Modeling surface electromyogram dynamics using Hammerstein-Wiener models with comparison of IIR and spatial filtering techniques

ANISH SEBASTIAN, PARMOD KUMAR, MARCO P. SCHOEN

Abstract— The national limb loss statistics paints a grim picture. Given the staggering limb loss numbers, the need to develop a "Smart Prosthetic Device" has never been more exigent. Despite years of effort by various government organizations and dedicated work on part of many scientists, we are still quite a ways away from creating the "perfect" prosthetic. Using electromyogram (EMG) signals to control prosthetic devices is and has been in the past, one of the most promising directions for this research. However, most of the control schemes being used, are based on either pre-programming the motion using threshold values of the EMG signal as reference, or using the root-mean-squared values of the EMG signal to actuate the prosthetic device. Using such a control strategy, makes it impossible to capture the underlying dynamics between EMG signals and the intended finger movements and forces. As a result of which the user needs to make an effort to learn to use the device, which can be very exhaustive. We propose to use system identification based dynamic models which are extracted from recorded surface EMG (sEMG) signals and the corresponding finger forces. A key influence on the resulting quality of such models is the filtering methods used for the EMG signals. This paper presents a thorough analysis of spatial filtering and other filtering methods as a possible solution to capture the dynamics of the sEMG signals, and perhaps in the future use these models to implement control schemes which would mimic the intricate force changes for a prosthetic hand. The different filters are compared on the basis of the EMG-finger force model fit percentages, obtained from System Identification using various Non-Linear Hammerstein-Wiener models. The nonlinear spatial filters gave better fit values as compared to the standard filtering techniques.

Keywords— **Spatial Filtering, Hammerstein-Wiener, Surface Electromyogram (sEMG), System Identification, Sensor Array, Modeling.**

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I. INTRODUCTION

ABOUT 50% of the people who need upper extremity prosthetics do not use them, [1]. This could be due any one of the common following reasons; Lack of a) Dexterity, b) Comfort and c) High Cost. Despite advances in the fields of manufacturing, electronics, signal processing, sensor design, and our understanding of biological signals, we still face a huge challenge designing a prosthetic device. This is due to the fact that such a device has to compete with one that nature has gifted us. A human hand is without doubt the best possible design. For a prosthetic hand, to encompass all of the human hands features and capabilities is as of now still a distant reality. Electromyogram (EMG) signals have been used for quite some time now in the control of prosthesis. The EMG signal is a small voltage signal (in mV), generated by skeletal muscles. This signal carries information of the objective the user would like to execute. Using surface EMG (sEMG) signals, researchers have been able to actuate motors on artificial prosthetic devices. EMG signals can be measured using intramuscular electrodes, needle electrodes, or by placing electrodes on the surface of the skin. The purpose for which the sEMG signal is being recorded generally determines whether it should be measured within the muscle using needle electrodes or surface measurement using electrodes on the skin would suffice. If, the purpose of recording the EMG signal is to look for diseases relating to a particular muscle, one might be better off using needle electrodes. On the other hand, if it is to be used to actuate motors on a prosthetic device, which a user might want to take off and wear without the need of medical supervision, surface EMG would suffice. Measuring the EMG signal on the surface of the skin is also less uncomfortable. This method is generally suited only for superficial muscles. Even though recording sEMG is favorable, it is plagued with many issues, such as crosstalk from firing of multiple motor points in the vicinity of the recording location, which can cause significant corruption of the signal at that site, motion artifacts, and poor signal if the motor unit is not identified correctly, etc. Needle electrodes, on the other hand, require trained medical professionals for appropriate placement of the electrodes in

the muscle. This paper investigates sEMG signals only with the objective to extract intended finger forces. The sEMG-force relationship is modeled using Hammerstein-Wiener models to characterize the dynamics. These models would characterize the controller dynamics for sEMG based prosthetic hands. We look to overcome the crosstalk issue in the measurement by using an array of nine (9) sEMG sensors, and utilizing spatial filters to isolate and improve the quality of the signals at the identified site for EMG recording. The sensor array was placed on the motor unit location, which was identified for the subject using a muscle stimulator. The sensors were then placed around the motor unit to form a 3x3 square matrix. The processed signal was then used for identifying various dynamical models for the prediction of the force, from the recorded sEMG signal, that was generated during various voluntary contractions of the subjects' hand. A comparison of the various outcomes (model fit values computed) from the system identification process, using signal processing techniques stated in the ISEK [2] guidelines and the spatially filtered signals are presented in this paper. The experiments were conducted for long durations also, in order to analyze the effects of the muscle fatigue on the model structures.

II.   PROBLEM FORMULATION

EMG signal should ideally be measured at a motor unit. A motor unit (MU) consists of an α-motoneuron in the spinal cord and the muscle fiber it innervates. Figure 1 shows the path of the signal form the brain to the muscle.
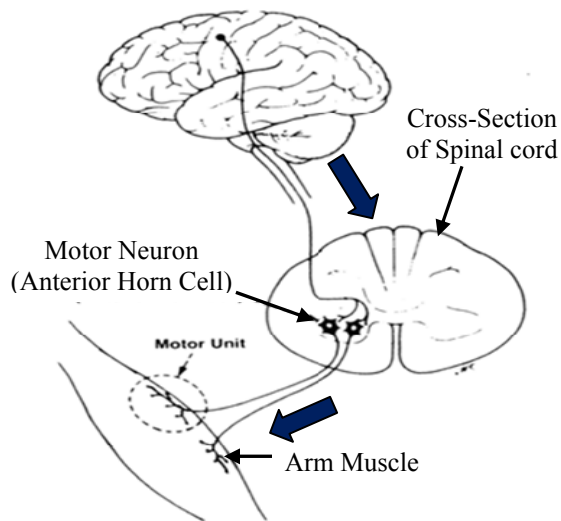

Fig. 1 sEMG signal pathway Brain – Motor Unit [3]

sEMG signals are influenced by multiple factors; physiological and non-physiological factors. The physiological factors are; A) Fiber membrane properties and B) Motor unit properties. Fiber membrane properties are further sub-divided into i) Average muscle fiber conduction velocity, ii) Distribution of motor unit conduction velocities, iii) Distribution of conduction velocities of the fibers within

the motor units and iv) Shape of the intracellular action potentials. Whereas the motor unit properties are subdivided into i) Number of recruited motor units, ii) Distribution of motor unit discharge rates, iii) Statistics and coefficient of variation of discharge rates and iv) Motor unit synchronization.

The non-physiological factors are; A) Antomic, B) Detection System, C) Geometrical and D) Physical. The anatomic factors include, i) Shape of the volume conductor, ii) Thickness of the subcutaneous tissue layers, iii) tissue inhomogeneities, iv) Distribution of the motor unit territories in the muscle, v) Size of the motor unit territories, f) distribution and the number of fibers in the motor unit territory, vi) Distribution and number of fibers in the motor unit territories, vii) Length of the fibers, viii) Spread of the endplates and tendon junctions within the motor units, and ix) Spread of the innervations zones and tendon regions among motor units. The detection system used also plays an important part in influencing the sEMG measurements. Some of the factors which need to be taken into account, with the detection systems, are i) Skin electrode contact (impedance, noise), ii) Spatial filtering for signal detection, iii) Inter-electrode distance, iv) Electrode size and shape, and v) Inclination of the detection system relative to the muscle fiber orientation, and vi) Location of the electrodes over the muscle. The geometrical factors are, i) Muscle fiber shortening and ii) Shift of the muscle relative to the detection system. And the physical factors are i) Conductivities of the tissue and ii) Amount of crosstalk from nearby muscles [4]. This is not a comprehensive list of all the factors that influence sEMG signals but provides an insight into the complexity that one might encounter while modeling sEMG-force or sEMG-joint angle data. Some of the processing methods implemented for EMG have been mentioned in [5-9]

Since sEMG is plagued by a multitude of issues, as pointed out in the previous paragraph, one cannot approach this problem by realistically trying to account for each of the variables in the measurement, nor can one oversimplify the problem at hand by assuming a simple linear or a non-linear relation between the sEMG signal and the corresponding finger force generated. Hence the approach presented in this paper is to assume a black-box model in order to deduce a suitable relation or model structure for the two signals. This approach has been found to be of merit in our previous studies and has been been reported in [10] & [11] to yield satisfactory fits percentages.

III.   PROBLEM SOLUTION

"Spatial filtering" is broadly defined as a method which computes spatial density estimates for events that have been observed at individual locations. These filters are used when there is no a priori curve to fit to a data series. Instead, it relies on nearby or adjacent values to estimate the value at a given point. These filters take out variability in a data set while retaining the local features of data. Spatial filtering is

principally associated with digital image processing. This method may be applied to almost any data in the form of a grid. The most common spatial filters are the low-pass and high-pass spatial filters. These are focal functions whose operation is determined by a kernel or neighborhood of **NxN** cells around each pixel or grid position [12]. Grid cells "covered" by a kernel are multiplied by the matching kernel entry and then the weighted average is calculated and assigned as the value for the central cell, *G*. For example, an asymmetric 3x3 kernel may look like the one shown in Equation (1), or any combination of the weights. Typically *a, b* are positive integers. If *a=b=1*, then the kernel provides a simple smoothing or averaging operation. The weights in the kernel can be modified for specific cases or data sets. In any case the weighted average is divided by the sum of the elements of the kernel. Filters of this type are sometimes referred to as low-pass filters.

$$\text{Symmetric Kernel} = \begin{bmatrix} a & a & a \\ a & b & a \\ a & a & a \end{bmatrix}. \qquad (1)$$

If the weights in the kernel is similar to the one in Equation (2) and *a, b, c* are positive integers, and if the following, *b>a>c*, is true, then the kernel is described as a Gaussian filter which is symmetric but center-weighted.

$$\text{Symmetric Kernel} = \begin{bmatrix} c & a & c \\ a & b & a \\ c & a & c \end{bmatrix}. \qquad (2)$$

The filtered grid value '*G*' of an *m=NxN* kernel matrix, with C_i set of coefficients and P_i - set of source grid values, is calculated as:

$$G = \frac{\sum_{i=1}^{m} C_i P_i}{\sum_{i=1}^{m} C_i} + B, \qquad (3)$$

where, *B* is often set to 0. *B* is a bias term to increase or decrease the resulting value of '*G*'. This kernel is also sometimes referred to as the '*filter mask*'.

Linear Spatial Filtering: Linear spatial filtering would modify the sEMG array data '*f*' by replacing the value at each location with a linear function of the values of nearby data points. Moreover, this linear function is assumed to be independent of the data point locations (*k, l*), where (*k, l*) are the indices of the data points in *f*, which is represented by a composite data matrix. This kind of operation can be expressed as convolution or correlation. For spatial filtering,

it's often more intuitive to work with correlation. The filtered result *g(k, l)* is obtained by centering the mask over pixel (*k, l*) and multiplying the elements of *f* with the overlapping elements of the mask and then adding them up. In other words, the objective is to amplify the activity of motor unit/s located closest to the recording site (ideally the actual motor location for the particular finger) and reducing the EMG signal generated by other motor units located further away or motor units of other fingers. Other ways to increase the selectivity of surface EMG recordings is by reducing the electrode size (i.e., skin–electrode contact area or inter-electrode distance) [13] and/or by applying temporal filters [14]. More recent work has focused on advances in the design of surface electrode arrays [15-16] to extract single motor unit information from sEMG. A large number of traditional [17–19] and adaptive [20] linear spatial filters have been extensively used to glean more information out of sEMG signals and to understand it much better.

For this paper, the experiments were carried out on a healthy male subject to extract dynamical models describing the relationship between sEMG-force signals. The motor points were located using a Muscle Stimulator, manufactured by Rich-Mar Corporation (model number HV 1100). The motor location of the ring finger was chosen for the experiments. The EMG detection system used was a Delsys, Bagnoli-16 channel EMG (DS-160, S/N-1116). The sensors used for measuring the sEMG action potentials were three pronged DE 3.1 differential surface electrodes. The subjects' skin was prepared, according to the ISEK standards, before the sensors were placed over the motor point. The electrodes were placed along the muscle fibers (Flexor Digitorum Superficialis) for recording sEMG. Multiple sEMG sensors in an array configuration were mounted on and around the identified motor unit, as shown in Figure 2.
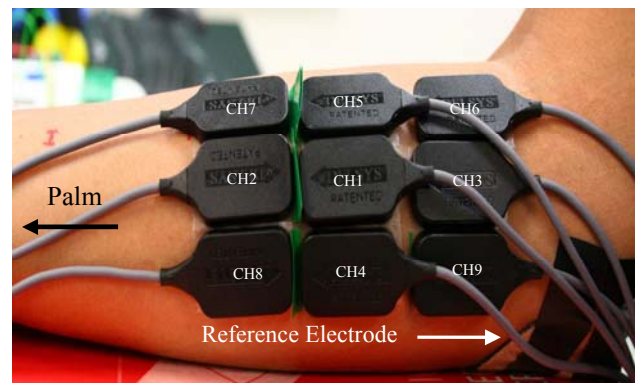

Fig. 2 Experimental Setup – Location of sEMG sensors

The subjects' hand was placed on a flat surface; the reference electrode was placed on the elbow where there is no sEMG signal. Sensor *CH1* was placed on the identified motor unit location. *CH2* and *CH3* were placed along the muscle fiber in front and behind *CH1* respectively. Channels 4-9 were placed in the orientation as shown in Figure 2. Nine different experiments were conducted and the corresponding sEMG

signal was measured simultaneously from all the nine sensors. The force generated by the subject's fingers, for a given motion, was measured using a stress ball with a force sensitive resistor (FSR) mounted on it.

The change in the resistance of the FSR is directly proportional to the force being applied. Figure 3 shows the location of the FSR on the stress ball. Experiments 1 and 2 were used to check for any spurious signals that might be recorded due to the slight angle at which the subjects' hand was held. Experiments 3 to 6 were done using a stress ball with a lesser stiffness as compared to experiments 7, 8 & 9.

Also, a thumb restrain was used for experiments 5-9. The thumb restrain is showed in the Figure 3. The stress ball was changed as we were also interested in looking at the changes in the sEMG signal when fatigue occurs, and also how it would affect the modeling for the relation between force-sEMG using System Identification (SI).
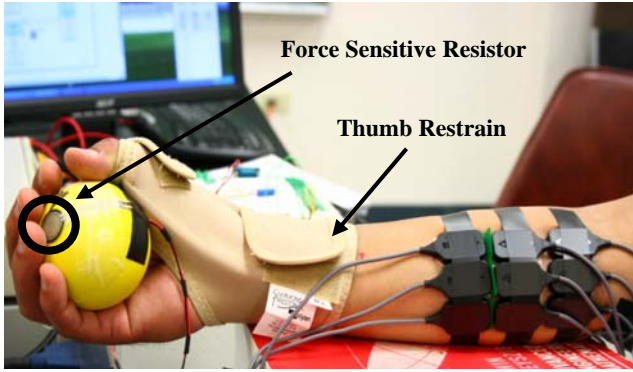

Fig. 3 Force Sensitive Resistor and Thumb Restrain

The linear spatial filters tested in this paper for isolating the motor unit action potentials (MUAPs) are; 1) Longitudinal Single Differential (LSD), 2) Transverse Single Differential (TSD), 3) Longitudinal Double Differential (LDD), 4) Transverse Double Differential (TDD), 5) Normal Double Differential (NDD), 6) Inverse Binomial (IB2) and 7) Inverse Rectangular (IR) Filter. The mask of these filters and the corresponding resultant equations on application of the mask to the grid data obtained from the sEMG array arrangement are given below.

$$\text{EMG Array Information, Spatial Filter Mask}$$

$$LSD = \begin{bmatrix} sEMG7 & sEMG5 & sEMG6 \\ 0 & 0 & 0 \\ sEMG2 & sEMG1 & sEMG3 \\ -1 & 1 & 0 \\ sEMG8 & sEMG4 & sEMG9 \\ 0 & 0 & 0 \end{bmatrix}$$

$$\text{Result Equation: } -sEMG2 + sEMG1$$

$$TSD = \begin{bmatrix} 0 & -1 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 0 \end{bmatrix} \quad LDD = \begin{bmatrix} 0 & 0 & 0 \\ -1 & 2 & -1 \\ 0 & 0 & 0 \end{bmatrix}$$

$$TDD = \begin{bmatrix} 0 & -1 & 0 \\ 0 & 2 & 0 \\ 0 & -1 & 0 \end{bmatrix} \quad NDD = \begin{bmatrix} 0 & -1 & 0 \\ -1 & 4 & -1 \\ 0 & -1 & 0 \end{bmatrix}$$

LSD Equation = sEMG1-sEMG2; *TSD* Equation = *sEMG1-sEMG5*. We can similarly deduce the equations for the other spatial filters.

$$IB2 = \begin{bmatrix} -1 & -2 & -1 \\ -2 & 12 & -2 \\ -1 & -2 & -1 \end{bmatrix} \quad IR = \begin{bmatrix} -1 & -1 & -1 \\ -1 & 8 & -1 \\ -1 & -1 & -1 \end{bmatrix}$$

In this paper, nonlinear spatial filters have also been discussed these have been reported in literature [21]. These are 1) 1-D Nonlinear Transverse spatial filter (NLT), 2) 1-D Nonlinear Longitudinal spatial filter (NLL), 3) 2-D Nonlinear spatial filter in Two- Orthogonal Directions (NLTOD) and 4) Nonlinear spatial filter in All Four possible Directions (NLAFD). The nonlinear spatial filters use the Teager-Kaiser Energy (TKE) Operator, [22]. This technique is a threshold 'energy' based approach where outliers are first detected and then replaced by their estimated values. This nonlinear operator differs from the common way to calculate the energy of a discrete-time signal as the average sum of its squared magnitudes. The energy of a generating system of a simple oscillation signal was computed as the product of the square of the amplitude and the frequency of the signal. It was found that this nonlinear operator exhibits several attractive features such as simplicity, efficiency and ability to track instantaneously-varying special patterns. Since its introduction, several applications have been derived for one-dimensional [23-24], and two dimensional signal processing [25]. The nonlinear spatial filters with the TKE operator incorporated are given as follows; the general form of nonlinear spatial filter using the (TKE) operator is given in Equation (4);

$$\Psi[x(n)] = x^2(n) - x(n+1)x(n-1) \tag{4}$$

a) 1-D Nonlinear Transverse Spatial Filter (NLT); Equation (5)

$$\Psi_{d,m}[x(m,n)] = x^2(m,n) - x(m-1,n)x(m+1,n) \tag{5}$$

b) 1-D Nonlinear Longitudinal Spatial Filter (NLL); Equation (6)

$$\Psi_{d,n}[x(m,n)] = x^2(m,n) - x(m,n-1)x(m,n+1) \qquad (6)$$

c) Nonlinear Spatial Filter in Two Orthogonal Directions (NLTOD): Equation (7)

$$\Psi_{d,2}[x(m,n)] = \Psi_{d,2m}[x(m,n)] + \Psi_{d,n}[x(m,n)]$$
$$(7)$$
$$= 2x^2(m,n) - x(m-1,n)x(m+1,n) - x(m,n-1)x(m,n+1)$$

d) Nonlinear Spatial Filter in all Four Directions (NLAFD): Equation (8)

$$\Psi_{d,4}[x(m,n)] = 4x^2(m,n) - x(m-1,n)x(m+1,n)$$
$$(8)$$
$$-x(m,n-1)x(m,n+1) - x(m-1,n+1)x(m+1,n-1)$$
$$-x(m-1,n-1)x(m+1,n+1)$$

IV. SIMULATION RESULTS

Plots of the raw data gathered are shown in Figure 4. The plots shown in Figure 4 represent the raw data collected from the nine channels of the sensor grid in the same orientation as shows in Figure 2.
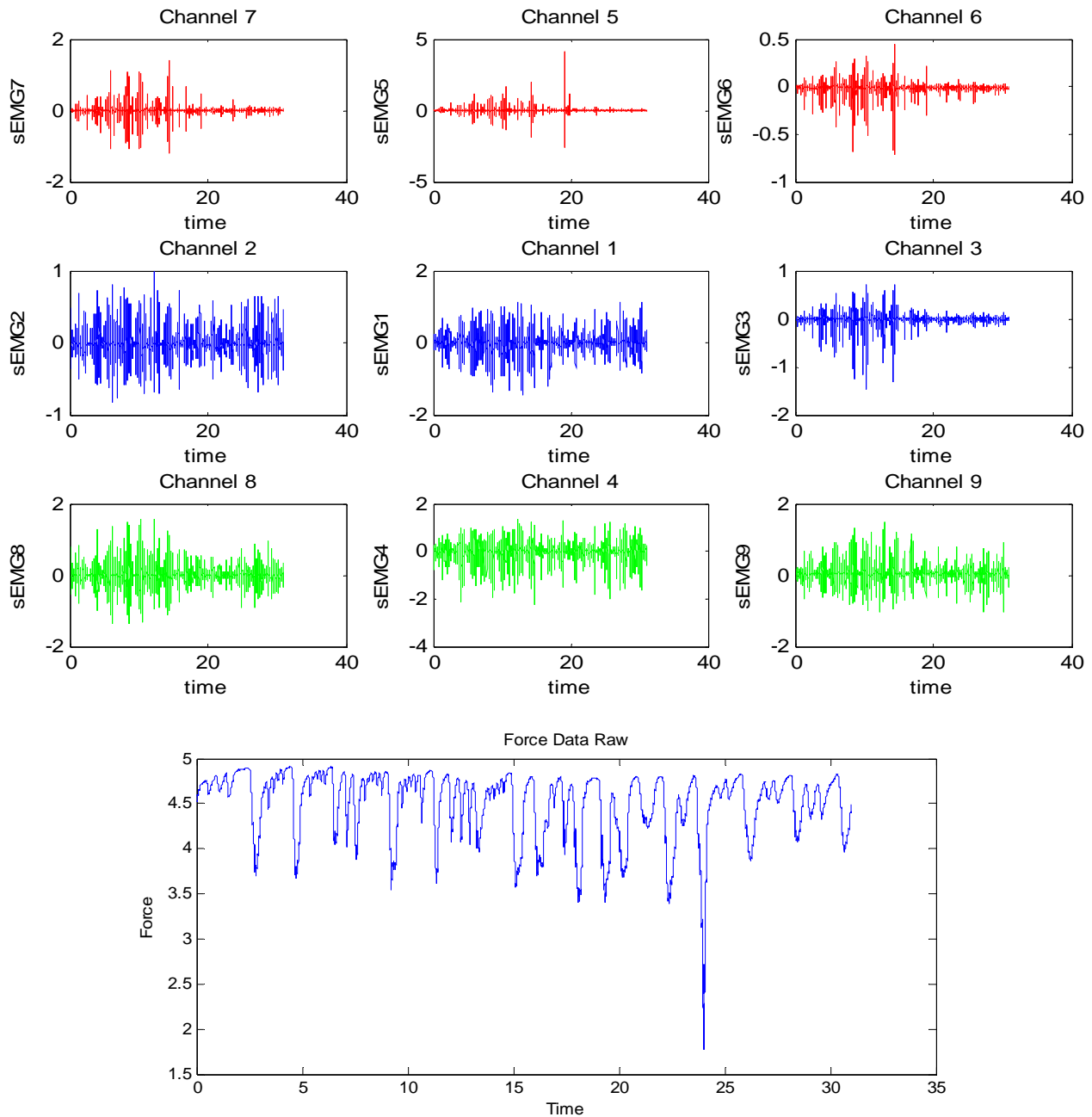

Fig. 4 sEMG Raw Signal Channels 1-9 & the corresponding Force signal

The data shown in Figure 4 is for comparison of the sEMG obtained from various location of the subject's arm. Notice the change especially in the amplitude of the sEMG at Channel 1, 4 & 5. Figure 5 shows the filtered sEMG (location CH1) at the motor point using four (4) IIR filters; 1) Bessel 2) Butterworth, 3) Chebyshev Type I and 4) Chebyshev Type II. The filter characteristics of these 4 filters were in accordance to the ISEK standards.

Figure 6 plots the filtered sEMG signal data from the sensor

array after they were filtered using various spatial filters. In addition to these 11 spatial filters. The relation of sEMG-Force was modeled using Non-Linear Hammerstein-Wiener models. This modeling method has been proven to work in the past [10], [11] in assuming a black-box model structure for the system. In order to model the sEMG-Force relation, the filtered data from the various experiments was split into various four (4) time windows.
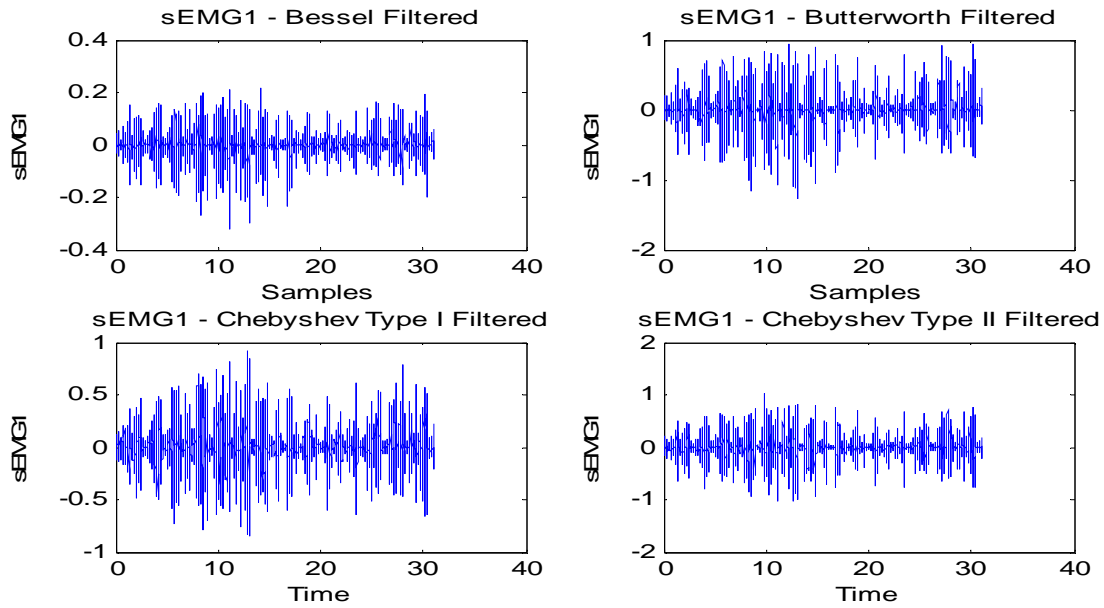

Fig. 5 sEMG1 at Motor Point (CH 1) Filtered using IIR Filters; Bessel, Butterworth, Chebyshev I & Chebyshev II
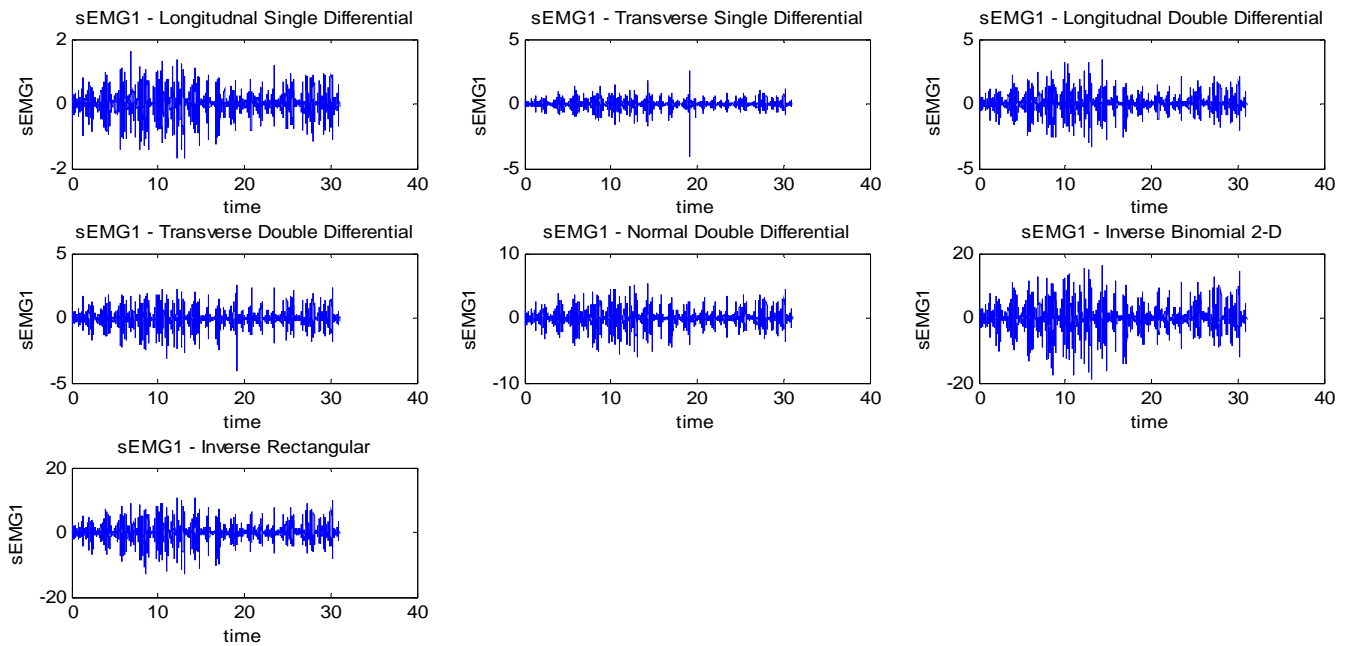

Fig. 6 sEMG1 at Motor Point of Ring Finger (CH 1) Filtered using Linear Spatial Filters; LSD, TSD, LDD, TDD, NDD, IB2 & IR

Equation 9 describes the general Hammerstein-Wiener model structure:

$$w(t) = f((g(t)), \quad b(t) = \frac{B_{j,i}(q)}{F_{j,i}(q)} w(t), \quad y(t) = h(x(t)), \quad (9)$$

where, $w(t)$ and $b(t)$ are internal variables, $w(t)$ has the same dimensions as $u(t)$ - input, and $x(t)$ has the same dimensions as $y(t)$ - output. $g()$ and $h()$ are the input and output non-

linearity functions respectively. $B(q)$ and $F(q)$ are regression polynomials. The model fit values are computed using Equation (10) as follows;

$$fit = 100 * \frac{1 - \|\hat{y} - y\|}{\|y - \hat{y}\|} \quad (10)$$

where, $\hat{y}$ is the estimated output by the model.
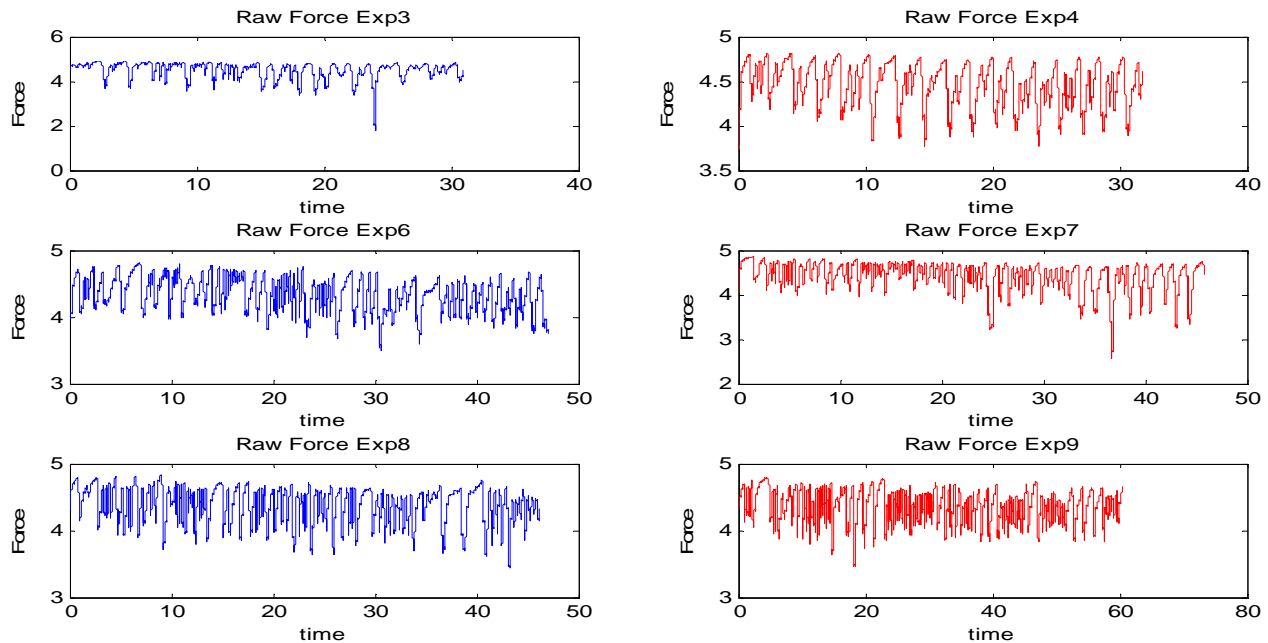

Fig. 7 Variations in Force levels; experiment 3, 4, 6, 7, 8 & 9

The time windows used for estimation and validation of the models were called 'ze' and 'zv' respectively. 'ze' contained 8000 sample points and 'zv' contained data points shifted by 2000 sample points. For example, if 'ze' was a time window between 2-6 seconds i.e. samples 4000-12000, then 'zv' was between 3-7 seconds i.e. 6000-14000 samples. Thus the Hammerstein-Wiener method uses 'ze' to estimate the model structure and based on this information predicts the next 2000 sample points. The data was filtered using the various filters mentioned in the previous sections. We would like to stress once again the point that the force was varied randomly and the subject was in no way trying to achieve maximum voluntary contractions during each cycle. A cycle is defined as the subject starting without any force on the stress ball, squeezing it (to any force level) and then going back to no force. The subject has to keep the finger in contact with the force ball throughout this cycle.

A plot of the variations in force achieved for 6 experiments is shown in Figure 7. The Matlab™ code for the Hammerstein-Wiener model is: $nlhw(ze, [n_a \; n_b \; n_k], ..., ...)$. The modeling was carried out by varying n_a - the number of past output terms used to predict the current output, n_b - the

number of past input terms used to predict the current output and n_k - the delay from input and output in terms of the number of samples for the various Hammerstein-Wiener models.

42 models with variations in n_a and n_b were tested while the value of n_k was kept as 1. The total number of models estimated were 15 (filter types) x 4 (time windows) x 42 models per time window x 4 experiments = 10,080 models. This paper does not list all these models but identifies and reports only the significant results of the analysis.

As an example, for experiment 3, for time window of 2-7 sec, the fit values obtained by varying n_a between 2-7 and n_b between 3-9, are shown in Figure 8. Figure 8 contains a lot of information as it shows 49 models fit percentages for each of the IIR and spatial filter types tested. The large variation in the model fit values can be attributed to the fact that the two data sets have poor correlation between one another. The significant result, for this time section, were noted for the Bessel and NLTO filters, these are plotted in Figure 9

The predicted model output plots for these values are shown in Figure 10.
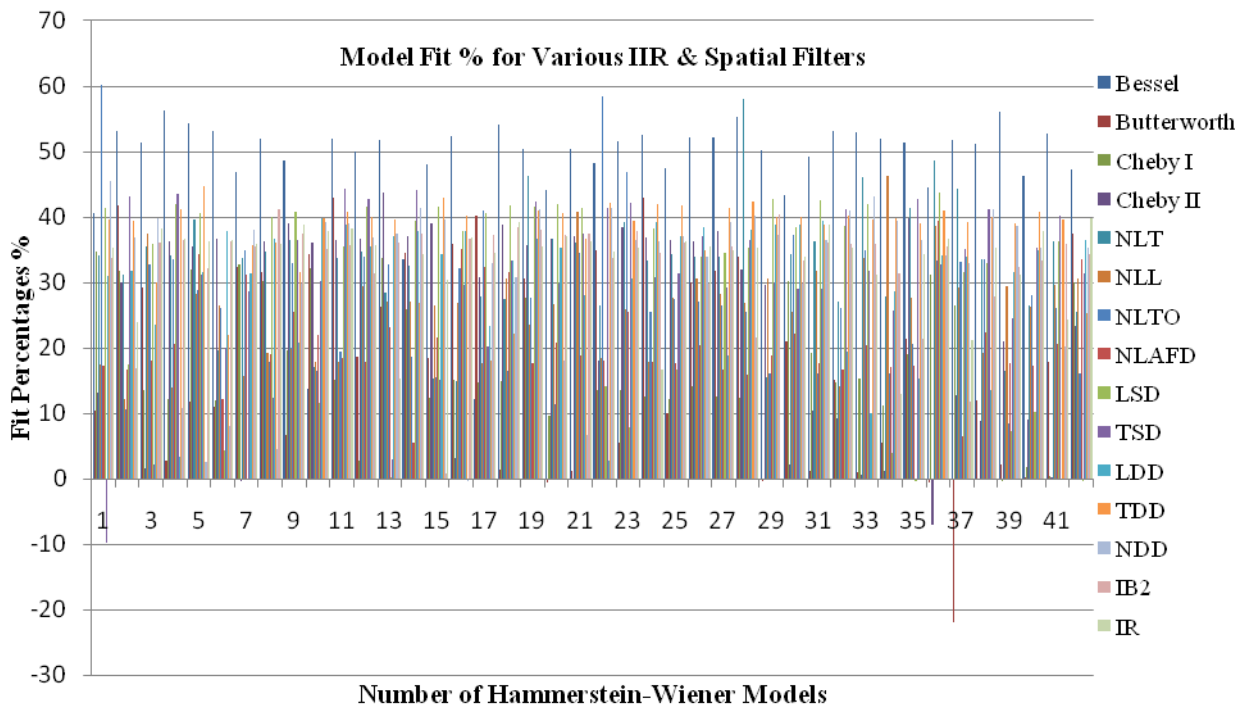
Fig. 8 Fit % for Hammerstein-Wiener Models – Various IIR & Spatial Filters (time window 2-7 sec, exp3)

Fig. 9 Fit % for Hammerstein-Wiener Models – Bessel & NLTO (time window 2-7 sec, exp3)

The other filters used also predict the future variations in force but the fit percentages were in the range of 30-48%. A key objective of this research is help develop a control regime which in not based on threshold values of force can incorporate the dynamics in the force. This would help to control the response of the artificial limb to be closer to that of the actual hand. Similarly we tested various models for the other experiments too. Another set of results which gave very

high values of fit was for the later time windows. This case was especially interesting as the subject had fatigued due to the repetitive experiments, but the Hammerstein-Wiener models did successfully capture the variations in the sEMG signal. The Hammerstein-Wiener models performed very well even as the sEMG signal changed and we obtained fit values in the high sixties.
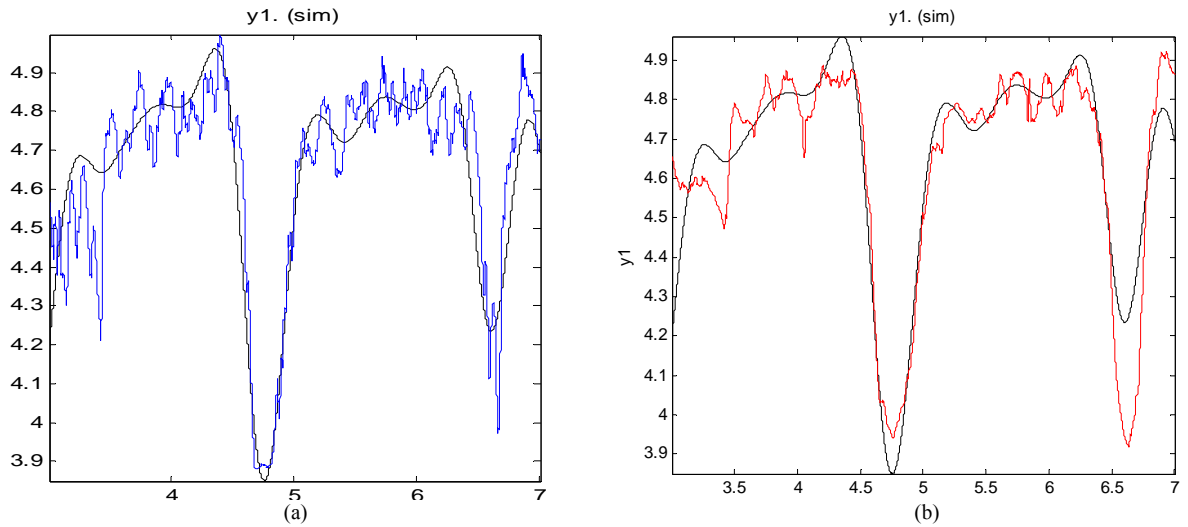
Fig. 10 Measured data (black) a) Bessel (blue) 56.36% and b) NLTO (red) 60.13% for exp 3 time window 2-7seconds.

Figure 11 shows the model fit values obtained for these later data windows. As can be seen from the plots, contrary to our expectations the Hammerstein-Wiener Models performed very well and produced very good fit values.
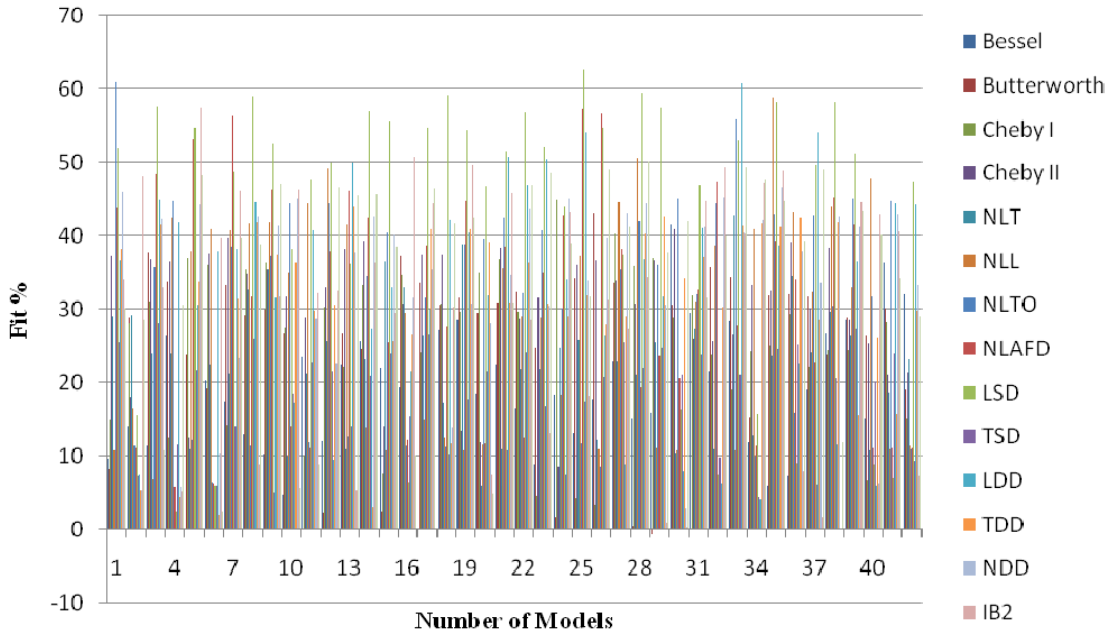

Fig. 11 Fit Values Obtained for Different Hammerstein-Wiener Models – Bessel, NLTO NLT, TDD, NDD, NLAFD Filters (time window 20-25 sec, exp5)

Figure 12, 13 and 14 shows the model output plots for some of the filters mentioned in Figure 11. The only IIR filter whose performance matched, and in a few cases exceeded, the performance of the linear and the non-linear spatial filters was the Bessel filter. As can be seen from Figure 12 the Bessel filter modeled the sEMG-force relation to 52.85 % though this is a slightly lower value than the Butterworth filter mentioned, the spread of the model fit values was more consistent in the range of 45-50% as compared to the Butterworth filter which had a far more spread out distribution.
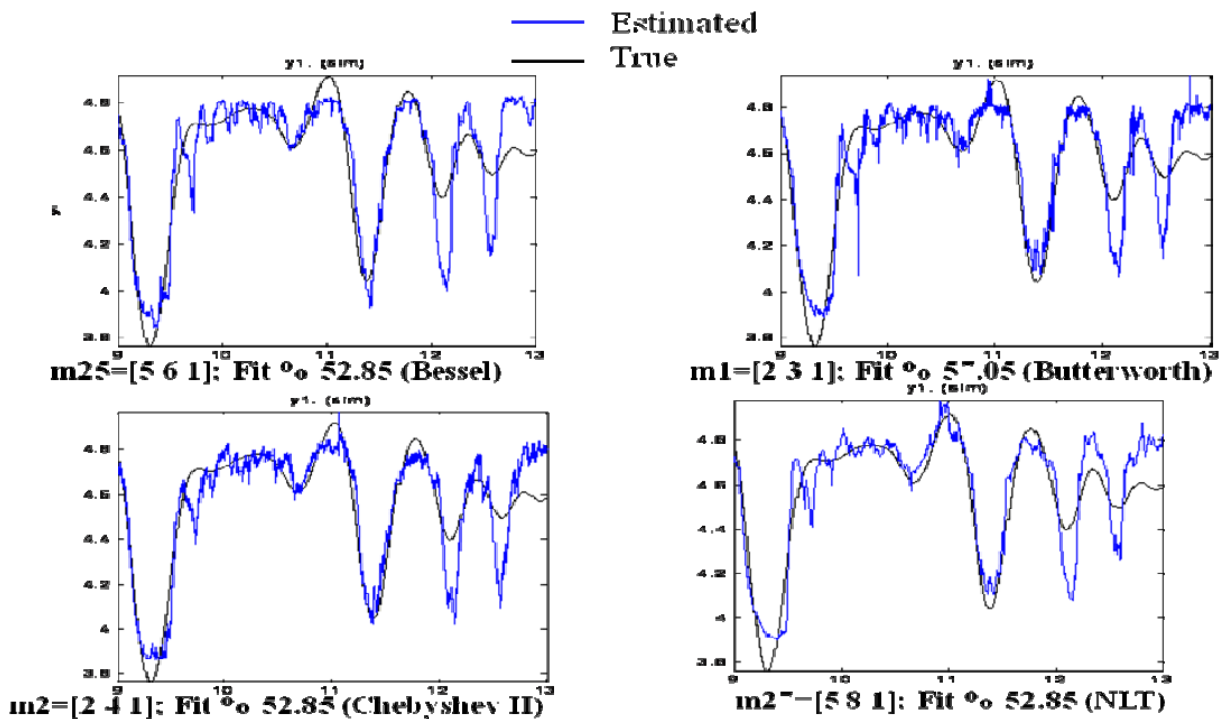
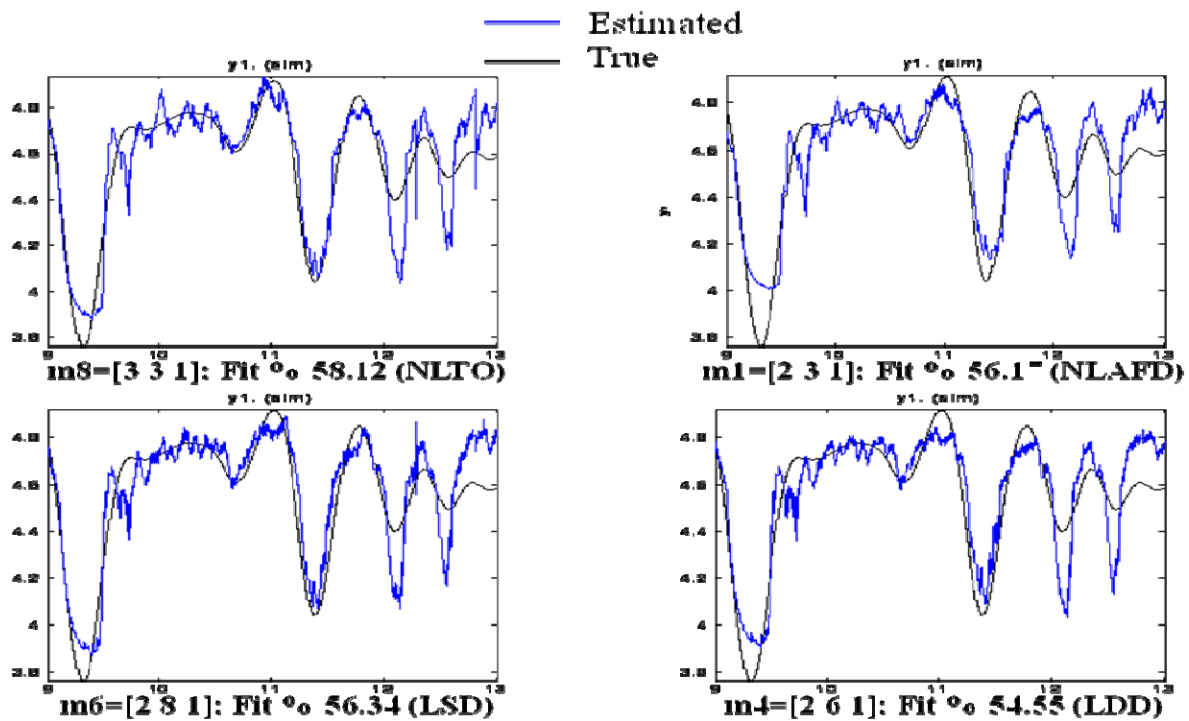Fig. 12 Measured Data (Black) & Estimated Data (Blue)

Fig. 13 Measured Data (Black) & Estimated Data (Blue)

V. CONCLUSION

The Hammerstein-Wiener models worked very well in capturing the dynamics of the force levels for the various experiments conducted. This method of modeling could help in improving the control over the motors used in prosthetic devices to mimic the actual changes force levels in a real hand. This method also performed very well in the scenarios where the subject did fatigue but the affects were successfully
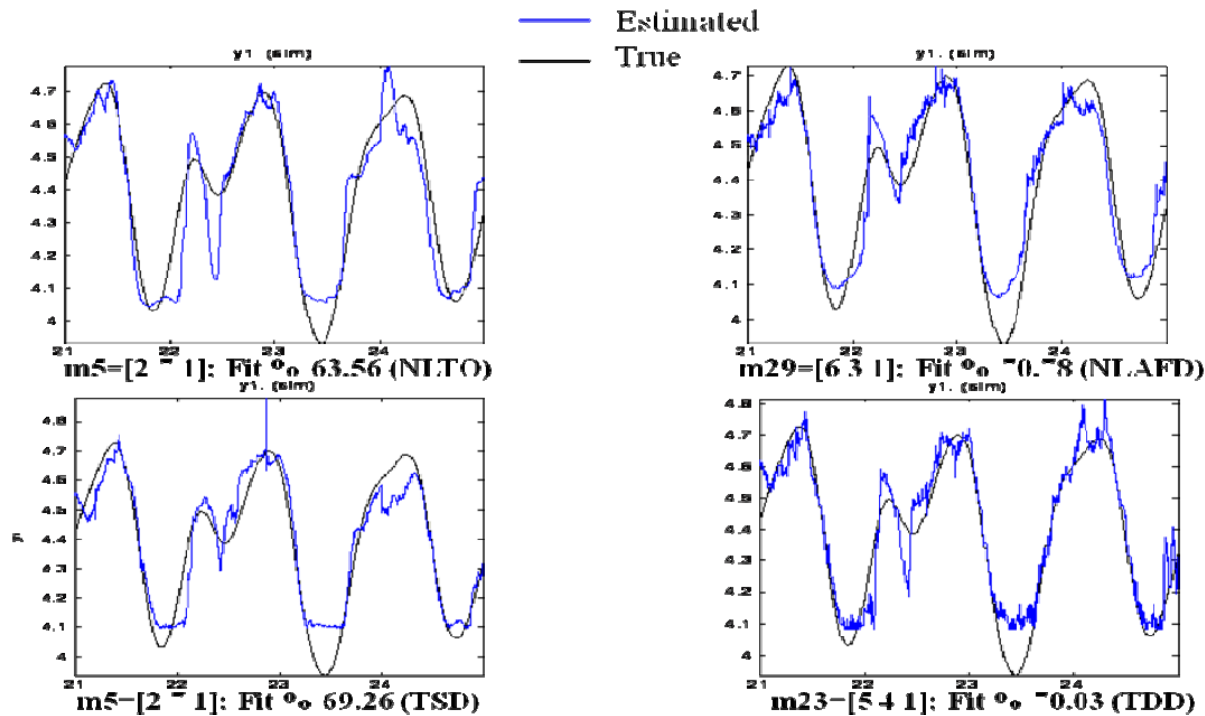
Fig. 14 Measured Data (Black) & Estimated Data (Blue)

modeled by the Hammerstein–Wiener models. The nonlinear and linear spatial filters (TDD, NDD and NLT, NLTO and NLAFD) did outperform the other filtering methods used especially for the later time windows. The only other filter which had a comparable performance to the spatial filters was the Bessel filter. Further investigation into reducing the wide range of the fit values obtained needs to be performed. One of the possible methods to pursue would be to use Genetic Algorithm to optimize the model parameters n_a and n_b and also the number of iterations used for the modeling of sEMG-force levels. One of the possible reasons for poor fit values could also be attributed to the model trying to over-fit the data sets.

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