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

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Authors: Parmod Kumar1*, Devanand R and Marco P. Schoen

Outline

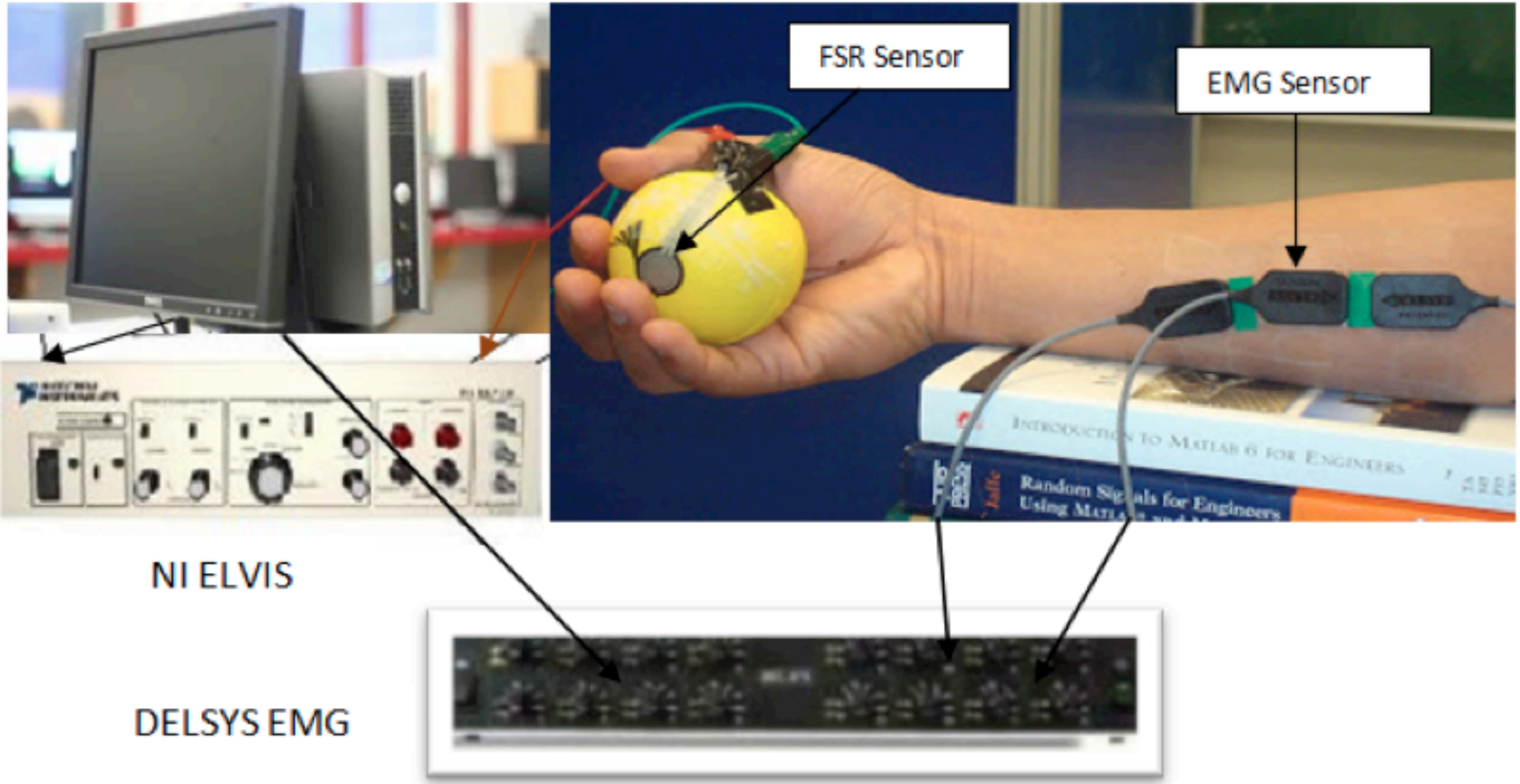
Introduction

- Skeletal muscle force and surface electromyographic (sEMG) signals have an inherent relationship.
- 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.
- 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.

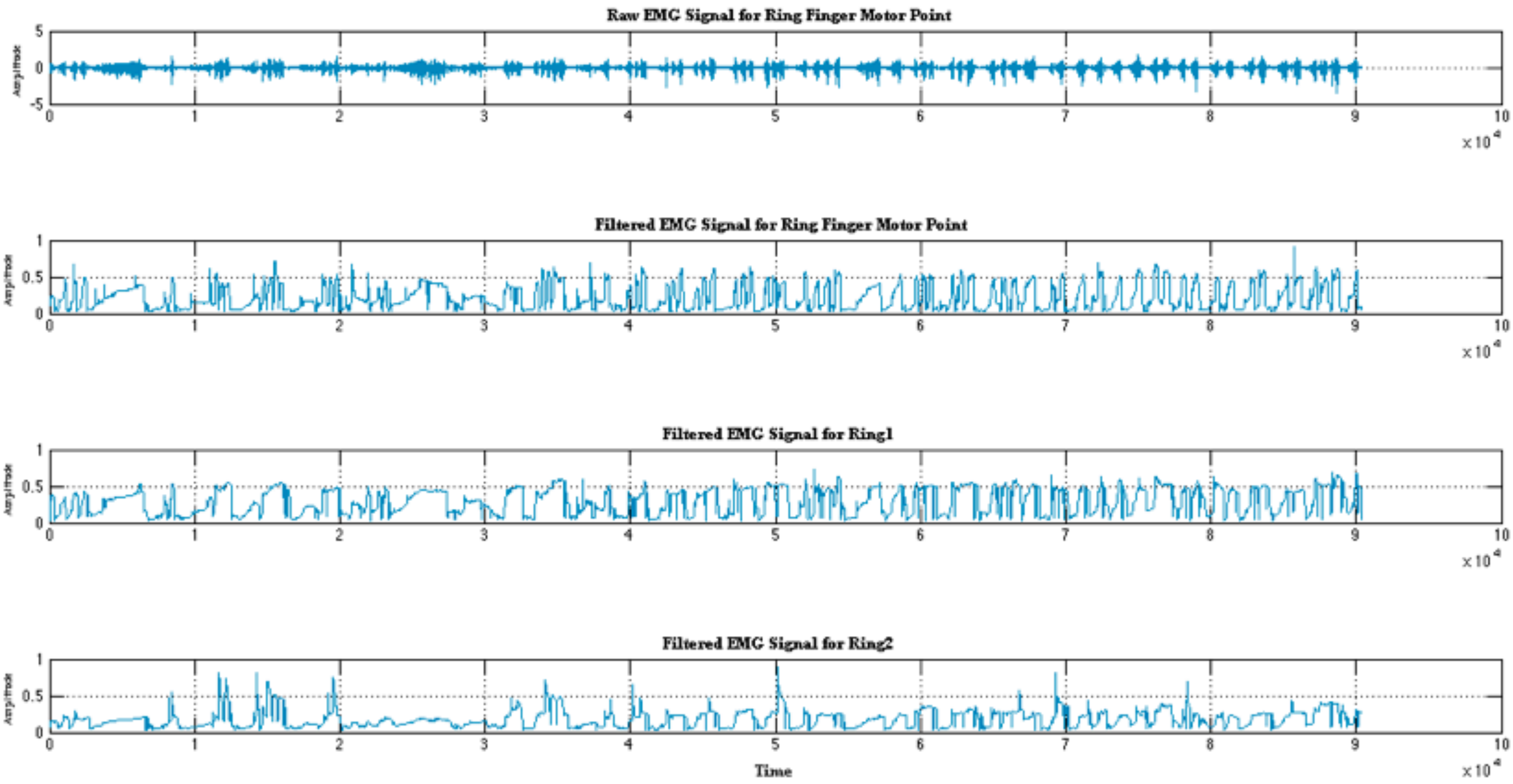
Motivation

- The number of people living with limb loss in USA are approximately 1.7 million, [1], [2].
- There is one in every 200 people has had an amputation, [1], [2].
- Reason for this number are: war injury, cancer and trauma, and due to complications of the vascular system (majority), [3], [4].
- A prosthetic limb can improve the quality of everyday life of an amputee by increasing the functionality.
- 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, which generate EMG signal (-5 and +5 mV).
- As sEMG is easily available, it is a natural choice to use as a control signal for the prosthesis, [5]-[13].
- To improve the quality of life of the people with upper-extremity we need good prosthetic hand.
- 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.

Experimental Set-Up and Data Collection

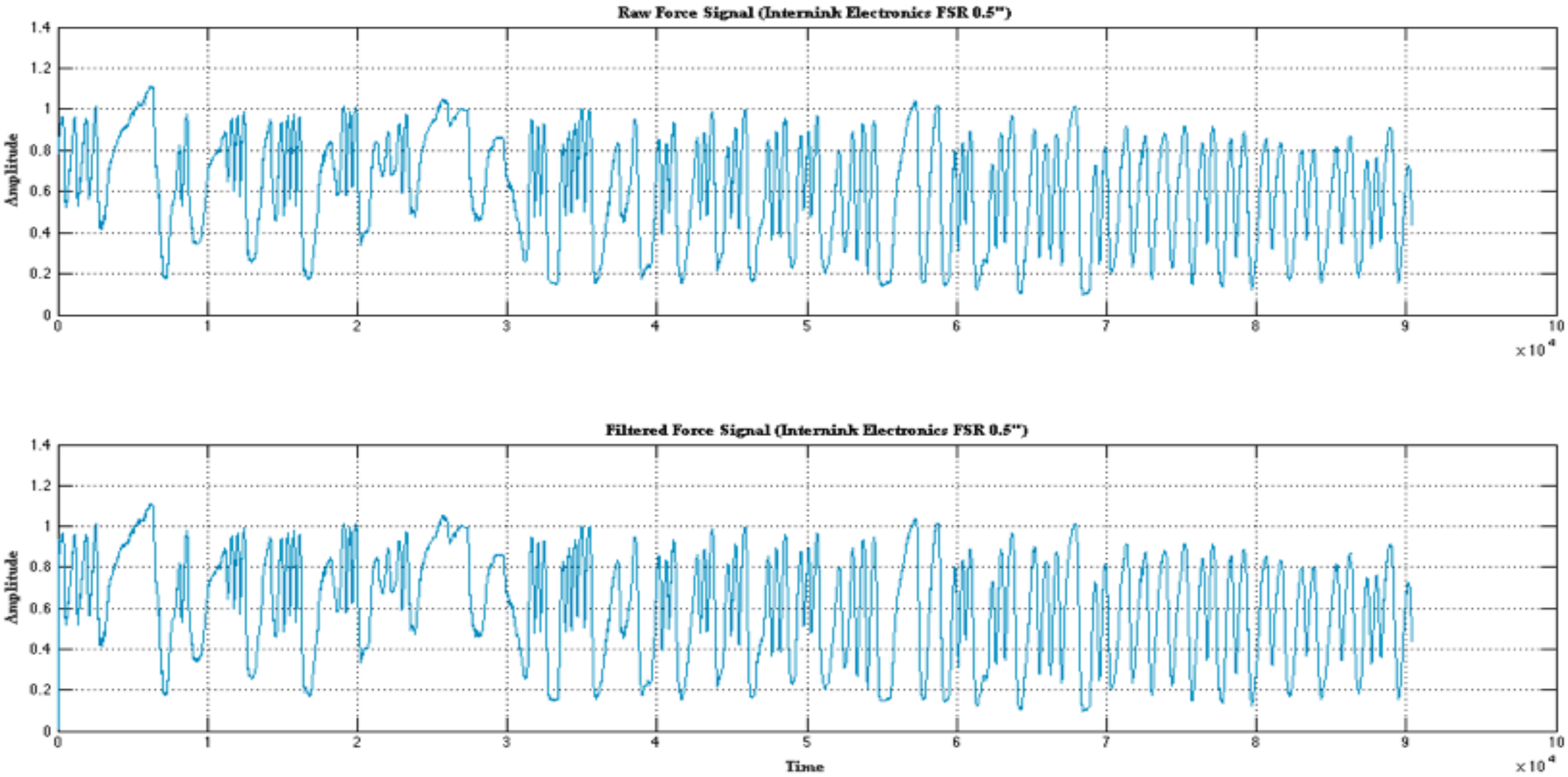


Pre-Processing/Filteration



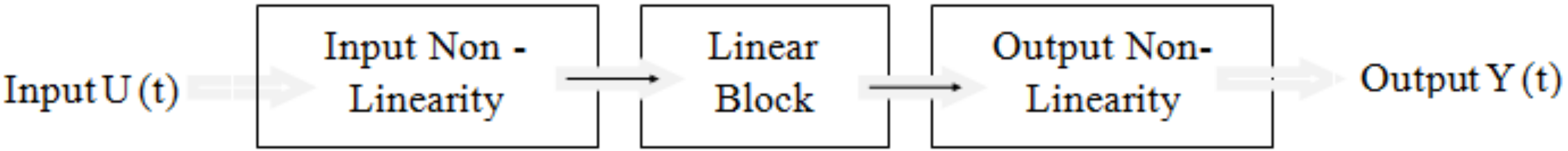
Raw sEMG vs. Half-Gaussian filtered sEMG signal for ring finger Motor Point, Ring1 and Ring2 sensors.

Pre-Processing/Filteration



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

NLHW Model



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

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.

Multiple Regression Model

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.

The response variable Y is given by the predictors $X_1, X_2, \ldots, X_p$, [23].

$$Y = \upsilon + v_1 X_1 + v_2 X_2 + \ldots + v_p X_p + error$$

where υ is the intercept and $v_1, v_2, \ldots, v_p$ are the regression coefficients, which are analogous to slope parameter in the simple linear regression equation.

Entropy Based Threshold Approach

- The two modeling methods, a nonlinear Hammerstein-Wiener model and Multiple Regression model 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.

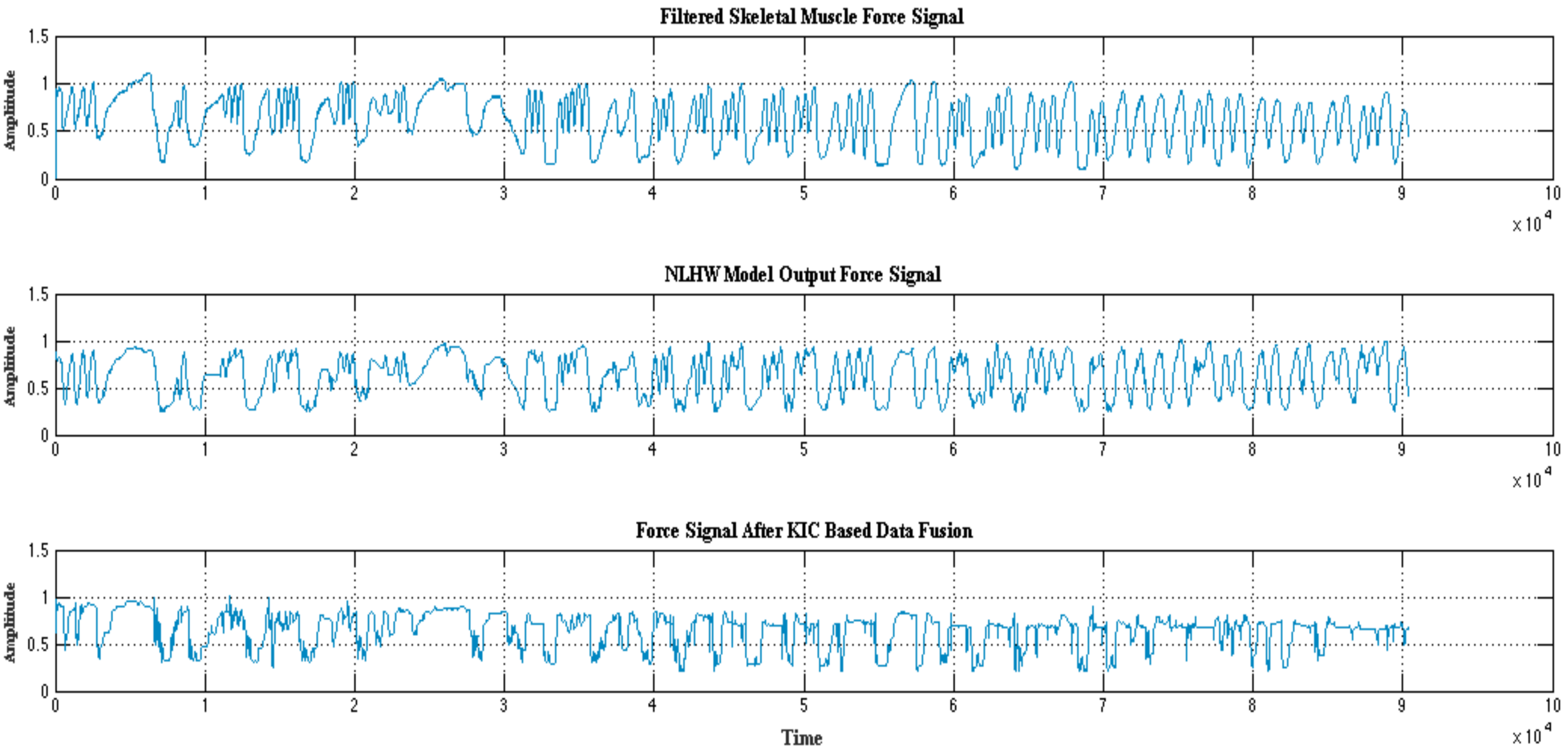
- In this threshold based approach, where we make the actuator on when we have sEMG value above a certain threshold, e.g. 40-50 % of the maximum sEMG amplitude.

Results and Discussion

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

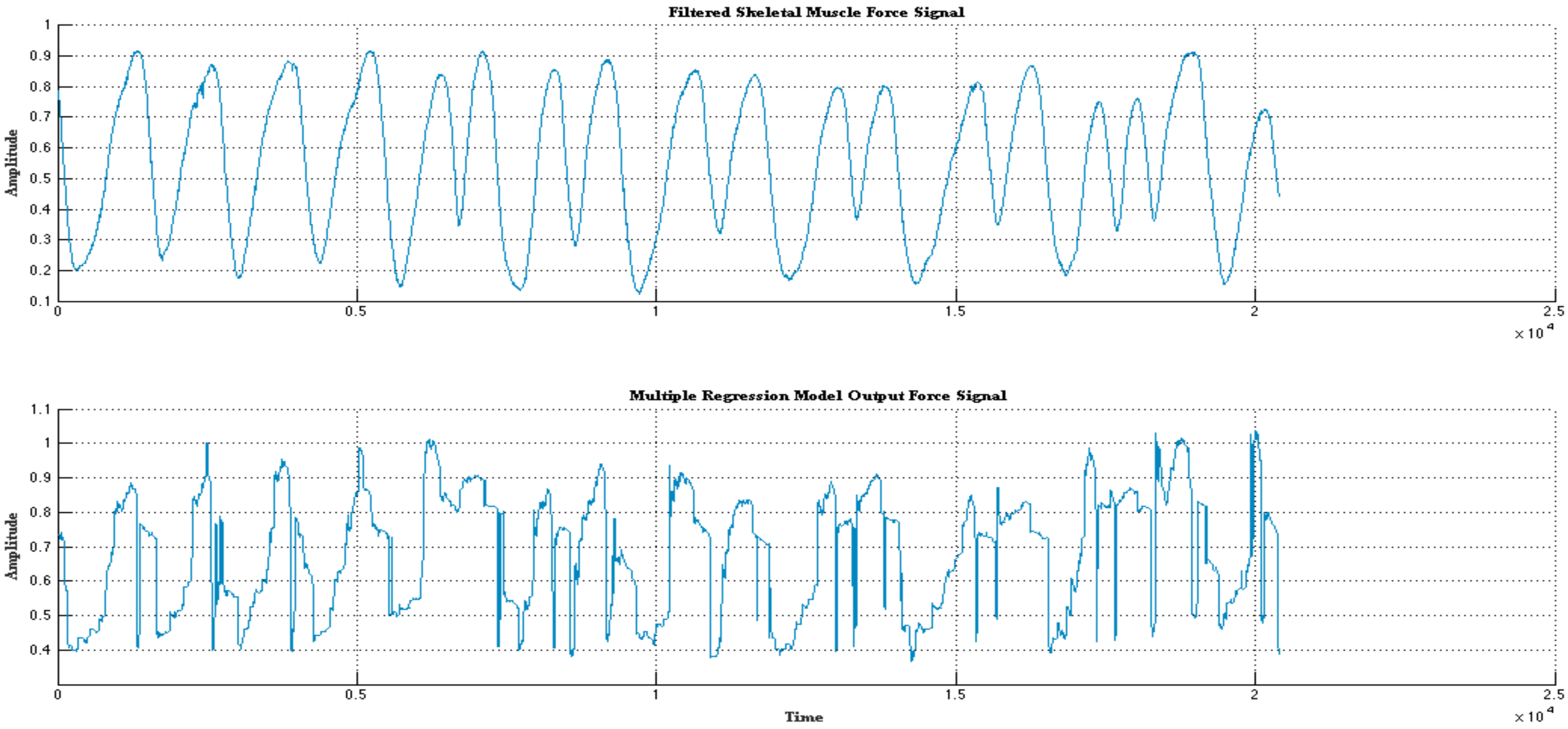
Model	Nonlinearity Class	Model Fit (%)
Ring Motor Point sEMG Signal	Pwlinear	40.17
Ring1 sEMG Signal	Sigmoidnet	33.45
Ring2 sEMG Signal	Pwlinear	24.46

Results and Discussion



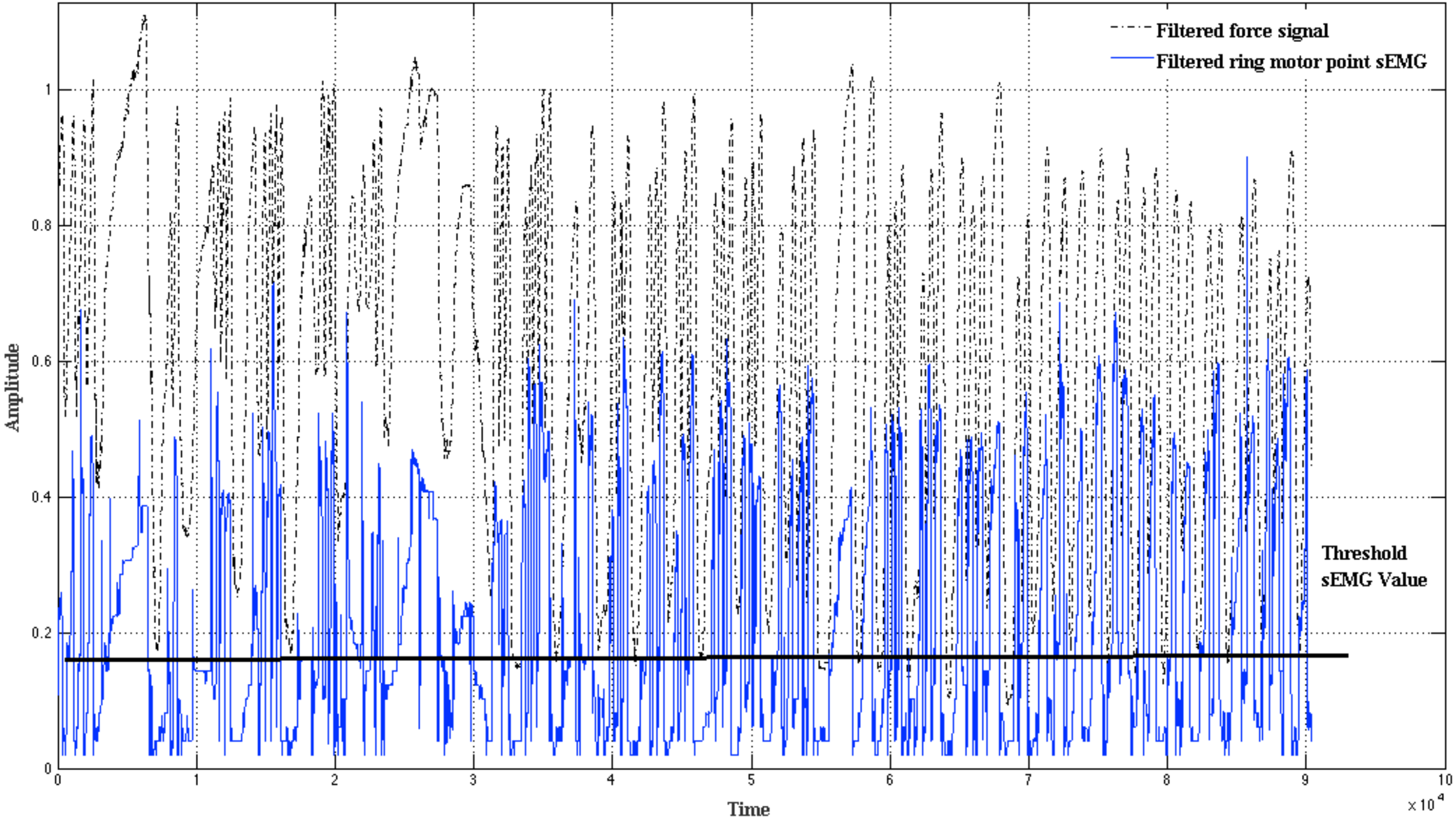
Nonlinear Hammerstein-Wiener Model Output, KIC Based Data Fusion Output, and Filtered Skeletal Muscle Force Signal.

Results and Discussion



Multiple Regression Model Output and Filtered Skeletal Muscle Force Signal.

Results and Discussion



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

Results and Discussion

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

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

Results and Discussion

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

Conclusions and Future Works

1. In this work we obtained models for skeletal muscle system, sEMG signal is considered as input and force signal as output.
2. Filtered sEMG and force signals are used for Nonlinear Hammerstein-Wiener Model, Multiple Regression Model and Threshold sEMG Value Based Approach.
3. Nonlinear Hammerstein-Wiener Model and Multiple Regression Model give good results for the measured data.
4. 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.
5. 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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