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Real Time Identification of Human Forearm kinematics from Surface EMG Signal using Artificial Neural Network Models

Retheep Raj[a]*, Rejith R[a] and K S Sivanandan[a]

[a] *Department of Electrical Engineering, National Institute of Technology Calicut, Kozhikode, Kerala.*

Abstract

This work identifies the human forearm kinematics in real time by utilizing the surface electromyography (SEMG) signal using two different artificial neural network models. Here, the SEMG signals from biceps brachii muscle are captured using Ag-AgCl electrodes. Two time domain features Integrated EMG (IEMG) and number of zero crossing (ZC) are derived from the measured SEMG signals after segmenting the raw SEMG signal into 250 millisecond window. These two time domain features are used as the input signals for identifying the human forearm kinematics. Human forearm kinematics is determined using two neural network models, (1) Multi Layered Perceptron Neural Network (MLPNN) model and (2) Radial Basis Function Neural Network (RBFNN) model. The results obtained from the both models are compared in this work. The results indicate that the RBFNN model is giving better identification results with an average regression coefficient value of 0.756767 and 0.389113 for the identification of angular displacement and angular velocity respectively when compared with MLPNN model.

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Keywords: Forearm Kinematics, Multilayered perceptron neural network (MLPNN), Radial basis function neural network (RBFNN), EMG, Integrated EMG, Zero crossing.

1. Introduction

The need for prosthetic limbs is increasing day by day since the number of amputees, either by birth or due to accidents are increasing every day. Myoelectric control based prosthesis is one of the best solutions for

* Corresponding author. Tel.: +91-9496452144;
E-mail address: retheepraj@gmail.com

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rehabilitation of such people [1]. Here the features derived from the SEMG signals are used for the automatic control of artificial limb [2]. Identification of human kinematics from SEMG signals and control are the two hot topics under myoelectric control based prosthesis. Better myoelectric control is achieved only when the identification of kinematics from SEMG are done with maximum possible accuracy.

Several techniques are available in the literature for identifying or estimating the human kinematics like angular displacement and angular velocity by utilizing the SEMG signals. H J Yu et al. [3] proposed a method to identify the elbow joint angle using a third order polynomial function model using root mean square (RMS) value feature of SEMG signal. Here they segmented the SEMG signal using disjoint window technique and extracted RMS value from each segmented window, and this extracted RMS value is used for identifying elbow joint angle. They conducted experiments on experienced subjects and obtained an average mean square error (MSE) of 1.4883 between estimated angle and actual angle. Qin Zhang et al. [4] also made an attempt to estimate the elbow joint angle using a linear state space model. Here a multiple input single output state space model is used for estimating the elbow joint angle and an adaptive method is used to train the proposed model. Here the SEMG signal is segmented into 15 millisecond window and calculated two time domain parameters peak to peak value and variance from each segmented window. They conducted experiments with three different weights and obtained an RMS error of less than 10%. Lizhi pan et al. [5] also used a state space model for estimating the finger joint angle using SEMG signal. Here the SEMG signals are segmented using overlapping windowing technique and they selected the window size as 200 milliseconds and the interval between two adjacent windows is selected as 50 millisecond. They extracted RMS value feature from each window for estimation of finger joint angle. The validation of the model is done using regression value, and they obtained a regression value of 0.843.

From the literature survey, it is clear that the kinematics of forearm movement can be decoded by utilizing the SEMG signals [6]. But most of the work conducted so far on the identification of forearm kinematics are done in offline mode and estimated only the angular displacement. Here an attempt is made to identify the human forearm kinematics (both angular displacement and angular velocity) in real time using neural network model. Also, a comparison is made between two different neural network models in the identification of forearm kinematics.

The rest of the paper is organized as follows. Section 2 explains the methodology of the experiment, which includes the signal acquisition and signal conditioning, data segmentation and feature extraction and methodology of identification of forearm kinematics. Experimental results and comparison of models are explained in section 3 and finally the conclusions in section 4.

2. Methodology

2.1. Signal acquisition and signal conditioning

SEMG signal is recorded from biceps brachii muscles of subjects during continuous flexion and extension of the forearm using Ag-AgCl surface electrodes. EKG sensor, Vernier make is used for acquiring and amplifying the SEMG signal. The gain of the EKG sensor is 1000. The amplified SEMG signal from the EKG sensor is taken into LabVIEW developmental system using National Instruments ELVIS-II development kit. The signal is sampled at a rate of 10Ksamples/sec and filtered using a third order IIR Butterworth band pass filter with lower cutoff frequency 20Hz and upper cutoff frequency 400Hz for removing the base line shift and high frequency noises [7]. The kinematics of elbow movements like angular displacement and angular velocity of the forearm are required for training and validating the model. A triple axis accelerometer ADXL 335 and supporting LabVIEW program is used for finding the kinematics of elbow movement. Block level diagram of the EMG driven prosthetic control system is shown in Fig. 1.

SEMG signals are acquired from 30 subjects with average height 169cm, average age of 26 and an average weight of 68Kg. A prior concern is taken from all the subjects, and proper training is given before the conduct of the experiment. The subjects are asked to stay in standing position and are instructed to perform continuous flexion and extension of the forearm for 10 number of times at slow speed (average angular velocity=30 degrees/sec). The experiment is repeated for two different speeds, medium (average angular velocity=80 degrees/sec) and fast (average angular velocity=105 degrees/sec). The SEMG signals are recorded using Ag-AgCl electrodes from the dominant hand of the subjects. One of the active electrodes is placed at the center of the biceps brachii muscle and other at the lower end of biceps brachii muscle. The reference electrode is placed at the upper side of palm [6]. The distance between the two active electrodes is kept as 3cm [8]. The pictorial representation of experimental setup and position of electrodes are shown in Fig. 2.

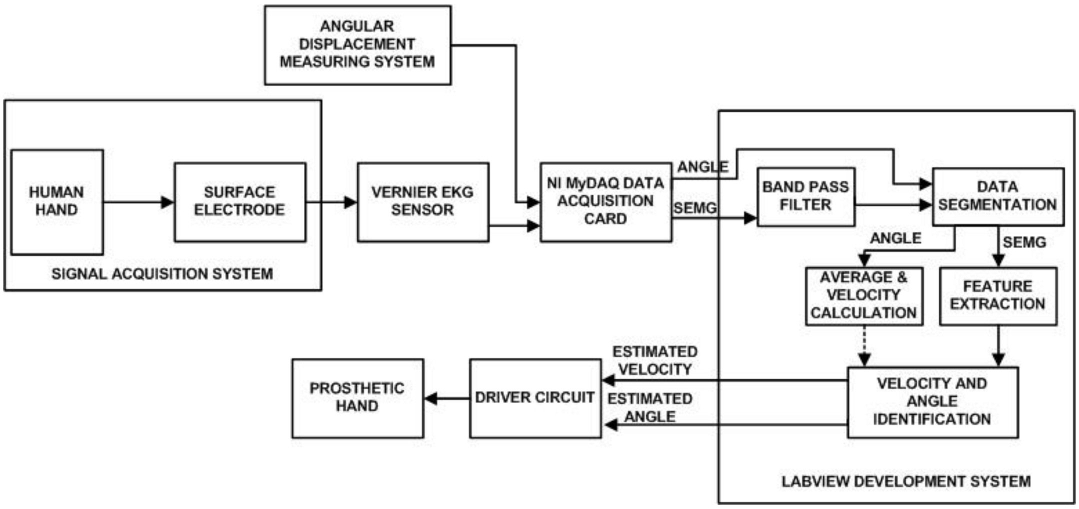

Fig. 1. Block level representation of EMG driven prosthetic control system.

Fig.2. Pictorial representation of experimental setup and position of electrode.

2.2. Data segmentation and feature extraction

After acquiring the SEMG signal and angular displacement signal into the LabVIEW development system, the signals are segmented into 250 millisecond window using disjoint window technique [9]. The angular displacement is averaged over every window, and the corresponding angular velocity is calculated by differentiating the angular displacement signal. Two time domain parameters, integrated EMG (IEMG) and zero crossing (ZC) are calculated from each window of SEMG data.

Integrated EMG is the mathematical integral of absolute value of raw SEMG signal and zero crossing is the count of number of times the SEMG signal crosses the X axis (zero line). The mathematical expression for IEMG and ZC is given as

$$\text{IEMG} = \sum_{k=1}^{N} |x_k \quad (1)$$

Where N is the number of samples of SEMG signals in one window and x_k is the SEMG signal.

$$\text{ZC} = \sum_{k=1}^{N} sign(-x_k * x_{k+1}) and \mid x_k * x_{k+1} \mid \geq 0 \quad (2)$$

$$sign(x) = \begin{cases} 1, x > 0 \\ 0, x < 0 \end{cases} \quad (3)$$

Where N is the number of samples of SEMG signals in one window and x_k is the SEMG signal.

2.3. Identification of forearm kinematics

Forearm kinematics are estimated using two different neural network model, (1) Multi Layered Perceptron Neural Network (MLPNN) model and (2) Radial Basis Function Neural Network (RBFNN) model.

MLPNN model is considered as the simplest neural network model [10]. Here a three layered feedforward perceptron model is proposed for the identification of forearm kinematics. The first layer is the input layer, second is the hidden layer, and the third layer is the output layer. Here the number of neurons in the input and output layer is two since the model is using two inputs (IEMG and ZC) for the identification of two kinematic outputs (angular displacement and angular velocity). The number of neuron in the hidden layer is arbitrarily selected as 200. Steepest descent back propagation algorithm is used for training the model.

RBFNN model is another type of model that is commonly used for identification of nonlinear systems [11]. RBFNN model is almost similar as MLPNN model, here in RBFNN model, the hidden nodes are implemented as a set of radial basis functions. The hidden layer converts from input space to a higher dimensional hidden space. Here a three layered RBFNN model is proposed with two input neurons, two output neuron, and 200 hidden neurons. The structure of proposed MLPNN model and RBFNN model is shown in Fig. 3.

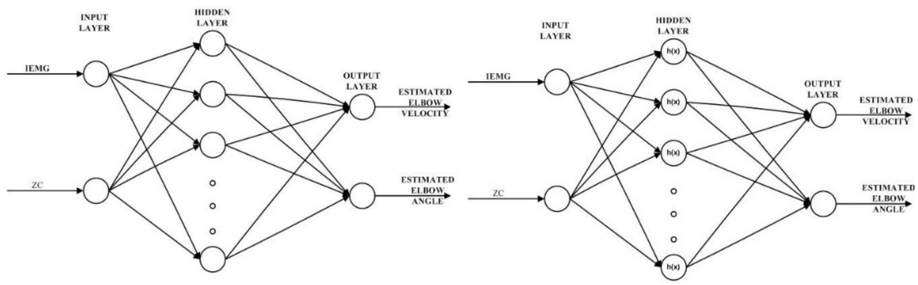

Fig. 3. Structure of MLPNN and RBFNN model.

3. Results

The experiment is conducted by asking the subjects to perform continuous flexion and extension for 10 number times for three different speed, slow (average angular velocity=30 degrees/sec), medium (average angular velocity=80 degrees/sec) and fast (average angular velocity=105 degrees/sec). The obtained data sets are divided into training and validation data so that each set contains five sets of flexion and extension data at three different speeds. The actual value of angular displacement and angular velocity is also recorded using an analog accelerometer and supporting LabVIEW software. The obtained SEMG data is segmented into 250 millisecond window and two time domain parameters IEMG and ZC are calculated from each window. Likewise, the kinematics data are also segmented into 250 millisecond window, and the values are averaged to obtain one set of angular displacement and angular velocity data for every 250 millisecond. The graph showing the relationship between angular displacement, angular velocity and IEMG for three different subjects are shown in Fig. 4. Also, the graph showing the relationship between angular displacement, angular velocity and ZC for three different subjects are shown in Fig. 5. The graphs clearly indicate that the value of IEMG and ZC changes nonlinearly with the increase in angular displacement and also the value have some dependency on the change in angular velocity.

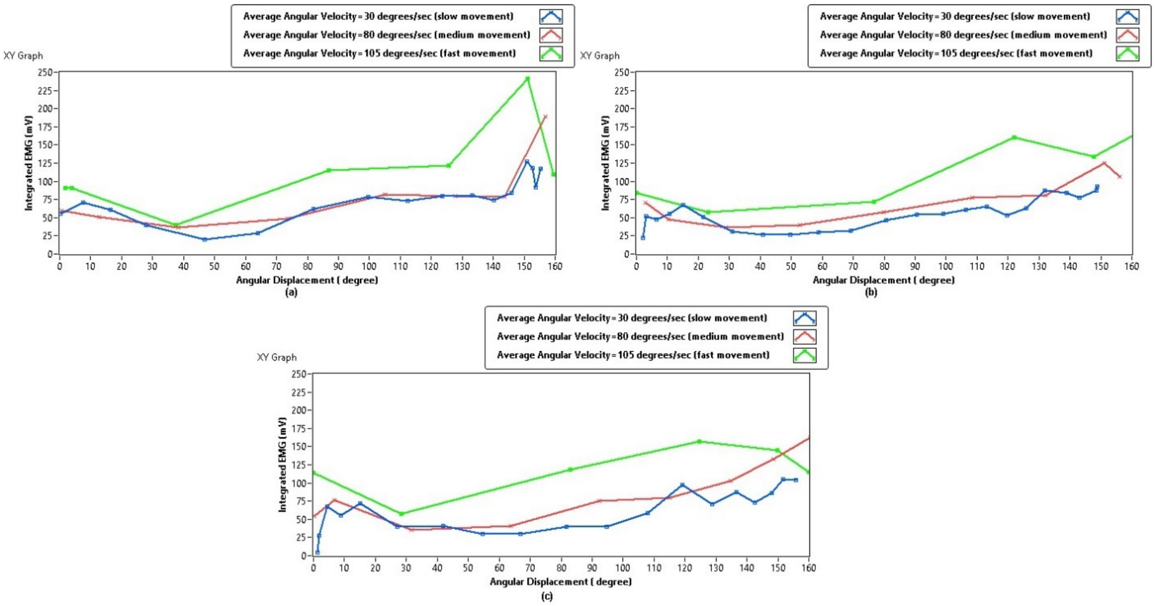

Fig. 4. Relationship between IEMG, angular displacement and angular velocity for three different subjects.

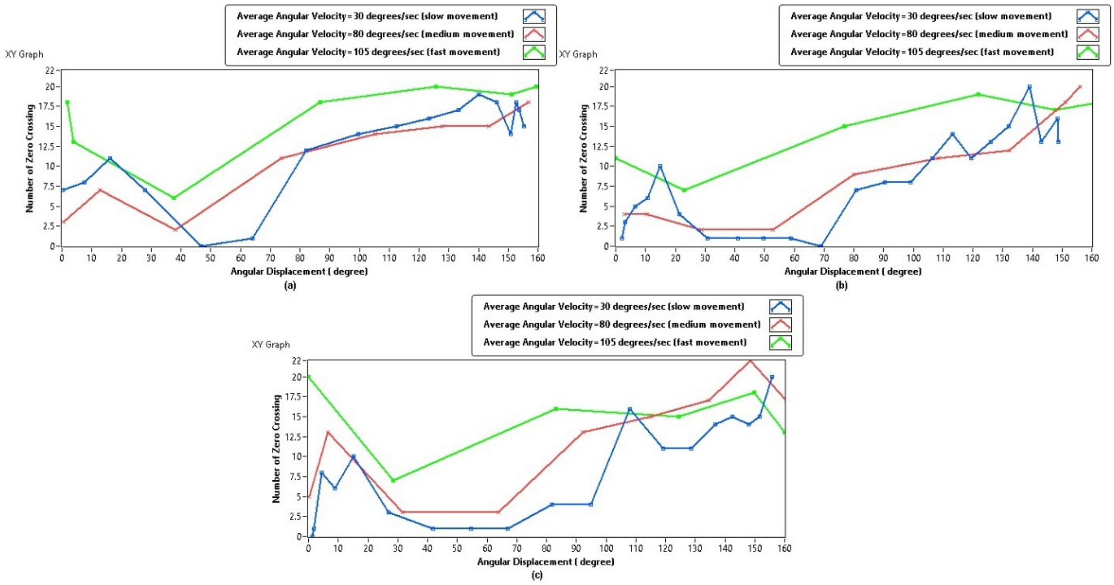

Fig. 5. Relationship between ZC, angular displacement and angular velocity for three different subjects.

The obtained value of IEMG and ZC of training data sets are given as the inputs to the MLPNN and RBFNN model, and the corresponding actual values of angular displacement and angular velocity are given as the outputs to the model for the purpose of training the model. The model is validated offline using the validation data. The graph showing the estimated and actual angular displacement for three different speeds, slow, medium and fast for MLPNN and RBFNN models are shown in Fig. 6. Also, the graph showing the estimated and actual angular velocity for three different speeds, slow, medium and fast for MLPNN and RBFNN models are shown in Fig. 7. The models are compared by calculating the regression coefficient value. Table 1 and Table 2 shows the regression coefficient value between estimated and actual value of angular displacement and angular velocity for two different models. The proposed model is also checked in real time with the help of National Instruments soft motion toolkit. Here the angular velocity and angular displacement are identified in real time using the proposed models, and the obtained outputs are given as inputs to the two dimensional robotic arm coded using LabVIEW soft motion toolkit. Fig. 8 shows the snapshots of online experimental results using two dimensional robotic arm. The results clearly indicate that the proposed method is giving a similar statistical result during estimation angular displacement in real time when compared with existing methods [5].Also, by using the proposed method both angular displacement and angular velocity can be estimated simultaneously, which can be utilised for the accurate control of prosthetic limbs.

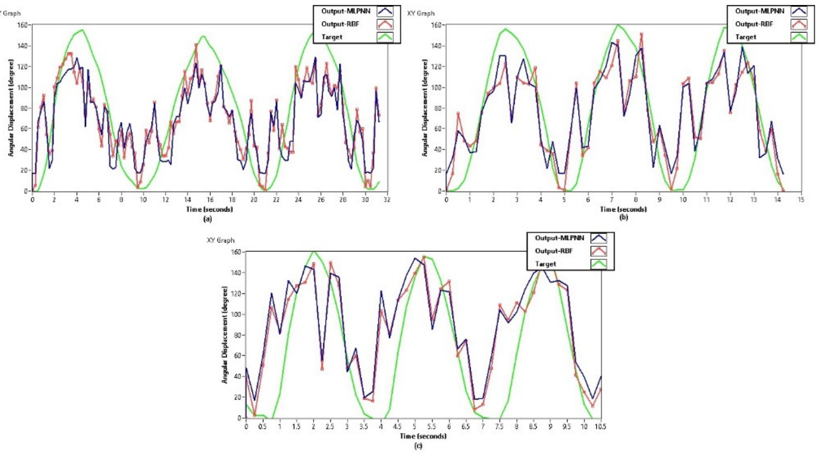

Fig. 6. Graph showing the estimated (MLPNN and RBFNN) and actual angular displacement for three different speeds, (1) slow, (2) medium and (3) fast for subject1.

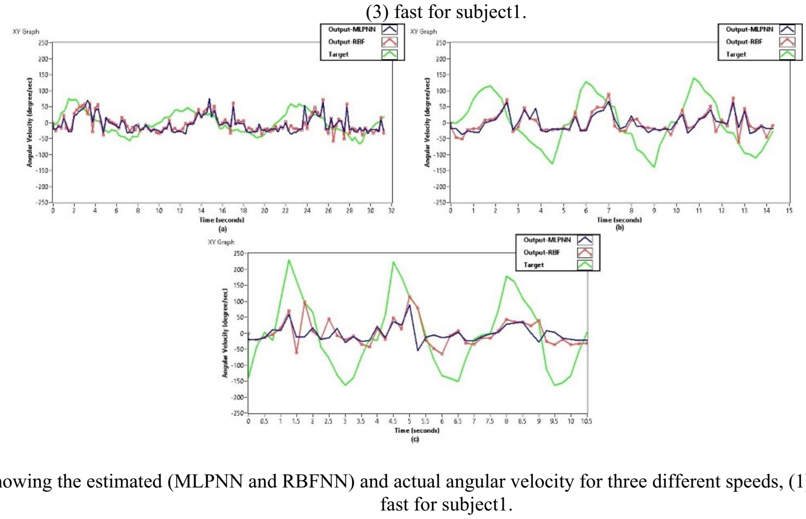

Fig. 7. Graph showing the estimated (MLPNN and RBFNN) and actual angular velocity for three different speeds, (1) slow, (2) medium and (3) fast for subject1.

Table 1. Regression value for Angular displacement identification using MLPNN and RBFNN model.

	MLNN model	RBFNN model
Slow	0.7368602	0.7515452
Medium	0.7658129	0.7661161
Fast	0.7265589	0.7526397

Table 2. Regression value for Angular velocity identification using MLPNN and RBFNN model.

	MLNN model	RBFNN model
Slow	0.2743245	0.3069173
Medium	0.2451323	0.2782420
Fast	0.5237438	0.5821791

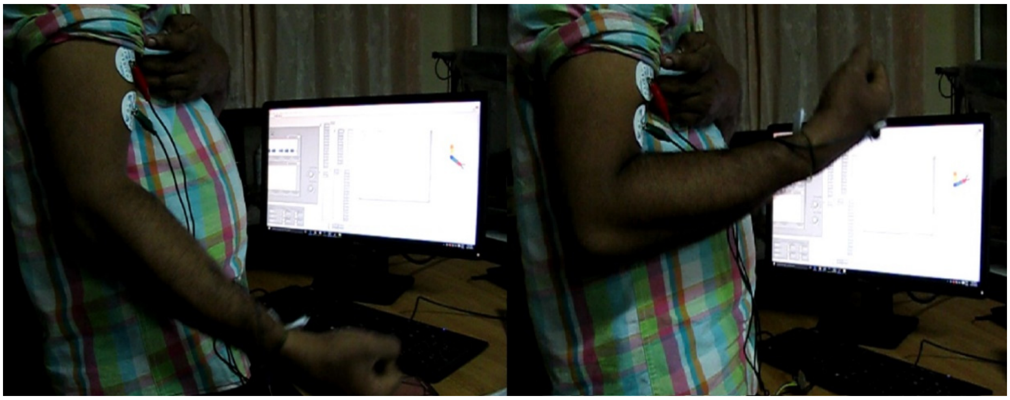

Fig. 8. Snapshots of online experimental results.

4. Conclusion

In this work, the human forearm kinematics are identified in real time using two different neural network model by utilizing SEMG signal. Here two time domain parameters are extracted from the SEMG signal obtained from the biceps brachii muscles during flexion and extension movement of the forearm in real time. The obtained parameters are fed as inputs to two different neural network model, MLPNN model and RBFNN model and decoded the kinematics of forearm. The results obtained using MLPNN model and RBFNN models are compared using statistical parameter, regression coefficient value. Results indicate that both the neural network model can be utilized for the identification of human forearm kinematics. Also it is clear from the experimental results that the identification accuracy is better with RBFNN model when compared with MLPNN model. Using RBFNN model an average regression coefficient value of 0.756767 and 0.389113 are obtained for the identification of angular displacement and angular velocity respectively. The corresponding values for MLPNN model is 0.74308 and 0.34773.

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