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Modeling of Surface EMG Signals using System Identification Techniques

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***Abstract*— Electromyogram (EMG) signal generated by the skeletal muscles during contraction or relaxation plays a significant role in many clinical and biomedical applications. The analysis of EMG signals helps to detect the human intention for movement. One of the major applications of EMG signal is in the control of prosthetic devices and exoskeletons.**

The aim of this study is to develop a mathematical model with surface EMG (sEMG) signals acquired from the biceps and triceps muscle as input and corresponding angular velocity of motion of fore-arm as output. The problem that arises while modeling is that the system model is "black-box" model. For solving this problem system identification techniques are used. A linear parametric model called ARX model and a nonlinear model called Hammerstein model are used for system identification and the performances of these system identification models are compared. The platform used for the development and comparison of models is LabVIEW.

Keywords*— sEMG; System Identification; ARX model; Hammerstein model.

I. INTRODUCTION

The electrical potentials or electrical activities generated by skeletal muscles during contraction or relaxation are known as Electromyogram (EMG) signals. In present days, EMG signals are used for many clinical and biomedical applications like control of prosthetic devices such as prosthetic hands, arms, lower limbs, etc. for disabled people and powered exoskeletons for elderly people, biomedical movement analysis, study of neuromuscular diseases, etc. There are two methods for acquiring EMG signals: (1) Intramuscular EMG method [1], which is an invasive method where a needle type electrode is inserted through the skin into the muscle and (2) Surface EMG method, which is a non-invasive method where a surface electrode is placed on the skin over the muscle. Even though intramuscular EMG method has several advantages like extremely sensitive, less cross-talks, deep musculature, etc., surface EMG method is preferred as it is safe, does not require medical supervision and easy to handle.

The main problem that arises while modeling sEMG signal is that it is a black-box model i.e. only input and output are known or measurable, while the parameters will be unknown or will have uncertain value. For solving this problem System Identification techniques are used. In recent years, study of a number of EMG signal models has been done for describing the motion of different human body moving parts like fingers, upper and lower arm, ankle [2], etc. In the case of study of arm movement, it is seen that in most of the papers [3], both biceps and triceps muscles were used for describing Flexion and Extension movements of arm and also for acquiring EMG signals. The EMG signal models developed in previous works were EMG-Force model or EMG-Torque model [3, 4] (i.e. EMG signals acquired were related to either the corresponding forces acting or to the torque developed) with a study condition of constant posture based on Maximum Voluntary Contraction (MVC) [3]. A model relating angular velocity of ankle and EMG acquired along Gactrocnemius-Soleus (GS) muscles were developed in paper [2]. In earlier works, system identification techniques using linear parametric models [5] (like AR, ARX, Output Error, etc.) were used for developing EMG signal models. In recent works, system identification techniques using nonlinear models like Hammerstein model [2, 3], Wiener model [3], etc. are used for developing the more accurate EMG signal model when compared to the linear models.

This work comprises of two stages: (1) Data acquisition and processing stage, and (2) System Identification stage. The data acquisition and processing stage involves acquisition and processing of sEMG signals acquired from biceps and triceps muscle and corresponding angular velocities of motion of fore-arm, which is discussed in Section II. In system identification stage, a mathematical model relating sEMG signals and angular velocity using a linear parametric model (ARX model) and a nonlinear Hammerstein model are explained in section III. Finally, performance ARX model and Hammerstein model for different cases are compared, which is discussed in section IV.

II. DATA ACQUISITION AND PROCESSING

A. Data Acquistion

The block diagram representation of data acquisition stage is shown in the Fig.1. For the acquisition of sEMG signals and angular velocities, two arm movements have been considered: Flexion and Extension. Based on different speeds of motion, there are four study conditions in this work: (1) Fast Flexion, (2) Fast Extension, (3) Slow Flexion and (4) Slow Extension. Signals are acquired from 3 subjects (2 male and 1 female, age ranging from 22 to 25 years) with sampling frequency of 1000Hz. Five signals (both sEMG and Angular Velocity) are acquired from each subject for each study conditions. Thus there are 15 signals for each study conditions.

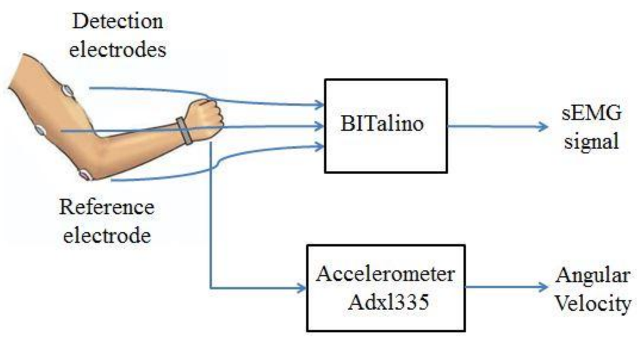

Fig.1. Block diagram representation of Data Acquisition stage

At first three surface electrodes are connected on the arm: two detection electrodes on the biceps and triceps muscles and one reference electrode on the elbow (which can be any bony part). The electrodes used are Ag-AgCl pre-gelled surface electrodes. The sEMG signals are acquired using a biomedical data acquisition device called BITalino. A 3-axis accelerometer – ADXL335 is used for acquiring acceleration of fore-arm corresponding to each sEMG signals, from which angular velocity is calculated.

B. Data Processing

The raw sEMG signals acquired from BITalino are in Bit form, which is first converted into voltage signals. These raw signals are then filtered by using a 4th order Butterworth band pass filter with cutoff frequency range of 50-150Hz [6].The acceleration values obtained by using ADXL335 and MyDAQ are in voltage form, which is to be converted to angular velocity in radian/sec [7]. For this acceleration values in voltage form are first converted into acceleration in g-force and then these g-force signals are converted into angles in radians. By taking the derivative of signals in angle form, angular velocity signals are obtained. Now the filtered sEMG signals and its corresponding angular velocity signals are sub divided into 20 segments and mean of each segment are found out. This is done for data reduction.

III. SYSTEM IDENTIFICATION

System identification can be defined as the process of deriving a mathematical model of a system using observed data (measured values of input and output data). In this paper, the measured data are sEMG signals and angular velocities. This stage consists of three steps:

(1) Split data- In this step input- output data acquired are divided into two sets: one for model estimation and other for model validation.
(2) Model Estimation- In this step system model based on different system identification methods is developed.
(3) Model Validation- In this step system model estimated is validated by using model validation data.

System identification models used in this work are: ARX model (linear model) and Hammerstein model (nonlinear model). Here out of 15 signals acquired, 9 are used for model estimation and remaining 6 for model validation.

A. ARX Model

ARX model is the simplest linear parametric model. Here ARX stands for Autoregressive (depending on past values) with Exogenous Input (input along with disturbance) model. The difference equation of ARX SISO model is given as:

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

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

$$\text{Let, } A(q) = 1 + a_1 q^{-1} + \cdots + a_{n_a} q^{-n_a} \quad (2)$$

$$B(q) = b_0 q^{-d} + b_1 q^{-1-d} + \cdots + b_{n_{b-1}} q^{-(n_{b}-1)-d} \quad (3)$$

where *q* is the shift operator.

Combining equations (1), (2) and (3), complete ARX model equation,

$$y(t) = \frac{B(q)}{A(q)} u(t) + \frac{1}{A(q)} e(t) \quad (4)$$

1) ARX Model Estimation-

The first step in model estimation is optimum model order selection. The method used in this work for optimum order selection is Akaike Information Criteria.

$$AIC = V_n \left[1 + \frac{2p}{N}\right] \quad (5)$$

where $V_n$is the prediction error, p is the no: of parameters and N is the no: of data points. As per this criterion, lower the value of *AIC*, higher will be the quality of the model.

Here the selected order ranges are: model transfer function denominator & numerator order (n_a & n_b) from 1 to 20 and system delay (d) from 0 to 10. The optimum order values obtained for different study conditions are given as:

Fast Flexion- n_a = 18, n_b = 20 and *d* = 9;
Fast Extension- n_a = 20, n_b = 20 and *d* = 8;
Slow Flexion- n_a = 18, n_b = 20 and *d* = 7;
Slow Extension- n_a = 20, n_b = 20 and *d* = 9.

Root Mean Square Error (RMSE) can be defined square root of mean of square of error difference between model response and actually observed response.

$$RMSE = \sqrt{\frac{\sum_{i=0}^{n-1} (y_{m_i} - y_{a_i})^2}{n}} \quad (6)$$

where $y_{m_i}$is the model response and y_{a_i} is the observed response of the system.

RMSE values obtained for different study conditions when estimation data set (signals used for model estimation) is given to the sEMG-Angular Velocity model developed are: Fast Flexion- 0.09655, Fast Extension- 0.11552, Slow Flexion- 0.117059 and Slow Extension- 0.12369.

2) ARX Model Validation-

RMSE values obtained when validation data set (different signals) is given to the sEMG-Angular Velocity model developed are: Fast Flexion- 0.15282, Fast Extension- 0.15139, Slow Flexion- 0.14183 and Slow Extension- 0.2243.

B. Hammerstein Model

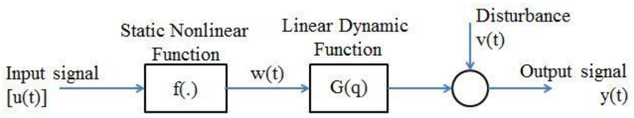

Fig.2. Hammerstein Model

The general block diagram representation of Hammerstein Model is shown in Fig.2. The main difference from a linear model is that it contains a static nonlinear function along with the linear dynamic function. The nonlinear function describes the nonlinearities present in the system. Here the nonlinear function used is a polynomial nonlinearity.

Static nonlinear function (Polynomial Nonlinearity),

$$w(t) = f[u(t)] = \beta_1 u(t) + \beta_2 u^2(t) + \cdots + \beta_m u^m(t) = \sum_{k=1}^{m} \beta_k u^k(t)$$

(7)

where β is the coefficients of polynomial nonlinear function and *m* is the order of the nonlinear function.

Linear dynamic function,

$$G(q) = \frac{b_0 q^{-d} + b_1 q^{-1-d} + \cdots + b_{n_b-1} q^{-(n_b-1)-d}}{1 + f_1 q^{-1} + \cdots + f_{n_f} q^{-n_f}} = \frac{B(q)}{F(q)}$$

(8)

where *b* and *f* are the unknown parameters of linear function, n_b and n_f are the order of coefficients *b* and *f*.

Combining equations (7) and (8), complete Hammerstein model,

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

(9)

1) Hammerstein Model Estimation-

In this work, a second order polynomial function is used as static nonlinearity. The values of nonlinear function coefficients obtained by trial and error method for all study conditions are: β_1=1 and β_1=2.

For linear dynamic function, Akaike Information Criteria is used for optimum order selection. Here the selected order range is: model transfer function denominator & numerator order (n_f & n_b) from 1 to 20 and system delay (*d*) from 0 to 10. The optimum order values obtained for different study conditions are given as:

Fast Flexion- n_f = 4, n_b = 12 and *d* = 2;
Fast Extension- n_f = 5, n_b = 14 and *d* = 0;
Slow Flexion- n_f = 5, n_b = 15 and *d* = 0;
Slow Extension- n_f = 10, n_b = 19 and *d* = 8.

RMSE values obtained for different study conditions when estimation data set (signals used for model estimation) is given to the sEMG-Angular Velocity model developed using Hammerstein system identification technique are: Fast Flexion- 0.09139, Fast Extension- 0.09505, Slow Flexion- 0.09797 and Slow Extension- 0.08685.

2) Hammerstein Model Validation-

RMSE values obtained when validation data set (different signals) is given to the sEMG-Angular Velocity model developed using Hammerstein system identification technique are: Fast Flexion- 0.13970, Fast Extension- 0.14149, Slow Flexion- 0.11436 and Slow Extension- 0.1903.

IV. RESULTS

The comparison between performance ARX model and Hammerstein model for different study cases are discussed in this section.

TABLE 1. Comparison between ARX and Hammerstein models

sEMG-Angular Velocity Model		ARX Model	Hammerstein Model
Cases	RMSE		
Fast Flexion	Estimation	0.09655	0.09139
	Validation	0.15282	0.13970
Fast Extension	Estimation	0.11552	0.09505
	Validation	0.15139	0.14149
Slow Flexion	Estimation	0.117059	0.09797
	Validation	0.141825	0.11436
Slow Extension	Estimation	0.12369	0.08685
	Validation	0.2243	0.1903

For all the four conditions RMSE values of Hammerstein model is less than that of ARX model which is shown in Table1.

Case 1: Fast Flexion

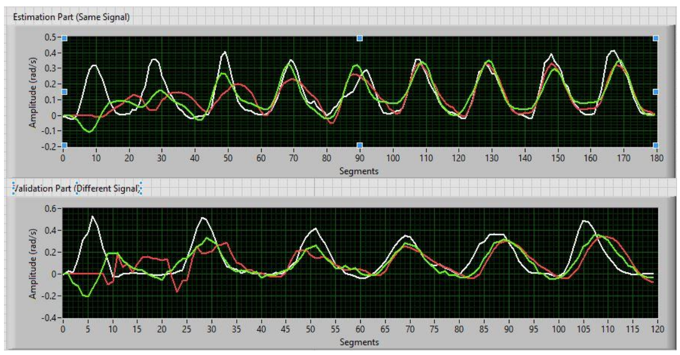

Fig.3. Fast Flexion model response. Upper Panel: Estimation Part. Lower Panel: Validation Part.

The responses of ARX model and Hammerstein model for Fast Flexion condition are shown in Fig.3. Here upper panel shows the response when estimation input set is given to the models and lower panel when validation input set is given. Here white signal represents actual response (i.e., measured angular velocity values); red signal represents ARX model response and green Hammerstein model response.

Case 2: Fast Extension

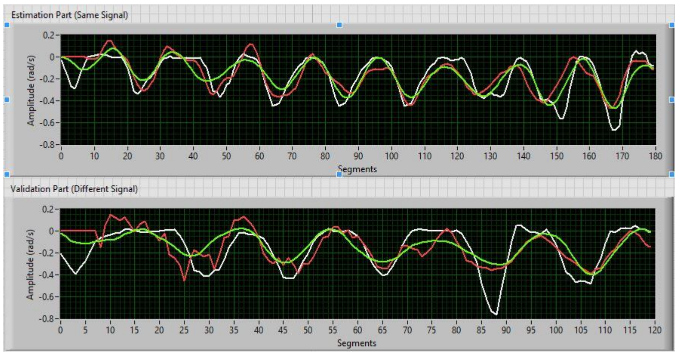

Fig.4. Fast Extension model response. Upper Panel: Estimation Part. Lower Panel: Validation Part.

Fig.4 shows the responses of ARX model and Hammerstein model for Fast Extension condition, where upper panel shows estimation part response and lower panel shows validation part response. Here white signal represents actual response; red signal ARX model response and green Hammerstein model response.

Case 3: Slow Flexion

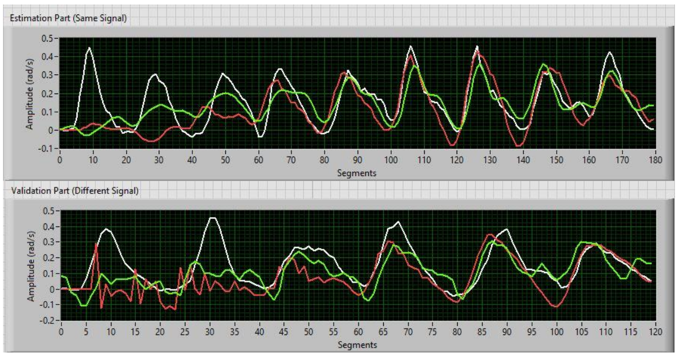

Fig.5. Slow Flexion model response. Upper Panel: Estimation Part. Lower Panel: Validation Part.

Fig.5 shows the responses of ARX model and Hammerstein model for slow flexion condition. Here white signal represents actual response; red signal ARX model response and green Hammerstein model response.

Case 4: Slow Extension

Similarly, Fig.6 shows the responses of ARX model and Hammerstein model for slow flexion condition.

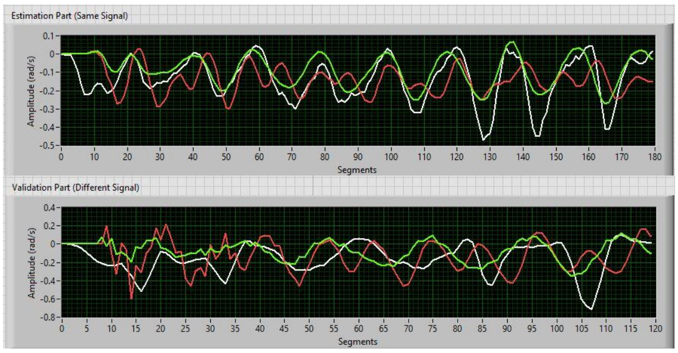

Fig.6. Slow Extension model response. Upper Panel: Estimation Part. Lower Panel: Validation Part.

V. CONCLUSION

In this paper, a mathematical model relating sEMG signals measured over biceps and triceps muscles and angular velocity of motion of fore-arm are developed using two system identification models: a linear parametric model (ARX model) and a nonlinear Hammerstein model. From results shown in Tables 1, it can be concluded that RMSE (root mean square error) values obtained for all the four study conditions, i.e. fast flexion, fast extension, slow flexion and slow extension based on Hammerstein model are less when compared to the linear ARX model.

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