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A Physiologically and Biomechanically Approximate Model for Surface Electromyography Amplitude Estimation

Changmok Choi, Hae-Dong Lee, and Jung Kim, *Member, IEEE*

***Abstract*—Surface electromygraphy (sEMG) provides information of the neural drive to the muscle, so muscle force estimation by sEMG is of high relevance in biomechanical studies and in bionic applications. Even though mean absolute value (MAV) has been widely used for sEMG amplitude estimation due to the probabilistic nature of sEMG, but it has been used without any comprehensive physiological justification. A physiologically and biomechanically approximate model for the force estimation would enable a clear understanding of the relationships between sEMG and the force, and it can be used as sEMG amplitude estimation method. We proposed a new sEMG amplitude estimation method comprising two procedures: MUAP (motor unit action potential) event detection and muscle force indication using a biomechanical muscle model. The estimation performances were evaluated with nine subjects and compared with MAV. The performance (R^2) of the proposed method (0.94 ± 0.03) outperformed it of MAV (0.90 ± 0.02). The method we proposed should be widely applicable to quantitatively analysis muscle activities by sEMG.**

I. Introduction

THE Surface electromygram (sEMG) from bipolar electrodes provides information of the neural drive to the muscle, so joint force estimation by sEMG is of high relevance in biomechanical studies and in bionic applications. Amplitude of the sEMG is frequently used to such applications as a measure of muscular effort and as an indicator of muscle force. The sEMG during constant force, constant-angle, non-fatiguing contractions can be well modeled as a Gaussian distribution. This probabilistic nature led to root-mean-square (RMS) processing as the standard techniques for sEMG amplitude estimation [1]. However, an mean absolute value (MAV) has been more widely used, and Clancy and Hogan showed that the MAV processor was the maximum likelihood estimator of the sEMG amplitude when sEMG was Laplacian distributed [2]. This procedure is that the EMG signal is full-wave rectified and averaged in a time window. The use of whitening filters before rectification can significantly improve the quality of estimates [3].

MAV necessarily requires rectifying sEMG, however the rectification process causes a considerable controversy. Neto and Christou recently stated that the rectification impairs the neural drive information [4]. Behind this argument, MAV with a rectification process has been used due to the probabilistic nature of sEMG, without any comprehensive physiological justification. Machine learning algorithms, such as support vector machine [5] and artificial neural network [6], have been used to estimate the joint force by sEMG. Bayesian filtering also has been used for the sEMG amplitude estimation [7]. However, these approaches have fallen short of obtaining physiological meanings and have cryptic internal parameters optimized for mapping sEMG to the force.

In this paper, we proposed a new sEMG amplitude estimation method comprising two procedures: MUAP event detection and muscle force indication using a biomechanical muscle model. A neuromuscular system is composed of inputs (excitatory stimulation, MUAPs), outputs (muscle force), and black box components, which act transfer function to modify the input to create the output. The inputs were created as pulses by MUAP event detection by extracting the neural drive from sEMG by ascertaining what percentage of the available MUs was recruited for the force generation rather than ascertaining the exact number of MUs. The rationale behind this approach is that the excitation level of the muscle is determined by the required percentage of available force (maximum voluntary contraction, MVC) rather than the absolute force required [8]. Then the next question that arises is how to model transfer function including the mechanical behavior of the muscle to produce force from the extracted pulses. Although muscle force production is an inherently nonlinear response of the neuromuscular system, reasonable force approximations have been achieved using linear systems [9]. A second-order system was used as the transfer function based on the frequency response simulation between the pulses and the muscle force. This method suggested that the pulses reflecting the neural drive to the muscle, and the pulses were fed into the biomechanical muscle model for the sEMG amplitude estimation.

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C. Choi was with the Department of Mechanical Engineering, Korea Advanced Institute of Science and Technology (KAIST), Daejeon, Republic of Korea. He is now with Future IT Research Center, Samsung Advanced Institute of Technology (SAIT), Yongin, Republic of Korea (e-mail: cm7.choi@samsung.com).

H. -D. Lee is with Department of Physical Education, Yonsei University, Seoul, Republic of Korea (xbridge1997@yonsei.ac.kr).

J. Kim is with Department of Mechanical Engineering, Korea Advanced Institute of Science and Technology (KAIST), Daejeon, Republic of Korea (phone: +82-42-350-3231; fax: +82-42-350-5230; e-mail: jungkim@kaist.ac.kr).

II. Materials and Methods

A. Experimental Setup

A force sensor (NANO17 SI-50-0.5; ATI Industrial Automation, USA) was used to measure forces induced by isometric index-finger abduction, and placed within aluminum frames. The sEMG from FDI was recorded using the DE-2.1 sensors (Delsys Inc., USA) and amplified (×1,000) by a Bagnoli™ 8-channel system (Delsys Inc., USA). Two data acquisition boards, NI PCI-6221 and NI PCI-6034 (National Instruments, USA), were used to record sEMG and force respectively, and installed to a personal computer running on a Pentium 4, 2.93 GHz processor.

Visual Studio 2005 (Microsoft, USA) with the OpenGL library was used to guide and visualize the finger force to subjects in real time. Matlab R2010a (Mathworks Inc., USA) with the Signal Processing Toolbox and the System Identification Toolbox was used for the data analysis. The force signals were sampled at 1kHz and low pass filtered using a finite impulse response (FIR) filter with a corner frequency 20Hz. The sEMG signals were sampled at 1kHz and band pass filtered using a FIR filter with a frequency range between 20 and 400 Hz [10].

B. Experimental Protocol

Nine (five male and four female) healthy volunteers with a mean age of 23.2 years (SD 4.2 years) participated in the experiment. The subjects were requested to sit comfortably on a chair, and their right forearms were positioned on a table beside the chair. The index finger was placed in a custom fit ring secured with the force sensor. The isometric maximal voluntary contractions (MVCs) of the sEMG and finger force were measured prior to the experiment. The subjects were instructed to produce a series of five MVCs as rapidly as possible.

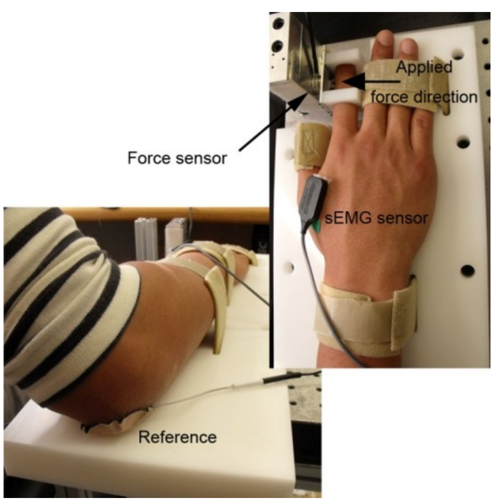

Fig. 1 Experimental setup.

Two bars were displayed on the monitor representing the target and measured forces, and the subjects were instructed to match the measured force bar to the target. The force range was limited to 20 percent of MVC to avoid muscle fatigue that was not considered in the force estimation model. The trajectory of the displayed target forces was a linear chirp in which the instantaneous frequency varies linearly with time (0.2Hz ~ 2Hz). Ten trials for recording sEMG and force were carried out for each subject, and sEMG and force were normalized to the MVC.

C. MUAP Event Detection

When many MUAPs simultaneously occur within close proximity, they make a signal with a greater peak, and it resembles a larger, single MUAP. The larger number of MUs is recruited in generating the muscle force, the larger peak of the summed MUAPs appears. Accordingly, the number of recruited MUs were approximated as the magnitude of sEMG at a peak of the summed MUAP. Also, the moment of the peak could approximate the time of the MUAP occurrence. The peaks in sEMG were detected by following criterion to detect a morphological feature of the peak:

$$\begin{aligned} &if\left(x_{i-1}-x_{i-2}\right)\times\left(x_i-x_{i-1}\right)<0, \quad && y_i = x_{i-1} \\ &\qquad else, && y_i = 0 \end{aligned} \quad . \tag{1}$$

x_i indicates normalized sEMG signal at time i, and y_i indicates the extracted pulse. The magnitude of pulses reflects what percentage of the available MUs were recruited for the force generation, because sEMG was normalized to MVC as aforementioned [8].

D. Joint Force Estimator Design

We designed the joint force estimator inspired from the mechanical behavior of the muscle. The pulse train was analogous to a series of MUAP that results in the muscle contraction. In the estimator, the height of the pulse represented the relative number of the recruited MUs for the contraction among the whole MUs. When a pulse occurred, a single twitch force was developed. When another pulse occurred and the applied time before the force had completely relaxed from the first twitch, a second twitch force was added on top of the first twitch. The resultant output can be expressed as a mathematical form of a convolution process.

$$Y(t) * M(t) = F(t) \quad . \tag{2}$$

Y(t), *M(t)*, and *F(t)* were the extracted pulses from sEMG, the muscle model, and the estimated forces, respectively.

The characteristic transfer function was used for the muscle model as follows:

$$M(s) = \frac{Kw_n^{\,2}}{s^2 + 2\zeta w_n s + w_n^{\,2}} \quad . \tag{3}$$

The parameters for this modeling strategy have mathematical definitions. Parameter K is the system gain, ω_n

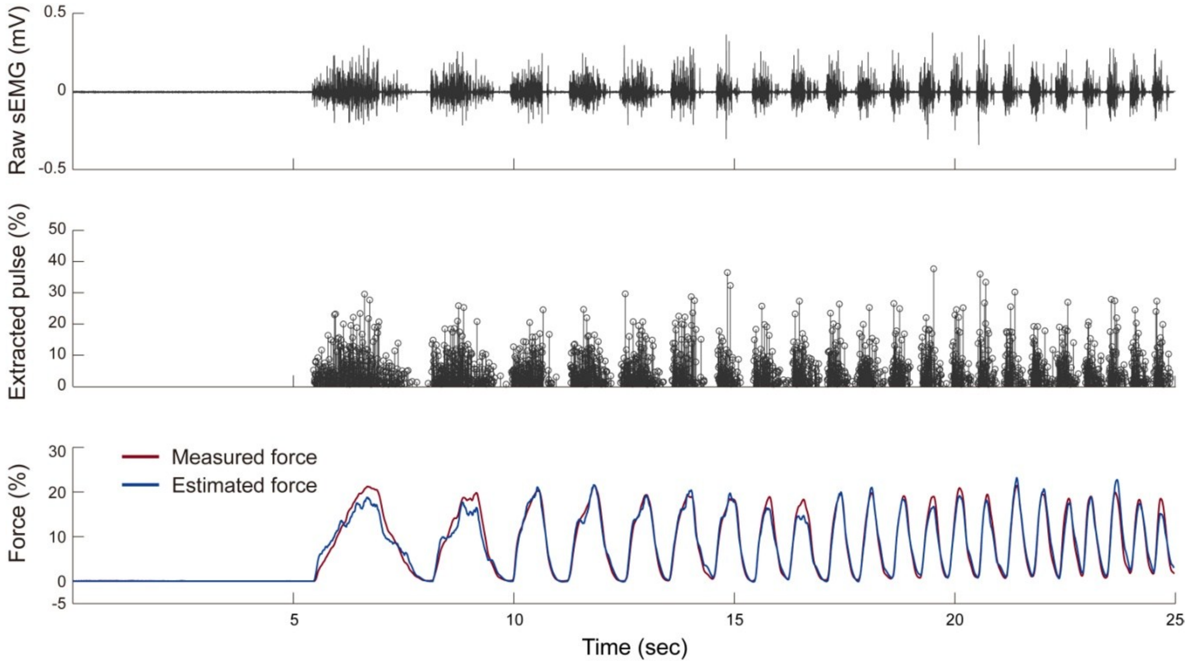

Fig. 2. Experimental results. Units of extracted pulse and force are percent with respect to the MVC.

is the natural frequency, ζ is the damping ratio, and s is the Laplace variable.

E. Joint Force Estimate Simulation

For each subject, ten model parameters were optimized based on respective ten datasets of the measured force and the extracted pulses from sEMG using the Levenberg-Marquardt method. Then, each model was tested using the other nine datasets that had not been used for the parameter optimization. The estimation performance was determined using R^2:

$$R^2 = 1 - \frac{\sum_{i=1}^{I}\left(\hat{f}(t) - f(t)\right)^2}{\sum_{i=1}^{I}\left(f(t) - \bar{f}(t)\right)^2} \quad (4)$$

Here $f(t)$, $\hat{f}(t)$, and $\bar{f}(t)$ are the measure force, the estimated force, and the mean of the measure force at time t, respectively.

III. Results and Discussion

A. Estimation Performance

Figure 2 shows an example of the force estimation using the proposed method. The upper plot shows the raw sEMG recorded during the experiment, and the middle plot shows the extracted pulses from sEMG. In the lower plot, the grey line represents the measure force and the black line represents the estimated force using the proposed model. The estimation performances for each subject were shown in Table I, and the overall R^2 was 0.94 ±0.03.

TABLE I. Estimate performances for each subject (R2, mean ± standard deviation).

Subject ID	***R^2***
A	0.91±0.02
B	0.96±0.01
C	0.92±0.03
D	0.95±0.01
E	0.92±0.05
F	0.94±0.01
G	0.94±0.04
H	0.93±0.03
I	0.94±0.01
Average	**0.94 ±0.03**

B. Extracted Muscle Model Parameters

The model parameters of equation (3) were extracted; K = 0.0178 ± 0.0068, W_n = 2.45 ± 0.26, and ζ = 0.90 ± 0.11. The extracted model parameters could be compared to the model parameters reported in the literature. Milner-Brown *et al.* have conducted an experiment to get a frequency response of the FDI muscle by electrical stimulation with a needle insertion and force measurement between the thumb and index finger [11]. They have reported the natural frequency as 2.4Hz and damping ratio as 1.2. Bawa and Stein have also reported the natural frequency of human soleus muscle as 2Hz and the damping ratio as between 0.7 and 1.0 [12]. The extracted model parameters for the force estimation here were consistent with these values in the literature.

C. Performance Comparison with MAV

We performed a comparison study to examine whether the proposed estimation model was more effective than using MAV with a linear regression. For using MAV, there is a trade-off between the responsiveness (rapid detection of onset or offset of muscle activation) and signal-to-noise ratio (SNR, in which the noise is defined as a variability in sEMG by Clancy [13]. When we use a large time window for MAV, it reduces not only variability in sEMG but also the rapid change, which could be intentional muscle activation. In addition, since MAV is a casual signal processor, this large time window introduces a significant delay. When we use a short window to reduce the delay effect, it increases the signal variability in sEMG. Therefore, the force estimation performance is dependent on the length of the window.

We used various window lengths (150 ms ~ 250 ms) for the MAV process, and applied a linear regression to each MAV result to get the estimated force by MAV. Among the 101 estimated forces regarding window lengths for each subject, we found the best performance, and compared the performances with them by the proposed model using a t-test with a significance level of $p < 0.01$. The overall R^2 of the MAV performance was 0.90 ± 0.02. The estimation performance with the proposed model was better than it of MAV with a linear regression.

D. Discussion

The MUAP event detection procedure was simplified about the measurement mechanism of sEMG as the linear summation of the MUAPs that contribute to the muscle contraction. In fact, magnitudes of sEMG are different with respect to the depth of individual muscle fibers [14]. However, it was highly difficult to localize the depth at which individual MUAPs occur from sEMG. Another limitation was that we did not consider the amplitude cancellation phenomenon of sEMG. The sEMG would underestimate the neural drive sent from the spinal cord to muscle as a result of the cancellation of positive and negative phases of MUAPs [15]. Even in isometric contraction, in addition, the relation between driving signal and surface EMG signal is influenced by various factors such as effects of fatigue, muscle length, velocity of shortening, temperature, or changes in skin conductance. There has been no attempt under our investigation to consider sophisticated models of such relationship, although such models could certainly be included for the successful sEMG amplitude estimation.

IV. Concluding Remarks

This paper proposed a new sEMG amplitude estimation method that was physiologically and biomechanically approximated. Our experimental results showed that the proposed model could estimate the joint force from sEMG with 0.94 ± 0.03 of R^2, and the performance was greater than it of MAV. Successful use of surface electromyography inherently depends on high stability and accuracy of the estimated signals as a measure of muscular effort and as an indicator of muscle force. Although there were remaining limitations to be resolved, our method showed great potential for the joint force estimation from sEMG and could be utilized for many applications such as rehabilitation [16], analysis of sports activities [17], and ergonomic design analysis [18].

References

[1] N. Hogan, and R. W. Mann, “Myoelectric signal processing: optimal estimation applied to electromyography--Part I: derivation of the optimal myoprocessor,” *IEEE Trans Biomed Eng*, vol. 27, no. 7, pp. 382-95, Jul, 1980.

[2] E. A. Clancy, and N. Hogan, “Probability density of the surface electromyogram and its relation to amplitude detectors,” *IEEE Trans Biomed Eng*, vol. 46, no. 6, pp. 730-9, Jun, 1999.

[3] E. A. Clancy, S. Bouchard, and D. Rancourt, “Estimation and application of EMG amplitude during dynamic contractions,” *IEEE Eng Med Biol Mag*, vol. 20, no. 6, pp. 47-54, Nov-Dec, 2001.

[4] O. P. Neto, and E. A. Christou, “Rectification of the EMG signal impairs the identification of oscillatory input to the muscle,” *J Neurophysiol*, vol. 103, no. 2, pp. 1093-103, Feb, 2010.

[5] C. Castellini, and P. van der Smagt, “Surface EMG in advanced hand prosthetics,” *Biol Cybern*, vol. 100, no. 1, pp. 35-47, Jan, 2009.

[6] C. Choi, S. Kwon, W. Park et al., “Real-time pinch force estimation by surface electromyography using an artificial neural network,” *Med Eng Phys*, vol. 32, no. 5, pp. 429-36, Jun, 2010.

[7] T. D. Sanger, “Bayesian filtering of myoelectric signals,” *J Neurophysiol*, vol. 97, no. 2, pp. 1839-45, Feb, 2007.

[8] E. P. Doheny, M. M. Lowery, D. P. Fitzpatrick et al., “Effect of elbow joint angle on force-EMG relationships in human elbow flexor and extensor muscles,” *J Electromyogr Kinesiol*, vol. 18, no. 5, pp. 760-70, Oct, 2008.

[9] F. Law, A. Laura, and R. Shields, “Mathematical models use varying parameter strategies to represent paralyzed muscle force properties: a sensitivity analysis,” *J Neuroeng Rehab*, vol. 2, no. 1, pp. 12, 2005.

[10] C. J. De Luca, L. D. Gilmore, M. Kuznetsov et al., “Filtering the surface EMG signal: Movement artifact and baseline noise contamination,” *J Biomech*, vol. 43, no. 8, pp. 1573-9, May 28, 2010.

[11] H. S. Milner-Brown, R. B. Stein, and R. Yemm, “The contractile properties of human motor units during voluntary isometric contractions,” *J Physiol-London*, vol. 228, no. 2, pp. 285-306, Jan, 1973.

[12] P. Bawa, and R. B. Stein, “Frequency response of human soleus muscle,” *J Neurophysiol*, vol. 39, no. 4, pp. 788-93, Jul, 1976.

[13] R. Merletti, and P. Parker, Electromyography : physiology, engineering, and noninvasive applications, [Hoboken, NJ]: IEEE/John Wiley & Sons, 2004.

[14] L. Mesin, “Simulation of surface EMG signals for a multilayer volume conductor with a superficial bone or blood vessel,” *IEEE Trans Biomed Eng*, vol. 55, no. 6, pp. 1647-57, Jun, 2008.

[15] S. J. Day, and M. Hulliger, “Experimental simulation of cat electromyogram: evidence for algebraic summation of motor-unit action-potential trains,” *J Neurophysiol*, vol. 86, no. 5, pp. 2144-58, Nov, 2001.

[16] U. Mali, N. Goljar, and M. Munih, “Application of haptic interface for finger exercise,” *IEEE Trans Neural Syst Rehabil Eng*, vol. 14, no. 3, pp. 352-60, Sep, 2006.

[17] L. Vigouroux, F. Quaine, A. Labarre-Vila et al., “Estimation of finger muscle tendon tensions and pulley forces during specific sport-climbing grip techniques,” *J Biomech*, vol. 39, no. 14, pp. 2583-92, 2006.

[18] Y. K. Kong, and B. D. Lowe, “Optimal cylindrical handle diameter for grip force tasks,” *Int J Ind Ergonom*, vol. 35, no. 6, pp. 495-507, Jun, 2005.