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REAL TIME ELBOW JOINT ANGLE ESTIMATION USING sEMG SIGNALS[1]

Yüzeyel EMG İşaretlerini Kullanarak Gerçek Zamanlı Dirsek Eklem Açısının Tahmini

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ABSTRACT

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 study 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 study 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.

ÖZET

Yüzeyel Elektromiyografik işaret, girişimsel olmayan şekilde edinilmesi ve kullanıcının isteğiyle doğrudan ilişkili olması sebebiyle protez cihaz kontrolü için uygundur. Bu çalışma, biceps ve triceps kaslarından edinilen Yüzeyel EMG işaretlerinden gerçek zamanlı dirsek eklem açısının tahmini için bir algoritma sunar. Çalışmada geliştirilen algoritma ortalama mutlak değer, ortalama karekök ve dalga boyu gibi zamana dayalı öznitelik çıkarma yöntemleri kullanır. Çıkartılan 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.

[1] Aynı başlıklı Yüksek Lisans tezinden üretilmiştir.

Introduction

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 study, 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 study, it is 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.

Feature extraction and classification methods are 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.

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° in continuous motion and RMS errors of below 10° in stepping motion with 20° and 30° 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. 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 study 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.

Material and Method

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 study for real-time joint angle estimation is given in Figure 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.

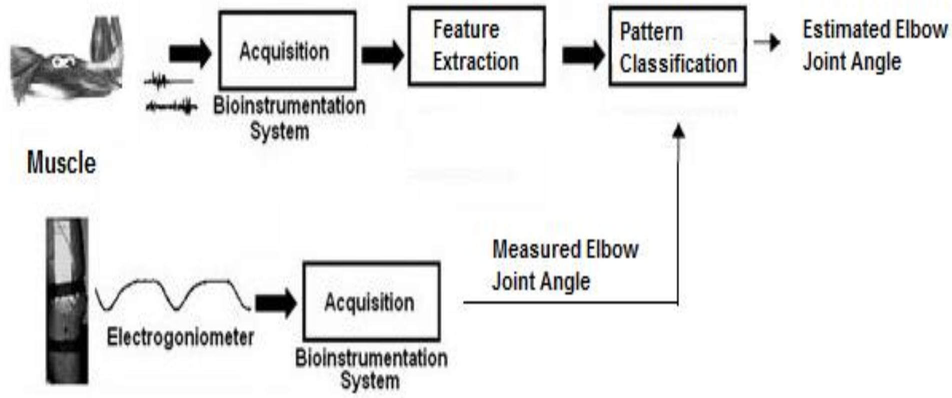

Figure 1. Block diagram for the estimation of elbow joint angle (Delis et al., 2009)

The sEMG signal is a superposition of individual motor unit action potentials (MUAPs) within the pick-up range of the surface electrodes. Raw sEMG can range between +/- 5000 microvolts and typically the frequency contents ranges between 6 and 500 Hz, showing most frequency power between ~ 20 and 150 Hz (Konrad, 2006)

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.

The Experimental Setup for Measurement and Data Acquisition

In this studies, BIOPAC MP36 system for EMG signals acquisition and an electrogoniometer for measuring the arm joint angle. 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.

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 2(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.

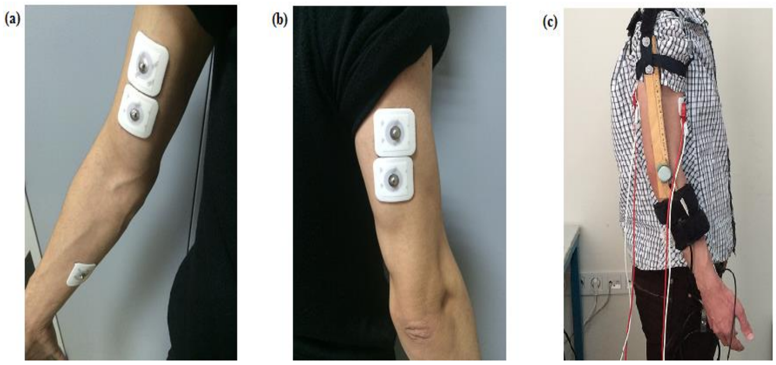

Figure 2. Placement of electrodes (a), (b) and electrogoniometer (c)

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 2(c)). The two channels of EMG data and the arm joint angle information were acquired using the BIOPAC MP36 data acquisition system.

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 1.

Table 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.

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.

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

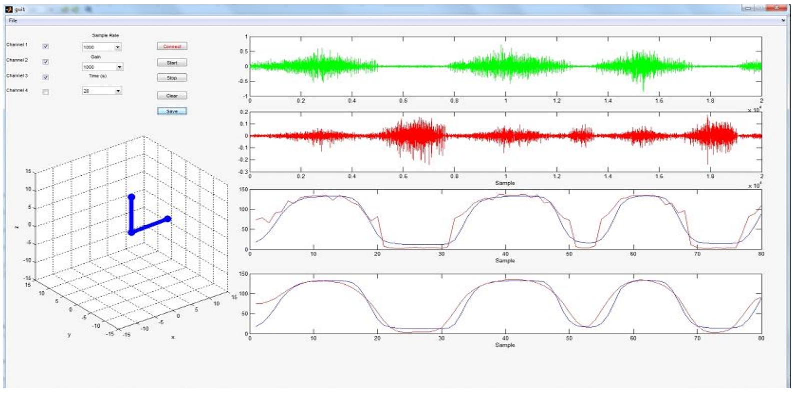

Figure 3.User interface for real time data acquisition

Elbow Joint Angle Estimation System Algorithm and Neural Network Structure

Figure 4 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.

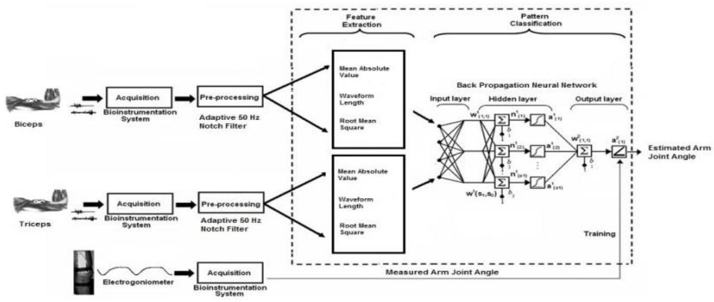

Figure 4. Block diagram of arm joint angle estimation algorithm (Delis et al., 2009)

In this study, 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 study. 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.

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 study 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 4).

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.

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 5.

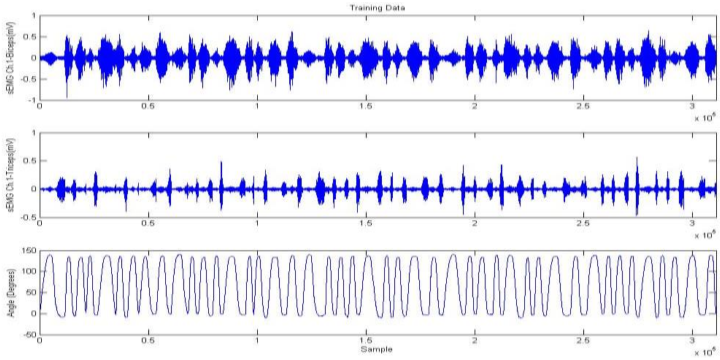

Figure 5. A sample training data for neural network

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 6.

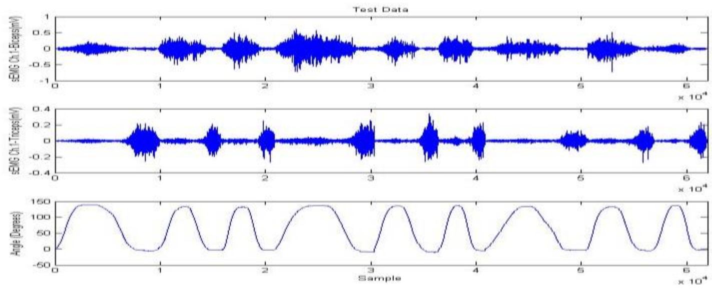

Figure 6. A sample of formed test data

Results

A part of real time data which was composed of measured EMG signal from biceps and triceps muscles was plotted at Figure 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.

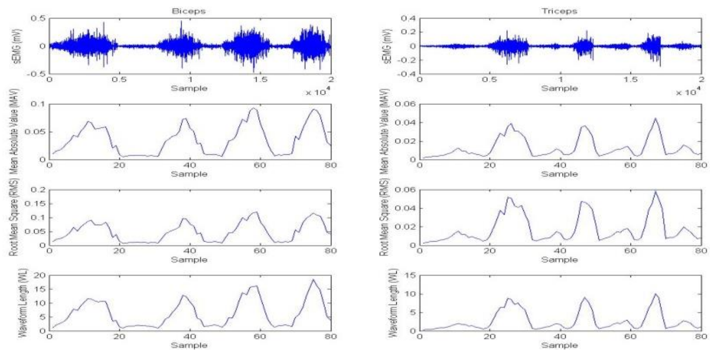

Figure 7.A part of real time data and feature graphs for MLP

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 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.

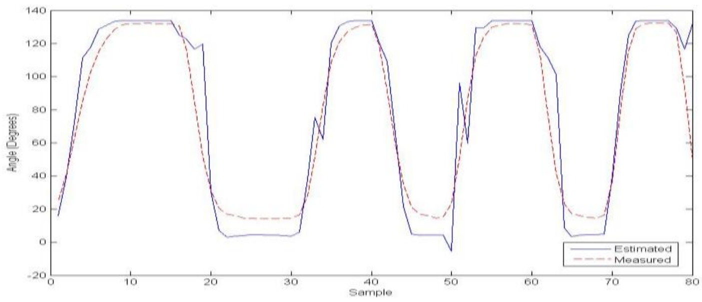

Figure 8. Real time estimated and measured arm joint angle using MLP neural network

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 9. It is also worthy to state here the range for elbow joint angle is approximately 130 degrees. Hence, average percentage error around 10 %.

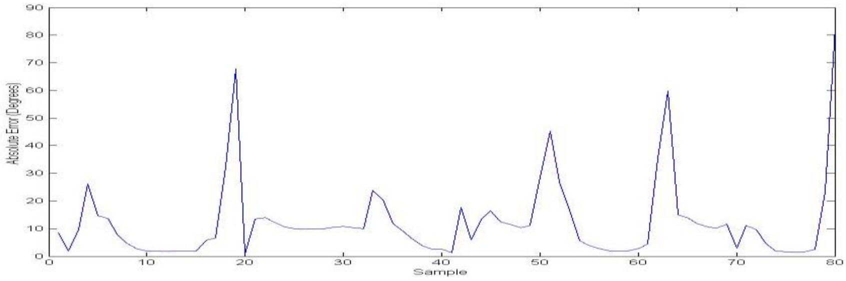

Figure 9. Absolute error of elbow joint angle estimation in MLP neural network using real time data

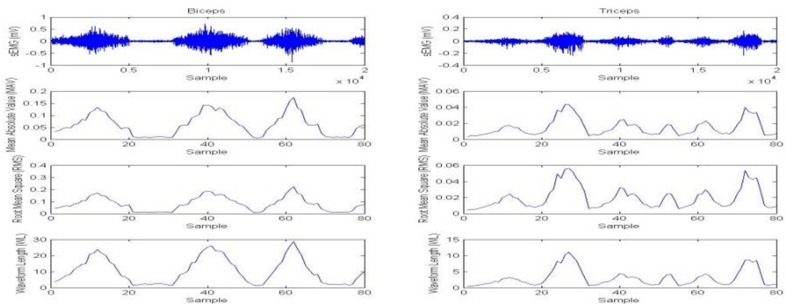

Figure 10. A part of real time data and feature graphs for GRNN

A part of real time data which was composed of measured EMG signal from biceps and triceps muscles was plotted at Figure 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 to test general regression neural network (GRNN) which was trained before and it was obtained estimated elbow joint angle in the end.

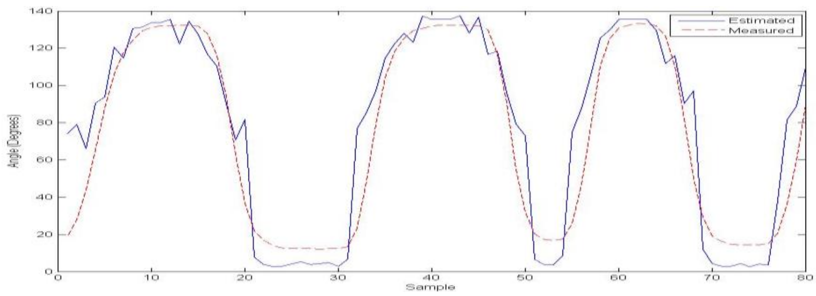

Figure 11. Real time estimated and measured arm joint angle using general regression neural network

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 11. 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.

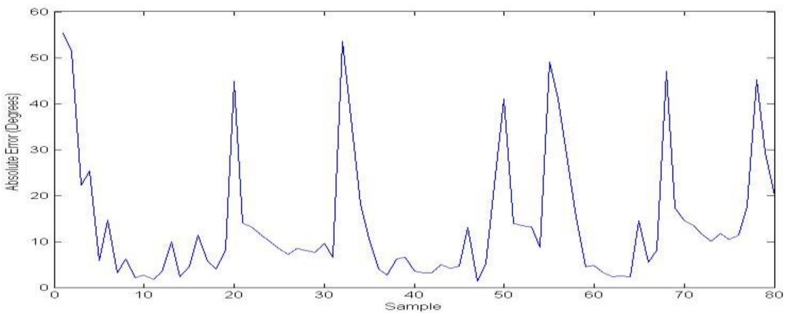

Figure 12. Absolute error of elbow joint angle estimation in general regression neural network during real time phase

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 12. It is also worthy to state here the range for elbow joint angle is approximately 135 degrees. Hence, average percentage error around 11%.

Table 2. Percentage accuracy of MLP and GRNN

Accuracy	**MLP %**	**GRNN %**
Real Time Data	89.63	88.35

Table 2 shows 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.

Discussion and Conclusion

It is seen that MLP method provides less error values than GRNN algorithm for real time data. Accuracy of elbow joint angle estimation using MLP algorithm is higher than GRNN algorithm in real time data. Accuracy value of estimated elbow joint angle at MLP is 89.63% for real time data.

At GRNN algorithm, performance of elbow joint angle estimation is low in real time data. Accuracy value of estimated elbow joint angle at GRNN is 88.35% for real time data respectively.

Mean square error (MSE) of MLP with three layers after 1000 epochs is 0.025601 in this study. When this value is compared with studies of Ahsan et al., it is seen that the value of MSE in this study which has neural network structure with fewer layer neurons and fewer feature vectors is lower than their studies. It is also obtained higher performance than their studies. All results are acceptable in terms of accuracy and response speed as compared to previous studies in literature.

References

AHSAN M. R., IBRAHIMY M. I. and KHALIFA O. O., 2012. EMG Motion Pattern Classification through Design and Optimization of Neural Network. International Conference on Biomedical Engineering, 978-1-4577-1991-2.

AUNG Y. M. and AL-JUMAILY A., 2012. Estimation of Upper Limb Joint Angle Using Surface EMG Signal. International Journal of Advanced Robotic Systems vol. 10, 369.

CHOWDHURY R. H., REAZ M. B. I., ALI M. A. B. M., BAKAR A. A. A. CHELLAPPAN K. and Chang T.G., 2013. Surface Electromyography Signal Processing and Classification Techniques. Sensors, 13, 12431-12466.

DELIS A.L., CARVALHO J. L. A., ROCHA A. F., FERREIRA R. U., RODRIGUES S. S. and BORGES G. A., 2009. Estimation of the Knee Joint Angle from Surface Electromyographic Signals for Active Control of Leg Prostheses. Brazil.

HAKOEN M., PIITULAINEN H. and VISALA A., 2015. Current State of Digital Signal Processing in Myoelectric Interfaces and related Applications. Biomedical Signal Processing and Control 18 pp. 334-359.

HAYKIN, S.S., 2009.Neural Networks and Learning Machines, Volume 10. Prentice Hall Upper Saddle River, NJ.

KONRAD, P., 2006. The ABC of EMG - A Practical Introduction to Kinesiological Electromyography. Noraxon, U.S.A, pp. 61

OSKOEI M. A. and HU H., 2007. Myoelectric Control System-A survey. Biomedical Signal Processing and Control 2, pp. 275-294.

PANG M., GUO S., HUANG Q., ISHIHARA H. and HIRATA H., 2015. Electromyography-Based Quantitative Representation Method for Upper-Limb Elbow Joint Angle in Sagittal Plane. J. Med. Biol. Eng. 35:165–177.

RAJ R. and SIVANANDAN K. S., 2015. Estimation of Elbow Joint Angle from Time Domain Features of SEMG Signals using Fuzzy Logic for Prosthetic Control. International Journal of Current Engineering and Technology, Vol.5, No.3, E-ISSN 2277 – 4106, P-ISSN 2347 – 5161.

RECHY-RAMIREZ, E. J. and HU, H., 2011. Stages for Developing Control Systems using EMG and EEG Signals: A survey. Technical Report: CES-513 ISSN 1744-8050.