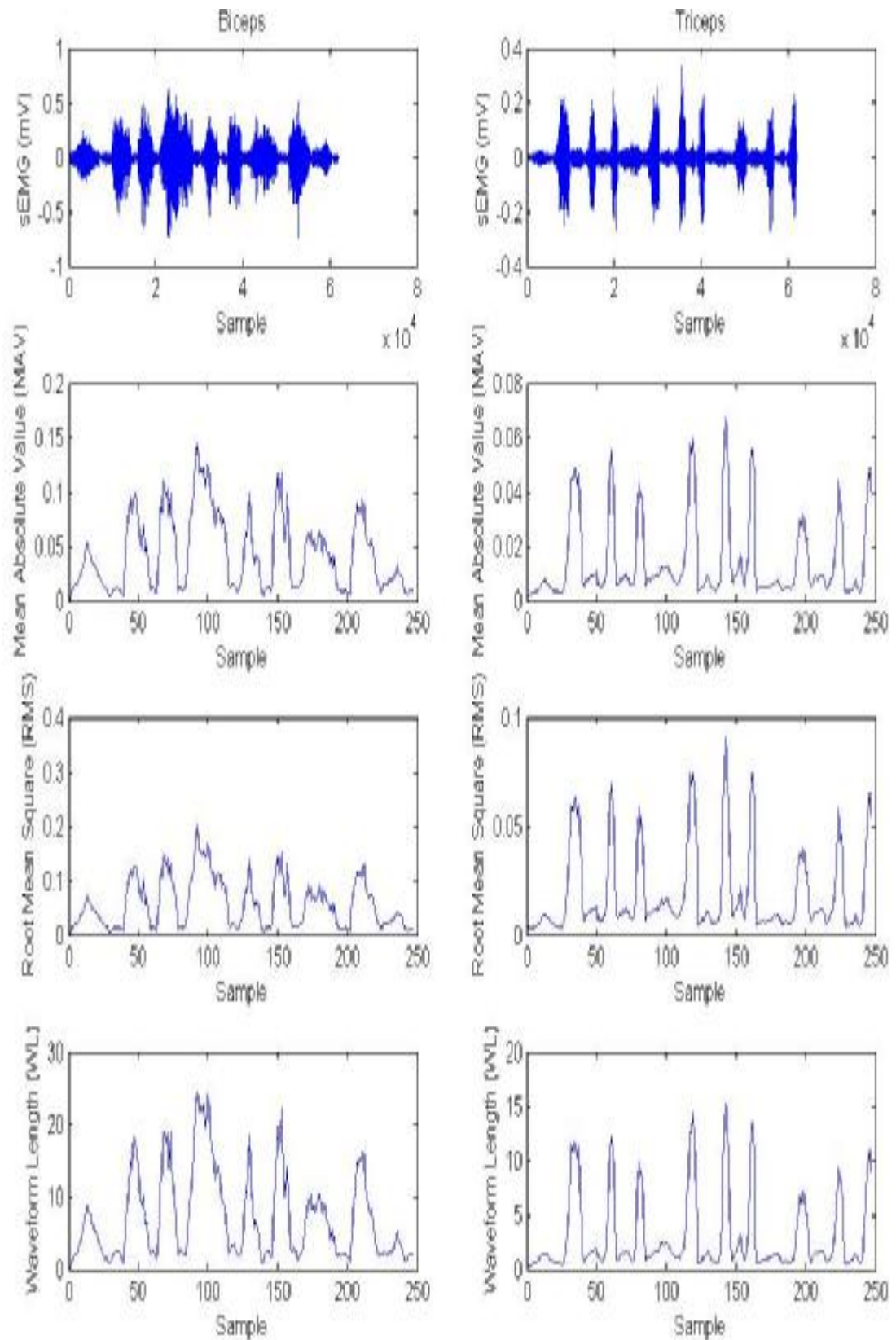
### MEASURED AND ESTIMATED ANGLE DURING MLP TEST STAGE



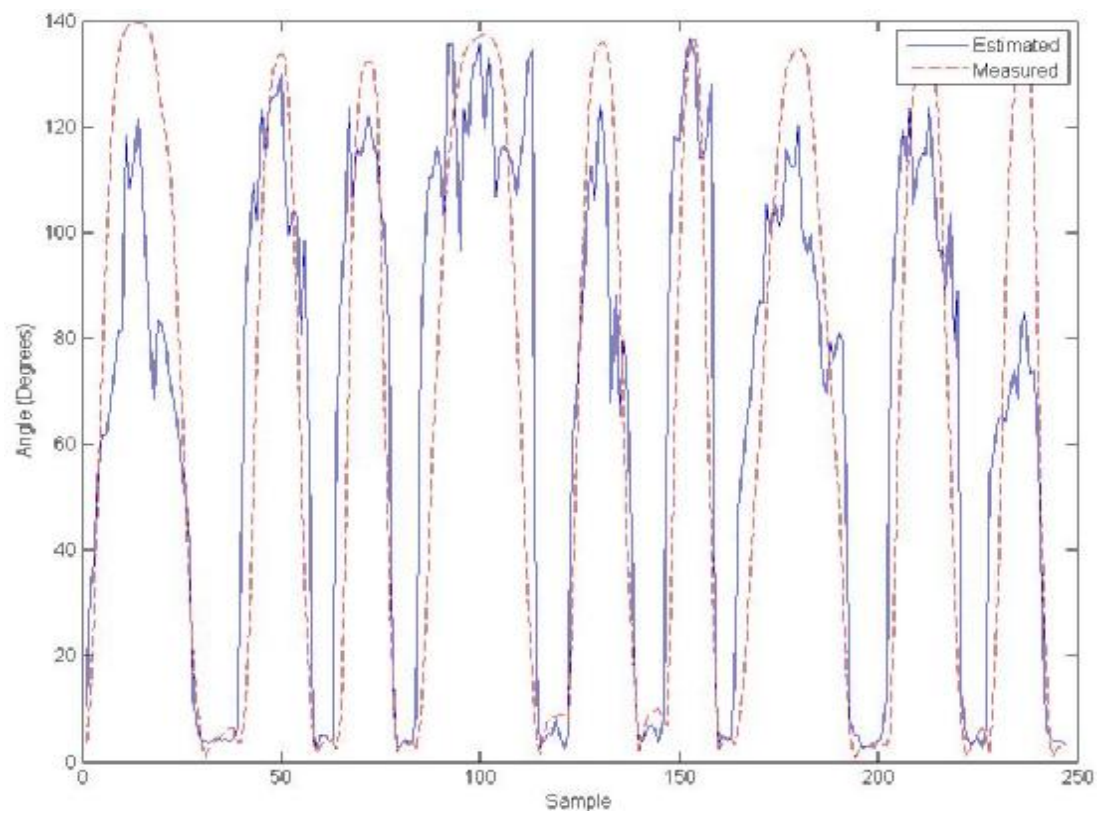
### ERROR OF ESTIMATED ANGLE DURING MLP TEST STAGE



## TEST DATA AND FEATURE GRAPH FOR GRNN



### MEASURED AND ESTIMATED ANGLE DURING GRNN TEST STAGE



### ERROR OF ESTIMATED ANGLE DURING GRNN TEST STAGE

