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sEMG and Skeletal Muscle Force Modeling: A Nonlinear Hammerstein-Wiener Model, Multiple Regression Model and Entropy Based Threshold Approach

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Abstract: Skeletal muscle force and surface electromyographic (sEMG) signals have an inherent relationship. Therefore, sEMG can be used to estimate the required skeletal muscle force for a particular task. Usually, the location for the sEMG sensors is near the respective muscle motor unit points. EMG signals generated by skeletal muscles are temporal and spatially distributed which results in cross-talk that is recorded by different sEMG sensors. This research focuses primarily on modeling muscle dynamics in terms of sEMG signals and the generated muscle force. Here we assume sEMG as input and force as output to the skeletal muscle system. We model the two using a nonlinear Hammerstein-Wiener model and Multiple Regression model. Since these two methods are not leak proof, so we propose an entropy based threshold approach, which is more robust and reliable in most of the practical and real-time scenarios. The proposed methods are tested with the data collected on different subjects.

Keywords: sEMG; Hammerstein-Wiener; keyword; Multiple Regression; Entropy

PACS Codes: ….

1. Introduction

In the United States the number of people living with limb loss are approximately 1.7 million and as per estimation there is one in every 200 people has had an amputation, [1], [2]. Reason for this number is multifaceted, some are because of war injury, some are because of cancer and trauma-related, and majority of the amputations occur due to complications of the vascular system, [3], [4]. A prosthetic limb can improve the quality of everyday life of an amputee by increasing the functionality.

Depending on the motor activation requirement, the central nervous system activates and control the flow of specific ions such as sodium (Na^{++}), potassium (K^{++}), and calcium (Ca^{++}) across the cell membranes. This generate EMG signal, which can be recorded on the surface of the limb as an electric voltage ranging between -5 and +5 mV. This is known as surface electromyography (sEMG). As sEMG is easily available, it is a natural choice to use as a control signal for the prosthesis. Some of the past research work based on sEMG can be found in [5]-[13].

To improve the quality of life of the people with upper-extremity we need good prosthetic hand, which should provide all the sensorimotor functions with a natural appearance. This research focus on the better and cost effective design for an upper-extremity prosthetic arm, to do so we need to have better estimation and prediction of the required force for a particular task from the sEMG signal. This paper is organized in different sections, present section is followed by 'Experimental Set-Up and Data Collection,' 'Signal Processing and Modeling,' 'Results and Discussion,' and 'Conclusions and Future Works.'

2. Experimental Set-Up and Data Collection

Experiment to collect the sEMG and skeletal muscle force signal was designed inside the University laboratory and data were collected on healthy undergraduate and graduate students who volunteered (see Figure 1).

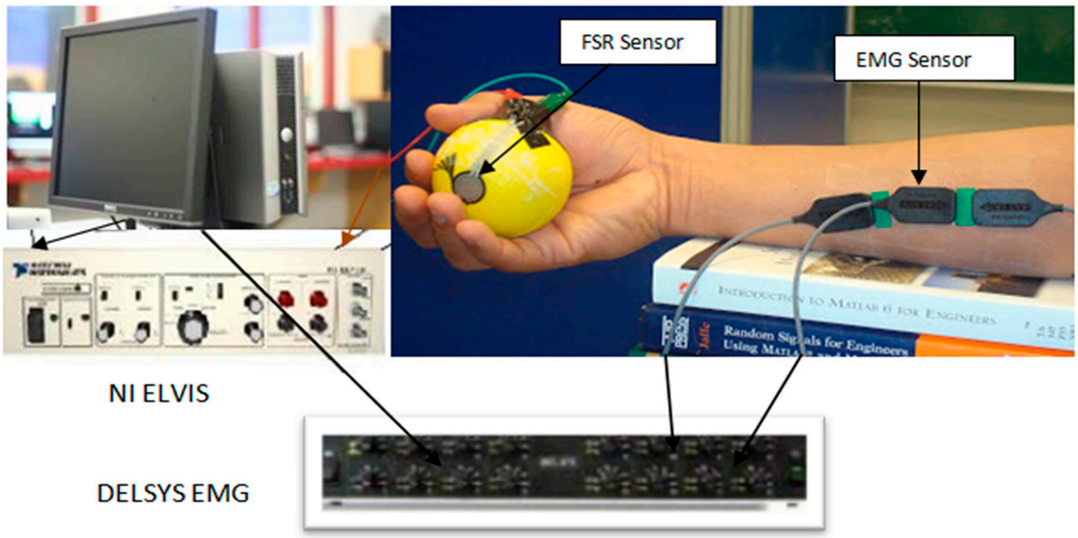

Figure 1: Experimental Set-Up (Subject with three sEMG sensors, along the muscle fiber and FSR on stress ball).

Both the sEMG and skeletal muscle force signals were recorded simultaneously with LabVIEW™ with a sampling rate of 2000 Hz. A DELSYS® Bagnoli-16 EMG system with DE-2.1 differential EMG sensors was used to record sEMG data. The corresponding force data was captured using Interlink Electronics FSR 0.5" circular force sensor. Motor point of the ring finger was detected on the main arm of the subjects and skin surface was prepared prior to placement of the sEMG sensors. International Society of Electrophysiology and Kinesiology (ISEK) protocols were followed for the sEMG data collection.

3. Signal Processing and Modeling

3.1 sEMG Signal Pre-Processing

sEMG signal are filtered with optimized nonlinear Half-Gaussian filter (see Figure 2). T. D. Sanger proposed that the Bayesian based filtering method yields the most suitable sEMG signals, [14]. These nonlinear filters are very effective for noise reduction, improve signal to noise ration (SNR) and the extracted signal best describe EMG. This has been useful for prosthetic applications with sEMG as control signal.

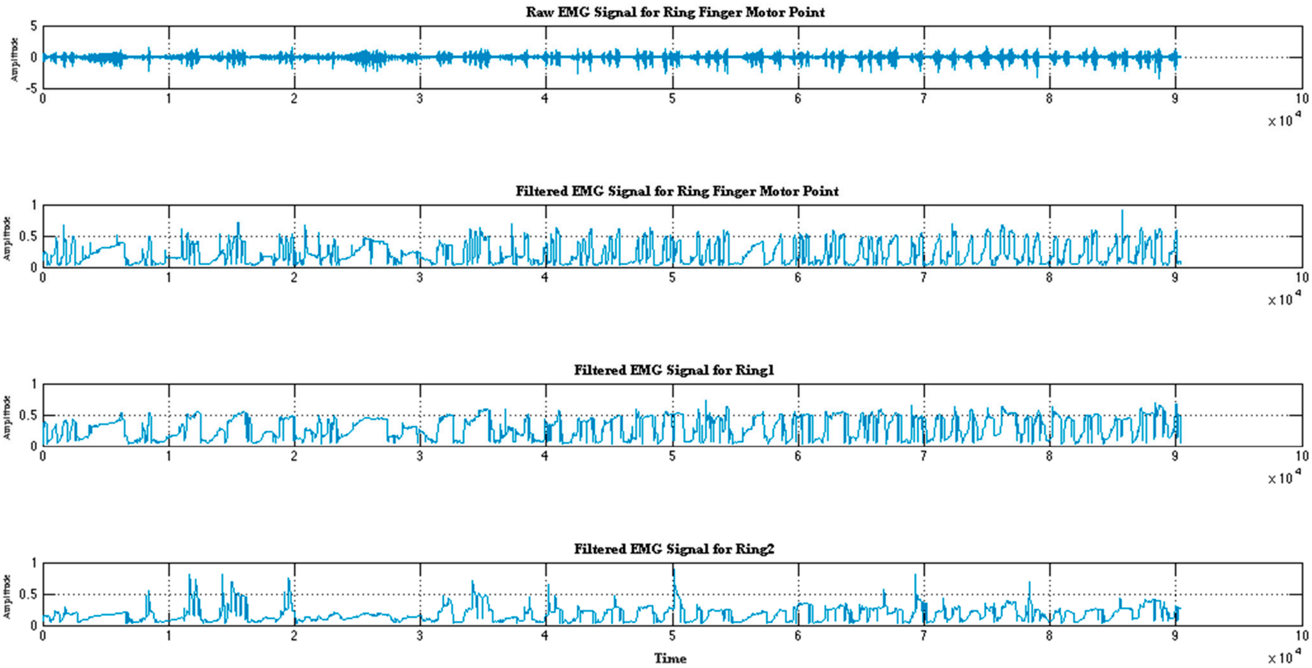

Figure 2: Raw sEMG vs. Half-Gaussian filtered sEMG signal for ring finger Motor Point, Ring1 and Ring2 sensors.

The EMG for the latent driving signal x is given by an instantaneous conditional probability $P(EMG/x)$ density, [14]. Present estimation algorithm of the Bayesian filter make use of the model for the conditional probability of the rectified EMG signal $emg = |EMG|$. An amplitude-modulated zero mean Gaussian noise sequence is used to represent EMG signals, [15]. The "Half-Gaussian measurement model" for the rectified EMG signal in [14] is given by Equation (1).

$$P(emg|x) = \frac{2 * exp(-\frac{emg^2}{2x^2})}{\sqrt{2\pi x^2}}. \quad (1)$$

The filtered random process with a random rate given by the conditional probability of the rectified EMG signal represents the EMG signal. Equation (2) is the discrete time representation of the Fokker–Planck partial differential equation, which gives the likelihood function for the random rate in time, [17].

$$p(x,t-) \approx \alpha * p(x-\varepsilon,t-1) + (1-2*\alpha) * p(x,t-1) + \alpha * p(x+\varepsilon,t-1) + \beta + (1-\beta) * p(x,t-1). \tag{2}$$

Here t is time, ε is bin width to discretize the latent driving signal x, the free parameters α and β are the expected rate of gradual drift and sudden shifts in the signal respectively. GA is an optimization algorithm based on observing nature and its corresponding processes, which is used to solve most often optimization and complex estimation problems, [16-18]. In GA, a solution is given by a set of parameters (genes, packaged as a chromosome) and the population of individual solutions is modified repeatedly. Successively, the population evolves over many iterations or generations and finally reaches an optimal solution. In this work, we used an elitism based Genetic Algorithm (GA) to optimize the free parameters α and β of the nonlinear Half-Gaussian filter model.

3.2 Skeletal Muscle Force Signal Pre-Processing

Chebyshev Type II filter with a 550 Hz pass frequency is used to filter skeletal muscle force (see Figure 3). This filter has a flat passband magnitude response, and an equiripple response in the stopband, it minimizes the error between the idealized and the actual filter characteristic over the range of the filter, [19], [20].

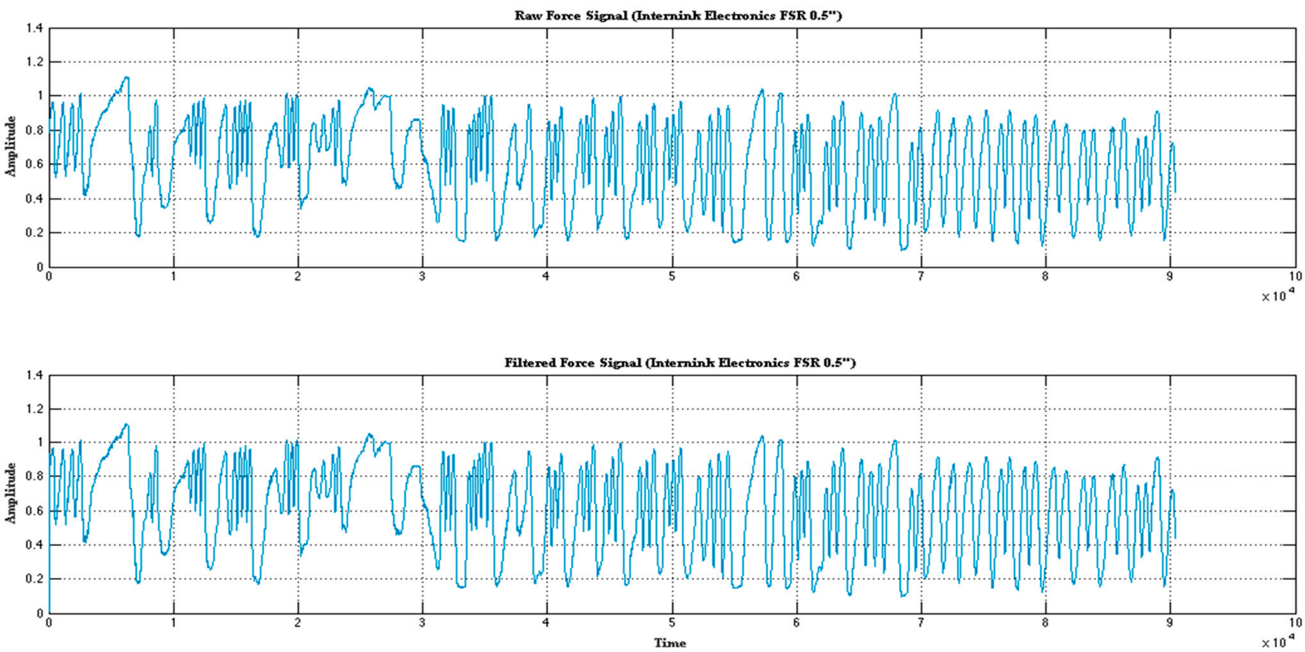

Figure 3: Raw skeletal muscle force signal vs. Chebyshev type II filtered force signal (Interlink Electronics FSR 0.5”).

3.3 Wiener-Hammerstein Modeling

The sEMG signal from three ring finger sensors and the skeletal muscle force signal are modeled using nonlinear Wiener-Hammerstein models with different nonlinearity estimators/classes. The Wiener-Hammerstein model uses one or two static nonlinear blocks in series with a linear block (see Figure 4), equations (3), (4), and (5) can describe the Wiener-Hammerstein structure, [21].

$$w(t) = f(u(t)) \tag{3}$$

$$x(t) = \frac{B_{j,i}(q)}{F_{j,i}(q)} w(t) \tag{4}$$

$$y(t) = h(x(t)) \tag{5}$$

Here $u(t)$ and $y(t)$ are input and output of the system, respectively, and f and h are nonlinear functions, which corresponds to input and output nonlinearity, respectively, $w(t)$and $x(t)$are internal variables, where $w(t)$ has the same dimensions as $u(t)$and $x(t)$and has the same dimensions as $y(t)$, and $B(q)$and $F(q)$corresponds to the linear dynamic block, these are polynomials in the backward shift operator.

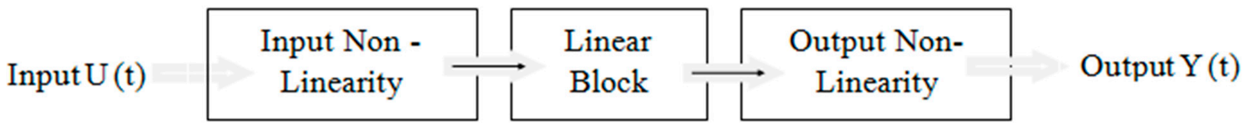

Figure 4: Nonlinear Wiener-Hammerstein Model Structure.

Table 1: Nonlinear Wiener-Hammerstein Models with Best Model Fit Values for Ring Motor Point, Ring1 and Ring2 sEMG Signal.

Model	Nonlinearity Class	Model Fit (%)
Ring Motor Point sEMG Signal	Pwlinear	40.17
Ring1 sEMG Signal	Sigmoidnet	33.45
Ring2 sEMG Signal	Pwlinear	24.46

The nonlinearity classes used in this work are Wavenet, Sigmoidnet, Pwlinear, Saturation, and Deadzone. For motor point and ring1 sensors, four nonlinear Wiener-Hammerstein models with different nonlinearity estimators/classes are obtained. The nonlinearity estimators/classes for different sensors and their corresponding model fit values (see Table 1).

3.4 Multiple Regression Model

Two broad classes of supervised learning (SL) are classification and regression. A learning method to estimate the relationship between a dependant variable and one or more independent variables is called Regression. Dependent variable is named as response and independent variable as predictors. The purpose is to predict the response with given predictors, [22]. Multiple regression is regression with two or more independent predictors, here we can use more than one factor to make a prediction whereas in case of simple regression we have only one causal factor. Multiple regression also lets you separate causal factors, analyzing each one's influence on what we are trying to explain, [23]. Mathematically, multiple regression with more than two independent variables tries to fit the hyper planes to the data points. The response variable Y is given by the predictors $X_1, X_2, \ldots, X_P$, [23].

$$Y = \upsilon + \nu_1 X_1 + \nu_2 X_2 + \ldots + \nu_P X_P + error \qquad (6)$$

where υ is the intercept and $\nu_1, \nu_2, \ldots, \nu_P$are the regression coefficients, which are analogous to slope parameter in the simple linear regression equation. That is, if $X_2 \ldots X_P$ is fixed, then for each change of 1 unit in X_1, Y changes ν_1 units. After the regression model is constructed, there are parameters, such as coefficient of determination orR^2value and p- values, to decide whether the constructed model is good or not. Closer the R^2towards 1, better is the model. But there are cases where even low value of R^2may predict better. For example, humans are generally harder to predict. So, a regression model for predicting information related to human with low R^2, typically near 0.5, can give a better model, [24].

In this work we have three input signals from three sEMG sensors, which we use to estimate/predict the force signal. The train and test data from a data set of 90400 observations have 70000 and 20400 number of observations respectively. The root mean square error, adjusted $R^2$and p-values are 0.204, 0.403 and 0 (for each predictor) respectively.

4. Results and Discussion

This section deals with the results and discussion. We obtained nonlinear Wiener-Hammerstein models for the sEMG and Skeletal Muscle Force signal pairs for three ring finger sEMG sensor using different nonlinearity classes, e.g. Pwlinear and Sigmoidnet, etc. Best model for each sensor (Motor Point, Ring1 and Ring2) is selected to simulate the output. In this work, we use Kullback Information Criterion (KIC) based adaptive data fusion algorithm on the three estimated outputs to obtain final single output (see Figure 5), [10]. Kullback's symmetric or J-divergence is sum of two directed divergences and a measure of the models dissimilarity, which is also known as KIC.

$$KIC(p_i) = \frac{n}{2} log R_i + \frac{(p_i+1)n}{n-p_i-2} - n\psi(\frac{n-p_i}{2}) + g(n), \qquad (7)$$

where $g(n) = n * log(n/2)$, n is the number of data points, $p = 2$, $\psi$is gamma function, R is residual square norm and i is model index, [10]. Along with this we applied multiple regression with three sEMG sensor signal as predictors and one force sensor signal as response variable (see Figure 6).

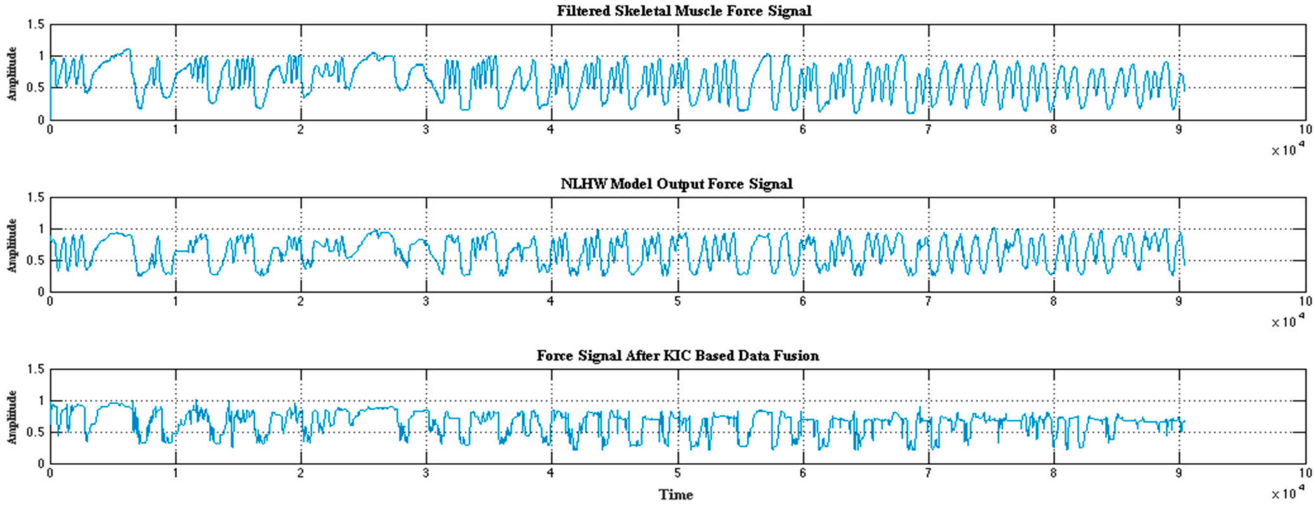

Figure 5: Nonlinear Hammerstein-Wiener Model Output, KIC Based Data Fusion Output, and Filtered Skeletal Muscle Force Signal.

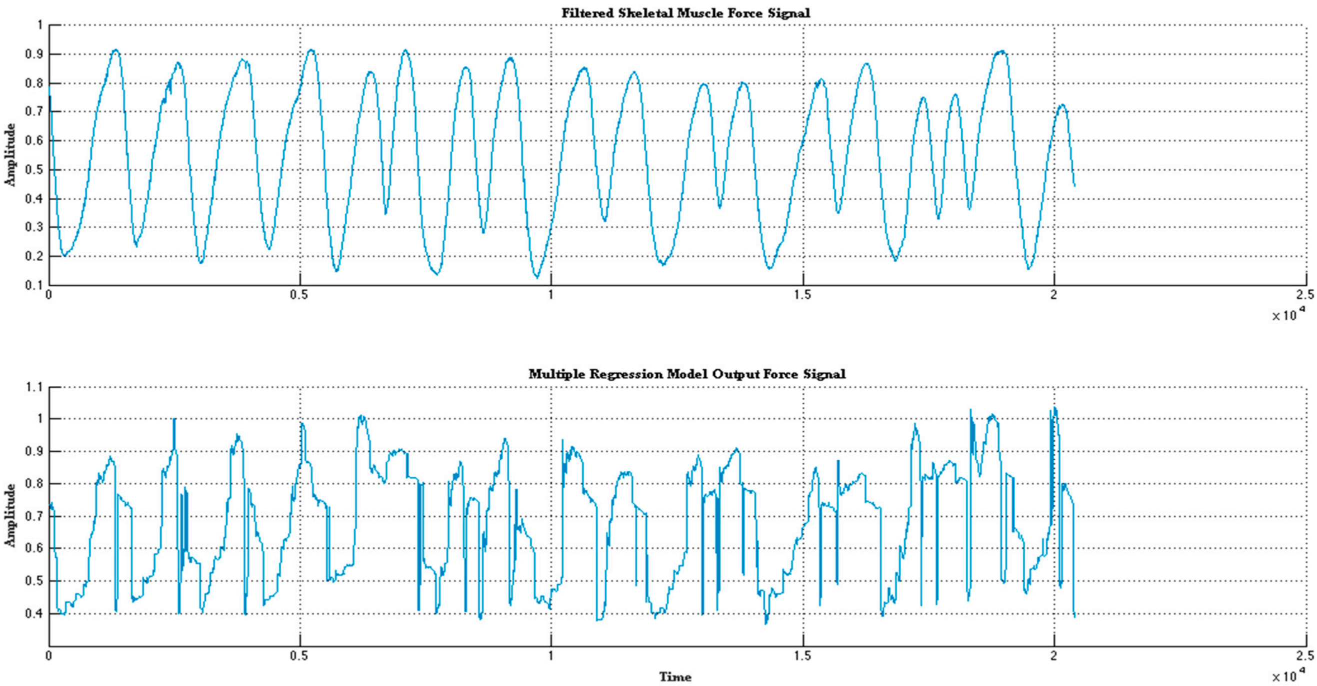

Figure 6: Multiple Regression Model Output and Filtered Skeletal Muscle Force Signal.

Both the methods seems to work fairly in this case and give model fit value over 40 %. This might not be the case all the time and for real time operation we can have more challenges. Therefore, for such scenarios we propose to use a threshold based approach, where we make the actuator on when we have sEMG value above a certain threshold, e.g. 40-50 % of the maximum sEMG amplitude (see Figure 7 and Table 2). Various statistical measures of the Ring Finger Motor Point sEMG and force signal are also computed (see Table 3).

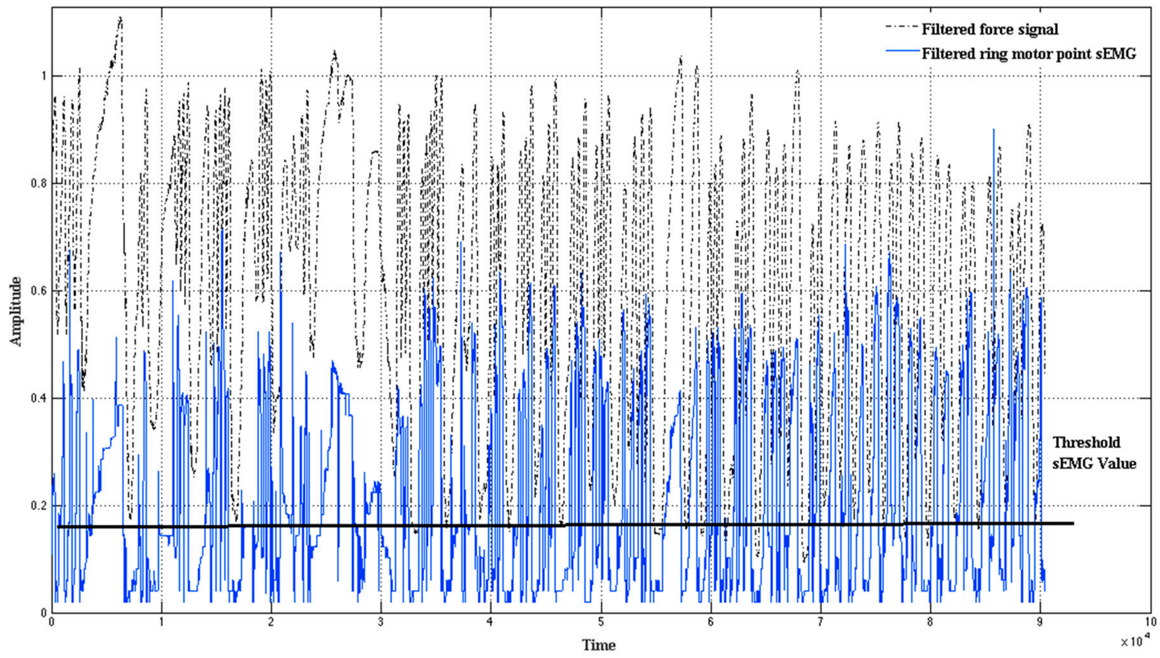

Figure 7: Ring Finger Motor Point sEMG vs. Skeletal Muscle Force: A Threshold sEMG Value Based Approach.

Table 2: Threshold Based Entropy Values for Ring Finger Motor Point sEMG and Force Signal.

Percentage	Entropy sEMG (Motor Point)	Entropy Force Signal
45 %	18632	59081
50 %	12357	54094
60 %	3785	43790
70 %	258	30752
75 %	30	22025
80 %	6	13822
90 %	4	2986
100 %	0	0

Table 3: Statistical Measures for Ring Finger Motor Point sEMG and Force Signal.

	Motor Point sEMG	Force Signal
Mean	0.2107	0.6134
Median	0.1441	0.6528
Maximum	0.9010	1.1119
Range	0.8806	1.0988
Variance	0.0297	0.0671
Kurtosis	2.1445	1.9080
Skewness	0.6975	-0.2679

5. Conclusions and Future Works

In this work we obtained models for skeletal muscle system, sEMG signal is considered as input and force signal as output. Filtered sEMG and force signals are used for Nonlinear Hammerstein-Wiener Model, Multiple Regression Model and Threshold sEMG Value Based Approach. Nonlinear Hammerstein-Wiener Model and Multiple Regression Model give good results for the measured data. For real time scenarios and robust results we propose a Threshold sEMG Value Based Approach, where we make the actuator on when the sEMG amplitude is at certain level. Future work will focus on more rigorous learning algorithms and sEMG from large number of sensors. Simulink model of the prosthetic hand will be used to present the results.

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