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Fusion of Spectral Models for Dynamic Modeling of sEMG and Skeletal Muscle Force

Chandrasekhar Potluri, *Member, IEEE*, Madhavi Anugolu, *Member, IEEE*, Steve Chiu, *Member, IEEE*, Alex Urfer, Marco P. Schoen, *Senior Member, IEEE*, and D. Subbaram Naidu, *Fellow, IEEE*

Abstract— **In this paper, we present a method of combining spectral models using a Kullback Information Criterion (KIC) data fusion algorithm. Surface Electromyographic (sEMG) signals and their corresponding skeletal muscle force signals are acquired from three sensors and pre-processed using a Half-Gaussian filter and a Chebyshev Type- II filter, respectively. Spectral models - Spectral Analysis (SPA), Empirical Transfer Function Estimate (ETFE), Spectral Analysis with Frequency Dependent Resolution (SPFRD) - are extracted from sEMG signals as input and skeletal muscle force as output signal. These signals are then employed in a System Identification (SI) routine to establish the dynamic models relating the input and output. After the individual models are extracted, the models are fused by a probability based KIC fusion algorithm. The results show that the SPFRD spectral models perform better than SPA and ETFE models in modeling the frequency content of the sEMG/skeletal muscle force data.**

I. INTRODUCTION

There are approximately 1.7 million people living with an amputation in the United States according to the amputation statistics provided by the National Limb Loss Information Center. It has also been suggested that one out of every 200 people in the U.S. has had an amputation [1]. H. Piper [2] introduced the first investigation into Electro Myographic (EMG) signals in 1921. EMG signals can be used in various applications such as clinical diagnosis, engineering applications, physical therapy, etc. During the past few decades, a wide array of studies have focused on the functionality of various upper extremity prostheses but investigators have yet to put forth a cost effective prosthesis that truly simulates normal human hand function [3]. The electromyographic (EMG) signal is the primary electrical activity of the skeletal muscles. These signals can be detected either with sensors placed on the surface of the skin or with needle sensors inserted into the muscle tissue. In this work, noninvasive technique is used to acquire the surface electro-myographic (sEMG) signals [4]. During muscle contraction, many motor units are activated at the same time. This contributes to interferences with the sEMG signal and cross talk, which is a major issue in accurate sEMG signal monitoring [5]. The number of motor units in individual muscles varies from person to person. Muscle fatigue begins at the onset of muscle contraction and progressively continues throughout the time of the muscle activation. Fatigue will induce an increase in motor unit recruitment and a decrease in mean medium frequency in the sEMG signal. The sEMG signals pass through numerous layers of tissues before reaching the skin surface [5]. The uncertainty of the sEMG signal presents a special challenge in their analysis. All of these factors increase the complexity of discriminating the content of the EMG signal against noise and interference. Identification of the content of the EMG signal should focus on the amplitude, frequency and amplitude-frequency using distinct methods. As the EMG signal is time dependent and amplitude modulated, it is spatially and temporally frequency encoded [6]. From the literature, it is apparent that sensor data fusion improves the output measurement quality [4]. In [7], a multi-channel grid surface electrode is employed. Using this, the spatial and temporal aspects of time varying potential distribution of the sensors on the skin can be recognized. sEMG data fusion algorithms were designed by the authors using time domain linear Output-Error (OE) models and non-linear Weiner-Hammerstein models in the past[4, 8, 9].

In this work, spectral models - Spectral Analysis (SPA), Empirical Transfer Function Estimate (ETFE), Spectral Analysis with Frequency Dependent Resolution (SPAFDR) –are obtained using sEMG and skeletal muscle force data. Finally, the spectral models are fused using the KIC algorithm for the improved estimation of skeletal muscle force. This paper is structured as follows. The experimental set up is given in Section II and Section III provides the background information for system identification and spectral models. Section IV details the results and discussion and in the last section, some conclusions are provided.

Chandrasekhar Potluri is with Measurement and Control Engineering Research Center (MCERC), Idaho State University, Pocatello, Idaho 83201 USA (e-mail: potlchan@isu.edu).
Madhavi Anugolu is with MCERC, Idaho State University, Pocatello, Idaho 83201 USA (e-mail: anugmadh@isu.edu).
Steve Chiu is with Department of Electrical Engineering and Computer Science, MCERC, Idaho State University, Pocatello, Idaho 83201 USA (email:chiustev@isu.edu).
Alex Urfer is with Department of Physical and Occupational Therapy, Idaho State University, Pocatello, Idaho 83209, (email:urfealex@isu.edu)
Marco P. Schoen is with Department of Mechanical Engineering, MCERC, Idaho State University, Pocatello, Idaho 83201 USA (e-mail:schomarc@isu.edu).
D. Subbaram Naidu is with Department of Electrical Engineering and Computer Science, MCERC, Idaho State University, Pocatello, Idaho 83201 USA (email: naiduds@isu.edu).

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II. Experimental Set-up

The experiments are conducted on a healthy male subject in order to acquire the sEMG and corresponding skeletal muscle force (y_f) signals. First, the skin surface is slightly abraded and cleaned with alcohol swabs and the test subject was prepared by following the ISEK standards [10]. A wet probe point muscle stimulator manufactured by Rich-Mar Corporation (Model number HV-1000) is used to identify the motor point of the flexor digitorum superficialis muscle. An array of three sensors are placed, one on the motor point and the other two adjacent to the motor point. A Delsys Bagnoli-16 channel EMG equipment is used to capture sEMG signal and the related skeletal muscle force (y_f)signal is acquired using Force Sensitive Resistor (FSR). Both of the signals are acquired at a sampling rate of 2000 samples/sec for duration of 10 seconds. The sEMG signal is filtered by using a Half-Gaussian filter and the skeletal muscle force signal (y_f) is filtered using a Chebyshev Type-II filter whose cut-off frequency is set to 550 Hz [10]. The Half-Gaussian filter is given by:

$$p(EMG|x) = 2\frac{\exp\left\{-\frac{EMG^2}{2x^2}\right\}}{\sqrt{2\pi x^2}}, \quad (1)$$

where $p(EMG|x)$ is the conditional probability, x is the latent driving signal, and EMG is the acquired data.

III. PROPOSED DESIGN

System Identification (SI) technique is utilized to achieve the dynamic relationship between sEMG and the skeletal muscle force (y_f). In [4, 8], sensor fusion is done by combining linear and non-linear time domain SI models. Combinations of different filters (Butterworth, Chebyshev, Exponential and Half-Gaussian filters) and different information criteria based on Akaike (AIC), Bayesian (BIC), and Kull-back (KIC) were used. A KIC criterion with Half Gaussian filtering gives the best EMG/Force model correlation [8]. In this work, spectral models are used to achieve SI. The idea is to capture and model the frequency content of the sEMG signal. Three spectral models of each type i.e. SPA, ETFE and SPAFDR are obtained for the sEMG from the three sensors and the corresponding skeletal muscle force (y_f) data. The detailed mathematical structures of the utilized spectral models are given below,

Spectral Analysis (SPA):

Consider a linear dynamic system,

$$y(t) = G(q)u(t) + v(t) \quad (2)$$

where $u(t)$ is the sEMG signal, $y(t)$-force signal,and $G(q)$ is the transfer function which gives the dynamic relationship between sEMG and force. $G(q)$ is evaluated on the unit circle

$$G(q = e^{jw}) \quad (3)$$

where ω is a frequency content of the signal. The SPA models are computed as follows,

Computing the covariance's and cross-covariance's from sEMG signal $(u(t))$ and skeletal muscle force signal $(y_f(t))$

$$\hat{R}_y(\tau) = \frac{1}{N}\sum_{t=1}^{N} y(t+\tau)y(t) \quad (4)$$

$$\hat{R}_u(\tau) = \frac{1}{N}\sum_{t=1}^{N} u(t+\tau)u(t) \quad (5)$$

$$\hat{R}_{yu}(\tau) = \frac{1}{N}\sum_{t=1}^{N} y(t+\tau)u(t) \quad (6)$$

Later, the Fourier transforms of the above three equations are computed by using,

$$\hat{\Phi}_y(\omega) = \sum_{\tau=-M}^{M} \hat{R}_y(\tau)W_M(\tau)e^{-i\omega\tau} \quad (7)$$

$$\hat{\Phi}_u(\omega) = \sum_{\tau=-M}^{M} \hat{R}_u(\tau)W_M(\tau)e^{-j\omega\tau}, \quad (8)$$

$$\hat{\Phi}_{yu}(\omega) = \sum_{\tau=-M}^{M} \hat{R}_{yu}(\tau)W_M(\tau)e^{-j\omega\tau}, \quad (9)$$

In (7), (8) and (9) $W_M(\tau)$ is the Hann window of width $-M$ to M. Where M is a scalar integer that sets the size of the lag window. The frequency-response function $\hat{G}_N(e^{j\omega})$ and the output nosie spectrum $\hat{\Phi}_v(\omega)$ are computed as,

$$\hat{G}_N(e^{i\omega}) = \frac{\hat{\Phi}_{yu}(\omega)}{\hat{\Phi}_u(\omega)} \quad (10)$$

$$\Phi_v(\omega) = \sum_{\tau=-\infty}^{\infty} R_v(\tau)e^{-j\omega\tau} \quad (11)$$

The frequency resolution is calculated by,

$$\zeta = \frac{2\pi}{M}\left(\frac{radians}{sampling\ interval}\right) \quad (12)$$

Empirical Transfer function Estimate (ETFE)

The ETFE function of (2) gives the transfer function estimate $G(e^{jw})$ at the frequencies

$$\omega = \left[\frac{[1:N]}{N}\right] * \frac{\pi}{T} \quad (13)$$

where $N = 128$(default)

$$U_f(\omega) = \sum_{\tau=-M}^{M} u(\tau)W_M(\tau)e^{-j\omega\tau} \quad (14)$$

$$Y_f(\omega) = \sum_{\tau=-M}^{M} u(\tau)W_M(\tau)e^{-j\omega\tau} \quad (15)$$

Dividing (15) by (14) and applying the Hann window as in the SPA models, with the length of the range of number of data points yields the frequency-response function $\hat{G}_N(e^{j\omega})$ and the output noise spectrum $\hat{\Phi}_v(\omega)$ same as (10) and (11). Both the SPA and ETFE have the same frequency resolution.

Spectral Analysis with Frequency Dependent Resolution (SPAFRD):

For the linear dynamic system given in (2) SPAFRD frequency response function returns transfer function estimate $G(e^{jw})$ as well as the spectrum additive noise. The sEMG and the skeletal muscle force data are converted into frequency domain $U(\omega)$ and $Y(\omega)$

The frequency domain data are formed as

$$avg\left[\frac{Y(\omega)conj\ U(\omega)*U(\omega)conj\ Y(\omega)}{\omega}\right] \qquad (16)$$

with a desired resolution of $\zeta(k) = 2(w(k+1) - w(k)$

The frequency-response function $\hat{G}_N(e^{j\omega})$ and the output noise spectrum $\hat{\Phi}_v(\omega)$ are computed as,

$$\hat{G}_N(e^{i\omega}) = \frac{\hat{\Phi}_{yu}(\omega)}{\hat{\Phi}_u(\omega)} \qquad (17)$$

$$\Phi_v(\omega) = \lambda T|H(e^{j\omega T})|^2 \ . \qquad (18)$$

Fusion Algorithm:

The Kullback Information Criterion (KIC) is a symmetric measure used in this paper for the fusion of spectral data. The mathematical form of the KIC is given as:

$$KIC(p_i) = \frac{n}{2}\log R_i + \frac{(p_i+1)n}{n-p_i-2} - n\psi\frac{(n-p_i)}{2} + g(n) \quad (19)$$

where, n is the number of data points p_i is the order of the model, ψ is the digamma function, and $g(n) = n * log\frac{n}{2}$.

After calculate the KIC for each of the three models, the following fusion algorithm was used in order to get the overall estimated finger force $\widehat{y_f}$,

1. The Spectral models $M_{f1}, M_{f2} \dots M_{fk}$ are computed using sEMG data (u_k) as input and force data (y_f) as output, for k number of sEMG sensors (Where $k = 3$ in this case).

2. Residual square norm is calculated by $R_i = \|y-\Phi_i\hat{\theta}_i\|^2 = \|y-\hat{y}\|_2$ where $\hat{\theta}_i = \{\Phi_i^T\Phi_i\}^{-1}\Phi_i^T y$,

$$\text{and } \vec{\Phi} = \begin{bmatrix} y_p^T & u_p^T & y_{p-1}^T & \cdots & {}_1 \\ {}_{p+1} & u_{p+1}^T & y_p^T & \cdots & {}_2 \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ y_{n-1}^T & u_{n-1}^T & y_{n-2}^T & \cdots & {}_{n-p} \end{bmatrix}$$

3. Using (19) model criteria coefficients are computed.

4. The model probability is computed by

$$p(M_{fi}|Z) = \frac{e^{-l_i}}{\sum_{j=1}^{k} e^{-l_j}}$$

l _ Model selection criteria coefficient.

5. Fused output model is computed by,

$$\hat{Y}_f = \sum_{i=1}^{k} p(M_{fi}|Z)\hat{y}_{fi}$$

IV. RESULTS AND DISCUSSION

In order to extract the best working spectral model for the sEMG and skeletal muscle force data three spectral models SPA, ETFE, SPAFDR are constructed based on the sEMG data from the individual sensor and the corresponding skeletal muscle force. The three spectral models of same type are fused using the KIC algorithm resulting in three fusion algorithm estimated force for each spectral model type $(\hat{Y}_{f(SPA)}, \hat{Y}_{f(ETFE)}, \hat{Y}_{f(SPAFDR)})$. The Pearson's correlation coefficient $(\rho_{X,Y})$ in percentage relating the actual force (y_f) from the FSR and the fusion algorithm estimated force $(\hat{Y}_f)$ for each spectral model is tabulated in Table 1.

TABLE I: COMPARISON OF CORRELATIONS OF INDIVIDUAL MODELS AND THE FUSED OUTPUT FOR SPA, SPAFDR AND ETFE

	Correlation $(\rho_{X,Y})$			
Models	(M_{f1})	(M_{f2})	(M_{f3})	**Fusion(** $\hat{Y}_f$**)**
SPA	32.52	29.68	36.19	50.29
SPAFDR	57.61	69.87	65.23	85.68
ETFE	N/A	N/A	N/A	-53.55

It is evident from Table I that SPAFDR models are yielding the better correlation. The ability to choose the frequency resolution in the SPAFDR models allows modeling of the frequency content of the sEMG signals. The inability of SPA and ETFE to model the non-linear frequencies and non-periodic inputs caused them to fail to capture the frequency of a transient sEMG signal. M_{f3} is constructed from the sensory data located on the motor unit. Therefore it is yielding better correlation than M_{f1}, M_{f2}. It is also clear that the KIC based fusion algorithm improves the skeletal muscle force estimation when compared to individual spectral models.

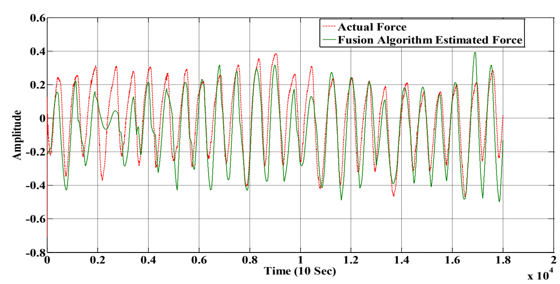

Figure. 1: Actual Force (y_f) and the Fusion Algoirhtm Estimated Force $(\hat{Y}_f)$.

Fig . 1 and Fig. 2 shows the actual force (y_f) and the fusion algorithm estimated force $(\hat{Y}_f)$ from the three SPAFDR models plotted together. The fusion algorithm estimated force follows the trends in the actual force and match up with the actual force.

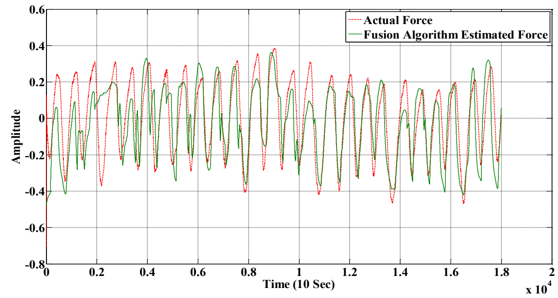

Figure. 2: Validation Plot.

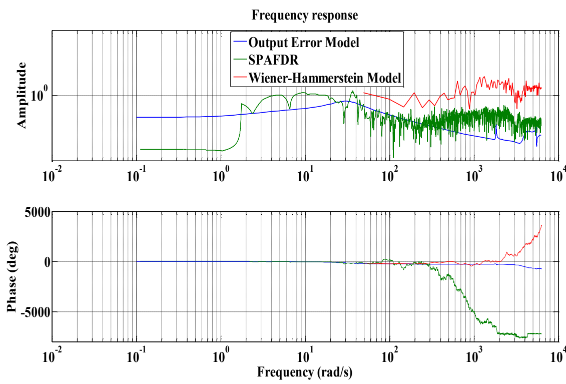

Figure. 3: Frequency Response of SPAFDR, Output-Error (OE) and Wiener-Hammerstein Models.

Fig 3 gives the frequency response in comparison with the SPAFDR based fusion force estimate using OE and Wiener-Hammerstein models that were previously developed by the authors [4, 8, 9]. It is interesting that the SPAFDR spectral models are capturing a different band of frequencies when compared to the other two models. This indicates that SPAFDR models are capturing more of the additional information than the time domain OE and Wiener-Hammerstein models. This difference can be due to reasons, such as model order selection, input design for the experiment, etc.

V. CONCLUSION AND FUTURE WORK

In this work, three different spectral models were analyzed. From the results, it is clear that SPAFDR gives better correlation between the actual force (y_f) and the fusion algorithm estimated force $(\hat{Y}_f)$, when compared to the other two spectral models SPA and ETFE. Since the sEMG is a non-periodic signal, the application of the Hann window and fixed resolution are the possible reasons for the failure of the SPA and ETFE model structures for capturing the characteristics of sEMG/skeletal muscle force signals. In addition, the results imply that the SPAFDR spectral models are capturing the frequencies that are not captured by OE and Wiener-Hammerstein models.

In future we plan to apply wavelet transforms on the sEMG signals to provide a better windowing of the useful frequency content of the sEMG signal. It will also be interesting to fuse both the spectral and the non-linear models for the improvement of the correlation between actual (y_f) and fusion algorithm estimated forces $(\hat{Y}_f)$.

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