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Identification of Surface EMG – Angular Velocity Model using Artificial Neural Network

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ABSTRACT: EMG signals have a significant role in many biomedical and clinical applications like control of prosthetic devices and powered exoskeletons, biomedical movement analysis, etc. This paper aims in developing an accurate model which relates surface EMG (sEMG) signals acquired from the biceps and triceps muscle with the Angular Velocity of fore-arm. The main difficulty that arises while modelingsEMG -Angular Velocity signals is its black-box nature. For solving this problem a nonlinear system identification techniques based on Artificial Neural Network (ANN) is used. Finally the performance of "sEMG – Angular Velocity" model developed using ANN will be compared with models obtained by using system identification parametric models like ARX (linear) and Hammerstein model (nonlinear). The models are developed and compared by using the software LabVIEW.

KEYWORDS: System Identification; EMG; Artificial Neural Network; Back propagation; ARX model; Hammerstein model.

I.INTRODUCTION

The electrical signals (electrical activities) produced by skeletal muscles during contraction or relaxation are known as Electromyogram (EMG) signals. Its analysis helps to detect the human intention for movement**.** Some of the major applications of EMG signals in biomedical and clinical fields are: - used as control of prosthetic devices (prosthetic hands, arms, lower limbs, etc.) and exoskeletons for disabled or elderly people, for theanalysis biomedical movements, study of neuromuscular diseases, etc. EMG signals can be acquired by using two methods: (1) Intramuscular EMG [1] (invasive method), it involves insertion of fine wire or needle type electrode through the skin into the muscle and (2) Surface EMG (non-invasive method), which involves placement of surface electrode on the skin over the muscle. Intramuscular method has many advantages: - is extremely sensitive, has deep musculature, has less cross-talk, etc. But in this paper surface EMG method is considered as it is safe, easy to handle and does not require medical attention.

The black-box nature of sEMG signal models are the main difficult that arises while modeling it i.e. only input and output will be available or measurable, while the model parameters will be unknown or uncertain. The method used for solving this problem is Black-Box System Identification. In recent years, a number of models relating EMG signal has been developed for describing different human body moving parts like fingers,ankle [2], upper and lower arm, etc. In the study of arm movement, in most of the papers both biceps and triceps muscles were used for describing Flexion and Extension movements of arm. In most of the previous studies, model that relates EMG signals with either the corresponding forces acting (EMG-Force model) or with the torque (EMG-Torque model)[3, 4] were developed with a study condition of constant posture based on MVC (Maximum Voluntary Contraction) [3].In paper [2], a model relatingEMG acquired along GS (Gastrocnemius Soleus) muscles with angular velocity of ankle were developed. The system identification models used for developing EMG signal models in earlier works were linear parametric models [5] (like AR, ARX, Output Error, etc.). In recent years, nonlinear parametric system identification models like Hammerstein model, Wiener model [3], etc. and there modified forms like Hammerstein model with cubic spline nonlinearity [2], subspace Hammerstein identification [6], PCI (Parallel Cascade Identification) [7], etc. are used for obtaining the more accurate EMG models when compared to the linear models.

This work contains of 3 stages: (1) sEMG and angular velocity signal acquisition, (2) signal processing and (3) "sEMG-Angular Velocity" model development (System Identification). The sEMG- angular velocity signal acquisition stage and signal processing stage are discussed in Section II. The "sEMG-Angular Velocity" model development

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usingby nonlinear Artificial Neural Network (ANN) model and also by using parametric models like ARX model (linear) and Hammerstein model (nonlinear) are explained in section III.Finally the performance "sEMG-Angular Velocity" model based on ANN model, Hammerstein model and ANN model for are compared, which is discussed in section IV.

II.SIGNAL ACQUISITION AND PROCESSING

A.Experimental Details

Three subjects (two male and one female) with age group between 22 & 25 years are used in this work for acquiring the sEMG - angular velocity signals with a sampling frequency of 1000Hz.Two arm movements considered in this paper for signal acquisition are: Flexion and Extension. The four study conditions considered in this paper based on different speeds of arm movement are: Fast Flexion, Fast Extension, Slow Flexion and Slow Extension. From each subjects 5 sEMG - angular velocity signals are acquired for each study conditions. Thus for each study conditions there are 15 signals. The time duration of each signal is 7 seconds (i.e. 7000 samples).

B. Signal Acquisition

Signal Acquisition stage block diagram is shown in Fig.1. In Fig.1 it can be seen that two surface electrodes (detection) are connected on the biceps and triceps muscles and one surface electrode (reference) can be connected to any bony area (here it is elbow). Pre-gelled Ag-AgCl electrodes are the surface electrodes used in this work. A biomedical acquisition device called BITalino is used for acquiring sEMG signals. A 3-axis accelerometer: - ADXl335 and a data acquisition device: - MyDAQ are used for acquiring fore-arm acceleration corresponding to each sEMG signals.

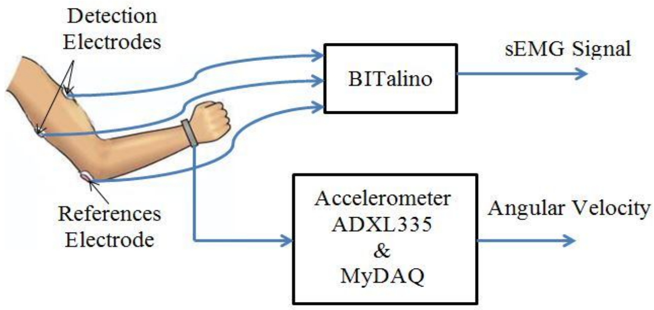

Fig.1. Signal Acquisition

C. Signal Processing

The amplitude of raw sEMG signals acquired using BITalino are in "Bit". At first it converted into voltage signal and then it is filtered by using (50-150) Hz 4th order Butterworth band pass filter [8]. The acceleration values acquired are in voltage form, which is to be converted to angular velocity in rad/s [9]. At first, the acceleration voltage signal is converted into acceleration signal in g-force. The g-force acceleration signal is then converted into angle signal in radians. The angular velocity signals in rad/s are obtained by taking the derivative of angle signal in radians. Finally for data reduction, the filtered sEMG signals and the angular velocity signals in rad/s are sub divided into 20 segments of 350ms each and then the mean values of each segment are found out.

III.SYSTEM IDENTIFICATION

System identification is a method used for developing a mathematical model of a system using measured input-output data. The block diagram representation of System Identification stage is shown in the Fig.2. In this work, sEMG signals and angular velocities are the observed input-output data and the aim is to develop "sEMG-Angular Velocity" model. The system identification technique contains 3 steps:

i. Split data- Here input and output data acquired (shown as $U(t)$ and $Y(t)$ in Fig.2) are divided into two sets: Estimation data set [$Ue(t)$ and $Ye(t)$] and Validation data set [$Uv(t)$ and $Yv(t)$].
ii. Model Estimation- Using the estimation data set [$Ue(t)$ and $Ye(t)$], a system model (M) is developed based on different identification models.

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iii. Model Validation- In this step, the estimated model (*M*) is validated by using Validation data set [*Uv(t)* and *Yv(t)*]. Lesser the error difference between the model response [*Ym(t)*] and desired response [*Yv(t)*], better will be the accuracy and performance of the estimated model.

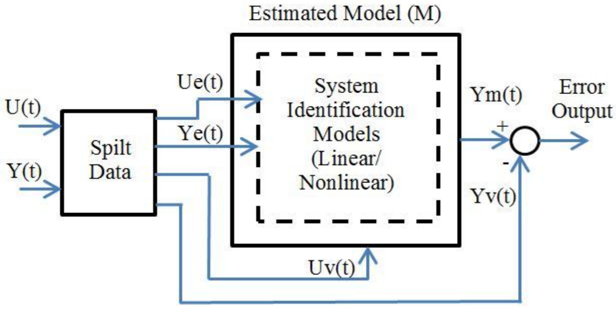

Fig.2. Block diagram representation of System Identification

In this work, out of 15 input-output signals acquired, 9 signals are used as estimation data set and remaining 6 signals are used as validation data set.Each signals contains 20 segments (as discussed in section II C.) and thus combination of 15 signals will contain 300 segments:- out of which 180 segments will be used as estimation data set and remaining 120 as validation data set. A linear model: - ARX model and two nonlinear models: - Hammerstein model and Artificial Neural Network (ANN) model are the system identification models used in this paper for “sEMG-Angular Velocity” model development.

A. ARX Model

Auto-regressive Exogenous Input (ARX) model is the simplest system identification linear model. SISO ARX model time domain equation,

$$y[t] = -a_1 y[t-1] - \cdots - a_{n_a} y[t-n_a] + b_0 u[t-d] + b_1 u[t-1-d] + \cdots + b_{n_{b-1}} u[t-(n_b-1)-d] + e[t] \quad (1)$$

where$a$ and b represents the unknown model coefficients of order $n_a$and n_b, d is the time delay and *e[t]* is the zero mean Gaussian white noise.

Let’s defined ARX model denominator and numerator terms as: $A(q) = 1 + a_1 q^{-1} + \cdots + a_{n_a} q^{-n_a}$and $B(q) = b_0 q^{-d} + b_1 q^{-1-d} + \cdots + b_{n_{b-1}} q^{-(n_{b-1})-d}$, where q is the backward shift operator. The complete ARX model equation is given as:

$$y(t) = \frac{B(q)}{A(q)} u(t) + \frac{1}{A(q)} e(t) \quad (2)$$

1) ARX Model Estimation-

Optimum model order selection is the initial step in ARX model estimation. The method used in this work for selecting optimum model order is Akaike Information Criteria.

$$AIC = E\left[1 + \frac{2P}{N}\right] \quad (3)$$

where$E$ is the prediction error, P is the no: of model parameters and N is the no: of data samples. As per Akaike Information criterion, lower the value of *AIC* shown in equation (3)higher will be the quality and performance of the estimated model. The order ranges selected in this work are as follows: n_a&n_b (model denominator & numerator order) from 1 to 20 and *d* (time delay) from 0 to 10. The optimum order values obtained for ARX model is shown in the table1.

TABLE1. Optimum order value for ARX model

	n_a	n_b	d
Fast Flexion	18	20	9
Fast Extension	20	20	8
Slow Flexion	18	20	7
Slow Extension	20	20	9

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Root Mean Square Error (RMSE) is a measure of square root of mean of square of error difference between model response and desired response of a system.

$$RMSE = \sqrt{\frac{\sum_{i=0}^{N-1}(Y_{m_i} - Y_{d_i})^2}{N}} \quad (4)$$

where Y_{m_i} is the model response and Y_{d_i} is the desired response. RMSE values obtained for the estimated ARX model when estimation data set is provided for different study condition are discussed in Table3.

2) ARX Model Validation-

RMSE values obtained for the estimated ARX model when validation data set is provided for different study condition are discussed in Table3.

B. Hammerstein Model

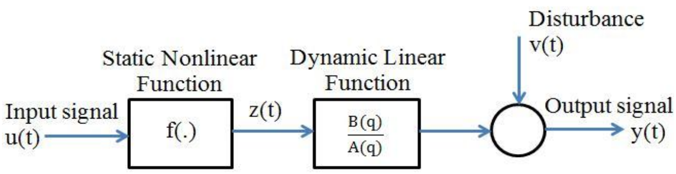

Fig.3. Hammerstein Model

Fig.3. shows Hammerstein Model block diagram representation. The advantage of Hammerstein model when compared to a linear model is that it contains a static (memory less) nonlinear function (which is used to describe the nonlinearities present in the system) along with the dynamic linear function. In this work, polynomial nonlinearity is used as the static nonlinear function, which is given as:

$$z(t) = \alpha_1 u(t) + \alpha_2 u^2(t) + \cdots + \alpha_m u^m(t) = \sum_{k=1}^{m} \alpha_k u^k(t) \quad (5)$$

where α is the unknown polynomial nonlinear function coefficient with order *m*.

The dynamic linear function transfer function is given as:

$$\frac{B(q)}{A(q)} = \frac{b_0 q^{-d} + b_1 q^{-1-d} + \cdots + b_{n_{b-1}} q^{-(n_{b-1})-d}}{1 + a_1 q^{-1} + \cdots + a_{n_a} q^{-n_a}} \quad (6)$$

where a and b are the unknown linear function coefficients with orders n_a and n_b respectively.

The complete Hammerstein model equation is given as:

$$y(t) = \frac{B(q)}{A(q)} \sum_{k=1}^{m} \alpha u^k(t) + v(t) \quad (7)$$

1) Hammerstein Model Estimation-

The static nonlinear function used in this work is 2nd order polynomial function. β_1=1 and β_1=2 are the unknown polynomial function coefficient values obtained by trial and error method for all study conditions. Here also Akaike Information Criteria is used for selecting optimum order for dynamic linear function. The optimum order values obtained for Hammerstein model is shown in the table2.

TABLE2. Optimum order value for linear dynamic function

	n_a	n_b	d
Fast Flexion	12	4	2
Fast Extension	14	5	0
Slow Flexion	15	5	0
Slow Extension	19	10	8

RMSE values obtained for the estimated Hammerstein model when estimation data set is provided for different study condition are discussed in Table3.

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2) Hammerstein Model Validation-

RMSE values obtained for the estimated Hammerstein model when validation data set is provided for different study condition are discussed in Table3.

C. Artificial Neural Network (ANN) Model

The ANN structure used in this work is "Multi-layer feed forward" neural network (shown in Fig. 4), which contains one or more hidden layers between the input and output units. In this work, only one hidden layer is considered since increase in number of hidden layers can cause computational complexity of the network.

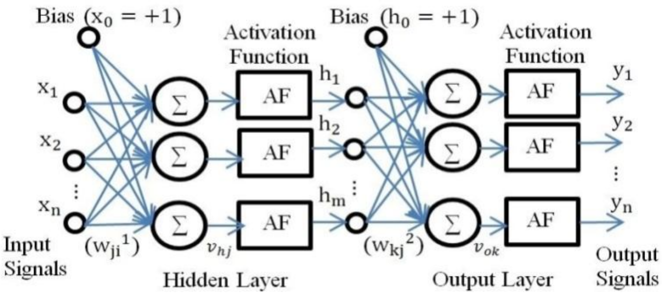

Fig.4. Multi-layer feed forward neural network

Here the nonlinear activation function (AF) used in hidden and output layer is "sigmoid function",

$AF = \frac{1}{1+e^{-\beta v}}$(8)

where$v$ is the net input and β is the steepness parameter (which taken as '1' in this work).

In Fig.4, $x(N) = (x_1, x_2, \dots, x_n)$ is the n dimensional input vector, $y(N) = (y_1, y_2, \dots, y_n)$is the n dimensional output vector, $h(N) = (h_1, h_2, \dots, h_m)$is the hidden layer output (where m is the no: of hidden neurons and N is the no: of iterations), '$x_0 = h_0 = +1$' are the bias value provided to the hidden and output layer, ${w_{ji}}^{(1)}$ is the weight matrix between input and hidden layer with bias weights [order- '$m \times (n+1)$'] and ${w_{kj}}^{(2)}$ is the weight matrix between hidden and output layer with bias weights [order- '$n \times (m+1)$']. Let '$d(N) = (d_1, d_2, \dots, d_n)$' be the known desired (target) output vector.

1) Back Propagation

The training algorithm used in this work for adjusting the synaptic weights (${w_{ji}}^{(1)}$ and ${w_{kj}}^{(2)}$) is "Back Propagation", which is the most widely used supervised learning algorithm of an ANN. The back propagation algorithm consists of four stages:

i. Initialization of synaptic weights by some random numbers between -1 and +1.

ii. Feed forward - The feed forward stage can be seen in Fig.4. Here each input neuron transmits the input signal (x_i) to each hidden neuron. Then these hidden neurons will calculate the activation function and transmits their output signal (h_j) as input to each output neuron. The output neurons will further calculate the activation function to get the response (y_k) for the given input samples.

Hidden layer net input, $v_{hj} = \sum_{i=0}^{n} {w_{ji}}^{(1)} . x_i$ (9)

Hidden layer response, $h_j = f(v_{hj}) = \frac{1}{1+e^{-\beta v_{hj}}}$(10)

Output layer net input, $v_{ok} = \sum_{j=0}^{m} {w_{kj}}^{(2)} . h_j$(11)

Output layer response, $y_k = f(v_{ok}) = \frac{1}{1+e^{-\beta v_{ok}}}$(12)

iii. Back Propagation of Error - In this stage, each output neuron response is compared with the desired response and this is done for calculating error information factor (or local gradient δ).

Output layer local gradient, $\delta_k = y_k(1 - y_k)(d_k - y_k)$(13)

Hidden layer local gradient,$\delta_j = h_j(1 - h_j) \sum_{k=1}^{n} \delta_k w_{kj}$(14)

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iv. Updation of synaptic weights - Here the synaptic weights are updated using the factor 'δ'. Weight adjustment term for: Output layer, $\Delta w_{kj} = \alpha\delta_k h_j$ (15)

$\therefore w_{kj}(new) = w_{kj}(new) + \Delta w_{kj}$(16)

Hidden layer, $\Delta w_{ji} = \alpha\delta_j x_i$(17)

$\therefore w_{ji}(new) = w_{ji}(new) + \Delta w_{ji}$ (18)

2) ANN Model Estimation

For ANN model estimation, there will be 180 input samples $[Ue]$ and180 output samples $[Ye]$. Here the no: of hidden neurons is chosen as 10. Thus the weight matrix ${w_{ji}}^{(1)}$ is of order '10×181' and ${w_{kj}}^{(2)}$ is of order '180×11'. The no: of iterations for weight updation is taken as 1000.RMSE values obtained for the estimated ANN model when estimation data set is provided for different study condition are discussed in Table3.

3) ANN Model Validation

For ANN model validation, there are 120 input samples $[Uv]$ and 120 output samples $[Yv]$. The no: of hidden neurons is chosen as 10. Here the weight matrix ${w_{ji}}^{(1)}$ is of order '10×121' and ${w_{kj}}^{(2)}$ is of order '120×11'.RMSE values obtained for the estimated ANN model when validation data set is providedfor different study condition are discussed in Table3.

IV.RESULTS

The performance of "sEMG-Angular Velocity" models based on ANN model, Hammerstein model and ARX model for different study conditions (Fast flexion, fast extension, slow flexion and slow extension) are compared in this section.

Case 1: Fast Flexion

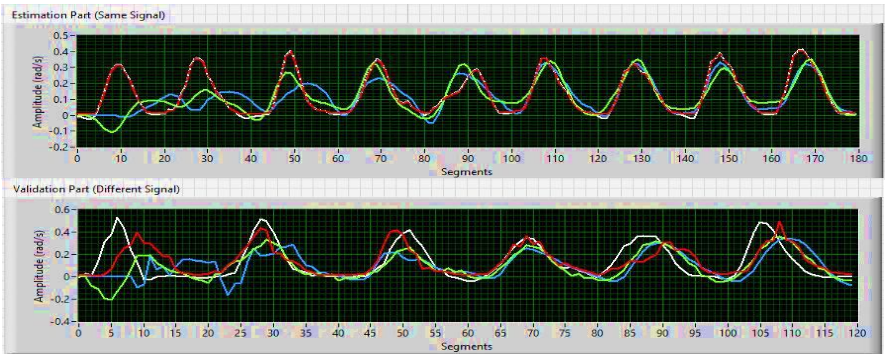

Fig.3 Model response for Fast Flexion condition.
Fig.3a: Estimation Part & Fig.3b: Validation Part.

ANN model, Hammerstein model and ARX model response for Fast Flexion are shown in Fig.3. Fig.3a shows the model response of Estimation Part i.e. when estimation input set is given to it and Fig.3b shows the model response of Validation Part i.e. when validation input set is given to it. In Fig.3 the desired response (i.e., observed angular velocity values) represented as white signal; ANN model response as red signal, Hammerstein model response as green signal and ARX model response as red signal.

Case 2: Fast Extension

ANN model, Hammerstein model and ARX model response for Fast Extension are shown in Fig.4, where Fig.4a shows the model response of Estimation Part and Fig.4b shows the model response of Validation Part. Here in Fig.4 the desired response represented as white signal; ANN model response as red signal, Hammerstein model response as green signal and ARX model response as red signal.

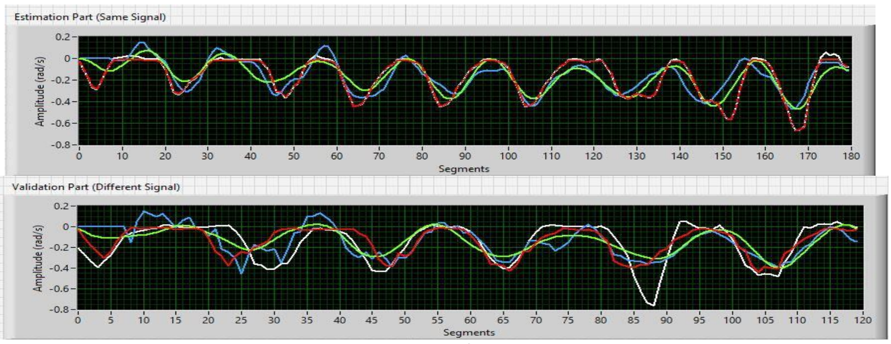

Fig.4. Model response for Fast Extension.
Fig.4a: Estimation Part &Fig.4b: Validation Part.

Case 3: Slow Flexion

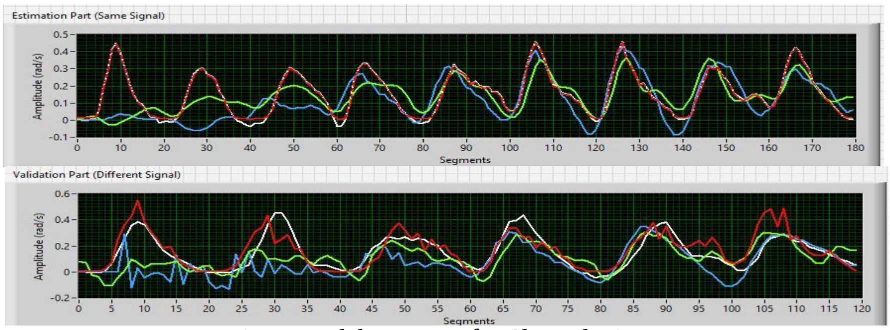

Fig.5. Model response for Slow Flexion.
Fig.5a: Estimation Part&Fig.5b: Validation Part.

ANN model, Hammerstein model and ARX model response for Slow Flexion are shown in Fig.5. Here the desired response (i.e., observed angular velocity values) represented as white signal; ANN model response as red signal, Hammerstein response as green signal and ARX response as red signal.

Case 4: Slow Extension

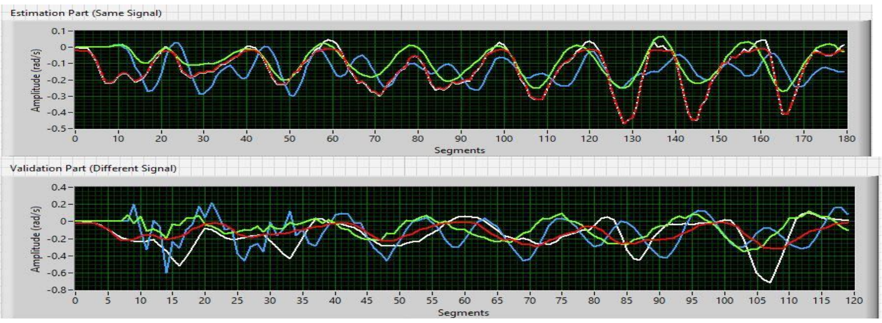

Fig.6. Model response for Slow Extension.
Fig.6a: Estimation Part &Fig.6b: Validation Part.

ANN model, Hammerstein model and ARX model response for Slow Extension are shown in Fig.6.

In all the four cases, it can be seen that Artificial Neural Network model response tracks the desired response much better when compared to the Hammerstein and ARX model response.

The root mean square error (RMSE) values (ie error difference between model response and desired system response) obtained for "sEMG-Angular Velocity" models based on ANN model, Hammerstein model and ARX model for different study conditions are shown in the table3.

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TABLE3. Comparison between performance of ANN, Hammerstein and ARX models

"sEMG-Angular Velocity" Model		ARX Model	Hammerstein Model	ANN Model
Study Conditions	**Root Mean Square Error**			
Fast Flexion	Estimation	0.09655	0.09139	0.00804
	Validation	0.15282	0.13970	0.12207
Fast Extension	Estimation	0.11552	0.09505	0.01197
	Validation	0.15139	0.14149	0.13408
Slow Flexion	Estimation	0.117059	0.09797	0.00945
	Validation	0.141825	0.11436	0.08554
Slow Extension	Estimation	0.12369	0.08685	0.01522
	Validation	0.2243	0.1903	0.12791

The table3 results shows that for all the four study conditions, the root mean square error (RMSE) values of both the nonlinear models are less when compared to the linear ARX model. While on comparing both the nonlinear models with each other, it can be seen that ANN model has better performance than that of Hammerstein model, since RMSE value of ANN model is less when compared to Hammerstein model.

V. CONCLUSION

In this paper, a mathematical model that relates sEMG signals obtained from biceps and triceps muscles with the corresponding angular velocity of motion of fore-arm are developed using three system identification techniques: ARX model, Hammerstein model and ANN model. From the simulation results (shown in Fig. 3, 4, 5 & 6) and the table3 results (RMSE values) it is proven that "sEMG-Angular Velocity" model based on Artificial Neural Network (ANN) is better when compared to the conventional parametric system identification models like Hammerstein and ARX.

REFERENCES

[1] Jonathan Monsifrot, Eric Le Carpentier, YannickAoustin, "Sequential Decoding of Intramuscular EMG Signals via Estimation of a Markov Model", *IEEE Transactions on Neural system and Rehabilitation*, vol. 22, no. 5, pp. 1030-1038, February 2004.

[2] Erika J. Dempsey, David T. Westwick, "Identification of Hammerstein Models with Cubic Spline Nonlinearities", *IEEE Transactions on Biomedical Engineering*, vol. 51, no. 2, pp. 237-243, February 2004.

[3] Edward A. Clancy, Lukai Liu, Pu Liu, and Daniel V. Zandt Moyer, "Identification of Constant-Posture EMG–Torque Relationship About the Elbow Using Nonlinear Dynamic Models", *IEEE Transactions on Biomedical Engineering*, vol.59, no. 1, pp. 205-211, January 2012.

[4] Qin Zhang, Mitsuhiro Hayashibe, Philippe Fraisse, and David Guiraud, "FES-Induced Torque Prediction with Evoked EMG Sensing for Muscle Fatigue Tracking", *IEEE Transactions on Mechatronics*, vol. 16, no. 5, pp. 816-825, October 2011.

[5] OmryPaiss and Gideon F. Inbar, "Autoregressive Modeling of Surface EMG and Its Spectrum with Application to Fatigue", *IEEE Transactions on Biomedical Engineering*, vol.34, no. 10, pp. 761-769, October 1987.

[6] KianJalaleddini, Robert E. Kearney, "Subspace Identification of SISO Hammerstein Systems: Application to Stretch Reflex Identification", *IEEE Transactions on Biomedical Engineering*, vol.60, no. 10, pp. 2725-2733, October 2013.

[7] Hashemi J, Morin E, Mousavi P, Hashtrudi-Zaad K, "Enhanced Dynamic EMG-Force Estimation Through Calibration and PCI Modeling", *IEEE Transactions on Neural Systems and Rehabilitaion Engineering*, vol. 23, no. 1, pp. 41-50, May 2014.

[8] Jingpeng Wang, Liqiong Tang, John E Bronlund, "Surface EMG Signal Amplification and Filtering", *International Journal of Computer Applications*, vol. 82, no. 1, pp. 15-21, November 2013.

[9] Zohar Aziz Ali Manjiyani, Renju Thomas, Keerthan Kumar R, Babu Varghese, "Devoplment of MEMS Based 3-Axis Accelerometer for Hand Movement Monitoring", *International Journel of Scientific and Research Publications*, vol.4, no. 2, pp. 1-4, February 2014.

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