A new approach for multi-channel surface EMG signal simulation

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Received: 7 October 2016 / Revised: 29 November 2016 / Accepted: 1 December 2016 / Published online: 9 January 2017
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Abstract Simulation models are necessary for testing the performance of newly developed approaches before they can be applied to interpreting experimental data, especially when biomedical signals such as surface electromyogram (SEMG) signals are involved. A new and easily implementable surface EMG simulation model was developed in this study to simulate multi-channel SEMG signals. A single fiber action potential (SFAP) is represented by the sum of three Gaussian functions. SFAP waveforms can be modified by adjusting the amplitude and bandwidth of the Gaussian functions. SEMG signals were successfully simulated at different detected locations. Effects of the fiber depth, electrode position and conduction velocity of SFAP on motor unit action potential (MUAP) were illustrated. Results demonstrate that the easily implementable SEMG simulation approach developed in this study can be used to effectively simulate SEMG signals.

Keywords Surface electromyogram (SEMG) · Single fiber action potential (SFAP) · Motor unit action potential (MUAP) · Gaussian function · Conduction velocity

1 Introduction

In order to understand the relationship between biological, physical or physiological characteristics and the parameters extracted from electromyogram (EMG) signals, many methods have been developed to simulate EMG signals in the past decades [1–10]. Colin Boyd [11] utilized a dipole representation to simulate the single fiber activity, and the motor unit (MU) was constructed from a uniform random group of single fibers. Nandedkar [12] proposed the use of a line source model of single fiber action potentials to simulate motor unit action potentials (MUAPs) recorded by concentric needle (CN) EMG, single fiber (SF) EMG, and macro-EMG electrodes. Farina [7] developed a model to precisely simulate EMG signals detected with surface electrodes.

Surface EMG (SEMG) measurements offer many advantages comparing with measurements using indwelling electrodes, especially when more detailed information such as membrane property of muscle fibers, action potential propagation velocity and anatomical characteristics of motor units is desired. Multi-channel SEMG recording techniques have been introduced [13, 14], in which one- or two-dimensional surface electrode arrays are employed, to better identify single motor unit action potentials even at high force levels [15]. The employment of multiple detection points along the muscle, combined with appropriate processing algorithms, allows the estimation of conduction velocity [16] and the decomposition of compound surface EMG signals into the constituent MUAP trains [17, 18]. Therefore, it is of great importance to develop multi-channel SEMG model to simulate multi-channel SEMG signals in order to advance surface EMG research and applications.

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Two main types of model have been developed and widely used in the field to simulate SEMG signals [19]. One is to model the generation of SEMG signals as a stochastic process that relies on the level of muscle activation. The other one is to employ the theory of electromagnetic field to calculate the detected MUAPs from the physiological structures of the neuromuscular system based on a precise description of MU anatomy. Both models are complicated and it is not easy for researchers who are not familiar with EMG simulation to implement.

In this study, a new and easily implementable SEMG simulation model was developed to simulate SEMG signals in order to facilitate SEMG applications. The volume conductor is modeled as a layered and anisotropic medium, which incorporates the skin, fat and muscles. The major factors under consideration in our simulation are listed in the following two groups.

1. Physiological factors:

- Number of motor units (MUs) and fibers within each of them.
- Spatial distribution of MU and fibers. Distance between recording site and fiber.
- Finite length of the fibers.
- Firing rate [mean and standard deviation (SD)].
- Shape of the extracellular potential.

2. Experimental factors:

- Localization of the electrodes.
- Sampling frequency.
- Stationary conditions (signal duration).
- Signal-to-noise ratio (SNR).

2 Materials and methods

2.1 Data model

Assuming that the muscle contraction is hold at constant-force level, the multi-channel SEMG can be described as a system of linear-time-invariant (LTI) multi-input-multi-output (MIMO) [20]. In Fig. 1, the K inputs $s_i(n)$ are convolved by the impulse responses $r_{ij}(n)$, which yields the H outputs $x_j(n)$ with noises:

$$x_j(n) = \sum_{i=1}^K \sum_{j=1}^H (r_{ij}(n) * s_i(n - \tau_{ij})) + w_j(n) \quad (1)$$

where $x_j(n)$ is the signal detected from the j -th channel, $w_j(n)$ the noise appearing in the j -th channel, $*$ the time-domain convolution, n the sampling time, τ_{ij} the delay time with respect to the original discharge times of the motor units, which is caused due to the differences of end plate

Fig. 1 The MIMO model with inputs $s_i(n)$, delay time τ_{ij} , channel impulse responses $r_{ij}(n)$, noise $w_j(n)$ and outputs $x_j(n)$

position and the length of axons as well as the limited conduction velocity of action potential of muscle fibers. $s_i(n)$ stands for an innervation pulse train (IPT) produced by the i -th motor unit, which can be modeled as:

$$s_i(n) = \sum_{k=-\infty}^{\infty} \delta[n - D_i(k)] \quad (2)$$

where $\delta(\cdot)$ denotes the Dirac impulse and $D_i(k)$ stands for the instant of time that the k -th action potential of the i -th motor unit appears.

2.2 Simulation of a single fiber action potentials

Extracellular SFAP can be generated by the sum of three Gaussian functions [21] and a modified expression to approximate the shapes of SFAP is given in this study by

$$\varphi(t) = A \sum_{i=1}^3 e^{-\left(\frac{t-C_i}{B}\right)^2} \quad (3)$$

where t is time, $A = A_y A_z A_x A_{cv}$ and $B = B_y B_z B_x B_{cv}$ (see the following section) are the amplitude factor and the bandwidth respectively, C_i is the Kernel function center.

One may approximate a particular triphasic action potential waveform with considerable accuracy by adjusting A and B . The relationship between SFAP waveform and

its three basic functions is shown in Fig. 2. After adjusting the initial parameters (A and B), the simulated monopolar and single differential SFAP shapes can be obtained as shown in Fig. 3.

2.3 Effects of the fiber depth, electrode localization and conduction velocity of SFAPs

The SFAP shape detected by electrodes can be considered as a function of the fiber depth, location of the electrodes and conduction velocity. Let

$$A = f_A(y_0, |z - z_0|, |x - x_0|, cv) \quad (4)$$

$$B = f_B(y_0, |z - z_0|, |x - x_0|, cv) \quad (5)$$

where y_0 denotes the depth of fibers, z denotes the position of detection point, z_0 denotes the position of fiber end plate in Cartesian coordinate system along the fiber direction, x denotes the of detection point, x_0 denotes the position of fiber end plate in Cartesian coordinate system perpendicular to the fiber direction, cv denotes the conduction velocity of SFAP. Note that the selection of mathematical functions F_A and F_B are not fixed, instead they can be flexibly selected to better mimic the muscle functions according to the needs. For example, the combinatorial forms of the elementary functions such as a linear, inverse or logarithmic function, etc. can be employed. In addition, the polynomial function can be used to fit the curve of relations (including the amplitude and band width) that reflects the true effect of the localization of the electrodes and other physiological parameters from the real SEMG signals. In our experiment, let

$$A_{y0} = \frac{C_{y0}}{y_0}, \quad C_{y0} > 0 \quad (6)$$

where C_{y0} is a constant.

$$B_{y0} = \log_a(y_0 + C_0), \quad C_0 > 1 \quad (7)$$

where a and C_0 are constants.

Fig. 2 The three basic Gaussian functions to generate a SFAP. The amplitude is normalized with respect to the absolute maximum value

$$A_z = \frac{C_{z0}}{\log_b(C_{z1}|z - z_0| + C_{z2})}, \quad C_{z0} > 0, \quad C_{z1} > 0, \quad C_{z2} > 1 \quad (8)$$

where b , C_{z0} , C_{z1} and C_{z2} are constants.

$$B_z = k \cdot |z - z_0| + u \quad (9)$$

where k and u are constants.

$$A_x = d \cdot |x - x_0| + e \quad (10)$$

where d and e are constants.

$$B_x = \log_f(C_{xB1}|x - x_0| + C_{xB2}), \quad C_{xB2} > 1 \quad (11)$$

where f , C_{xB1} and C_{xB2} are constants.

$$A_{cv} = l \cdot cv + m \quad (12)$$

where l and m are constants.

$$B_{cv} = \frac{C_{Bcv}}{cv} \quad (13)$$

where C_{Bcv} is a constant. Note that the above equations and parameters are chosen qualitatively rather than quantitatively for simulation, which means these equations and parameters can represent the essential characteristics of SEMG signals, but they need to be properly selected to precisely mimic SEMG signals. Note that the changes in conduction velocity of MUAP will not only result in the changes in MUAP shapes, but also result in the changes in the delay time with respect to the original firing time. An original IPT of MU and its delayed version are presented in Fig. 4. The $cv1$, $cv2$ and $cv3$ are used to denote the conduction velocity at the early, intermediate and late stages respectively. Suppose $cv1 > cv2 > cv3$, the delay time $td1$, $td2$ and $td3$ should satisfy $td1 < td2 < td3$.

2.4 Simulation of motor unit action potentials

The MUAP is recorded as a linear summation of all SFAPs in this MU [22]. For the simplification purpose, the diameter and action potential conduction velocity of fibers in each MU are regarded as identical. $SFAP_j(t)$ and $MUAP_i(t)$ are used to denote the action potential propagated along the j -th muscle fiber and the action potential of the i -th MU respectively. The $MUAP_i(t)$ can be described in Eq. (14) according to [23].

$$MUAP_i(t) = \sum_{j=1}^{N_i} SFAP_j(t - \tau_j)b \quad (14)$$

where N_i is the number of fibers contained in the MU, b is the binary number (equal to 1 or 0 corresponding to the j -th active or not active fiber), τ_j is the delay time which is caused due to the position of neuromuscular junction and conduction velocity of SFAP.

Fig. 3 Simulated SFAP with monopolar and single differential detection. **a** A detected monopolar SFAP. **b** Single differential SFAP consists of the sum of three Gaussian functions. The amplitude is normalized with respect to the absolute maximum value

Fig. 4 Different conduction velocity causes the changes in the delay time with respect to original IPT

2.5 Simulation of MUAP trains and SEMG signals

Each MUAP train can be described as a mathematical convolution of the MUAP wave shape [24] (here also termed as channel impulse responses) with the firing instants (a sequence of Dirac functions). Denotes the MUAP train of the i -th MU from the j -th channel by $MUAPT_{ij}(t)$, which is given [23] by

$$MUAPT_{ij}(t) = \sum_m^{N_f} MUAP_{ijm}(t - \zeta_{ijm}) = r_{ij}(t) * s_i(t - \tau_{ij}) \quad (15)$$

where $MUAP_{ijm}(t)$ is the m -th MUAP appearing in the MUAP train of the i -th MU from the j -th channel, N_f is the number of pulses in the MUAP train, ζ_{ijm} is the m -th pulse of the i -th MU from the j -th channel, $r_{ij}(t)$ is the channel impulse responses from the j -th channel, $s_i(t)$ is the IPT produced by the i -th motor unit [see Eq. (2)] and τ_{ij} is the delay time with respect to the original IPT of the MU from the j -th channel, which is caused by the conduction velocity of SFAP.

A complete model to simulate SEMG regards the interference pattern as a summation of the MUAP trains [1]. Denotes the SEMG signals from the j -th channel by $SEMG_j(t)$, according to the Eq. (1) and [23], it follows that

$$\begin{aligned} sEMG_j(t) &= \sum_{i=1}^{N_{mu}} MUAPT_i(t) + w_j(t) \\ &= \sum_{i=1}^{N_{mu}} (r_{ij}(t) * s_i(t - \tau_{ij})) + w_j(t) \end{aligned} \quad (16)$$

where N_{mu} is the number of active MUs in the signals, $w_j(t)$ is the noise appearing in the j -th channel.

3 Results

3.1 Effects of the fiber depth, electrode localization, conduction velocity of SFAP and the inclination of the detection array on the simulated SEMG signals

Figure 5a shows the effects of the fiber depth on the simulated SEMG signals. The fiber depths were of 1 mm and 6 mm, the half fiber length of 50 mm and the conduction velocity of 4 m/s were utilized in the simulation respectively. The middle position was selected as the end plates for all fibers, and the surface electrodes were placed 20 mm distance from the end plate of the fiber. Figure 5b shows the effect of transversal displacement of detection points. The SFAP shapes were detected by 3 different electrodes (perpendicular to the direction of fibers) respectively, with distances ($x - x_0$) of 0, 10, and 20 mm from the detection point to the endplate of the fiber. The depth (y_0) of 1 mm was utilized. The fiber length of 50 mm and the conduction velocity of 4 m/s of SFAP were employed, respectively. Figure 5c shows the effect of different conduction velocity of SFAP, and the SFAP shapes were detected by the same point electrodes. The conduction velocity of SFAP has been set to 5 m/s, 4 m/s and 3 m/s, respectively. The fiber length and depth have been set to 50 mm and 1 mm, respectively. Figure 5d shows the effect of electrode array misalignment, the SFAP shapes were detected by the same

Fig. 5 Effect of different parameters on the SFAPs. **a** Effect of fiber depth on the SFAP shapes. **b** Effect of transversal displacement of detection points on the SFAP shapes. **c** Effect of conduction velocity of SFAP on the SFAP shapes. **d** Effect of array misalignment on the SFAP shapes

point electrodes. The inclination angle α of the array has been set to 0° , 10° and 20° respectively. The fiber length, depth and conduction velocity of SFAP have been set to 50 mm, 1 mm and 4 m/s, respectively.

3.2 Simulated motor unit action potentials, MUAP trains and SEMG singles

Figure 6 shows the temporal distribution of action potential shapes of fibers contained in one particular MU. The corresponding MUAP shapes are also presented in the figure, which are the summation of the corresponding SFAP shapes. The MU is composed of 50 fibers, with the center depth of 1 mm and the conduction velocity of 4 m/s. The half fiber length of 60 mm and the spread of 5 mm were employed for both tendon regions.

Figure 7 shows the MUAP shapes of one simulated MU detected with a linear array of point electrodes, with the inter-electrode distance of 3 mm along the fiber. The center depth and conduction velocity were set to 1 mm and 4 m/s respectively. The MU consists of 50 fibers. The fiber length

is 60 mm in either direction; and both tendon regions have the same spread of 5 mm. Generally, only main waveform of MUAP (also termed as propagating component) is needed in most cases for verifying some algorithms. Therefore, non-propagating component is not considered here.

Figure 8 shows the simulated MUAP trains, synthetic signal and corresponding frequency spectrum in one channel. The simulated SEMG signal is composed of 10 MUAP trains. The signals were recorded with a 64-channel SEMG grid (64 electrodes arranged in 8 columns and 8 rows with the inter-electrode distance of 5 mm). The center depths of all motor units were uniformly distributed. A random number of muscle fibers (uniformly distributed between 10 and 50) were assumed in all motor units. For the simplification purpose, the conduction velocities of all MUAPs were set to 4.0 m/s. The length of all fibers was set to 50 mm and the tendon and end plate positions of the fibers were uniformly distributed in a range of ± 5 mm. The firing rate of motor units was set to 15 ± 5 Hz, and total 10 active motor units were assumed. The signals were

Fig. 6 Temporal distribution of SFAPs and the synthetic MUAP. **a** The temporal distribution of SFAP shapes outside the innervation zone. **b** The temporal distribution of SFAP shapes within the innervation zone. **c** The MUAP shapes corresponding to the *top left*

panel detected outside the innervation zone. **d** The MUAP shapes corresponding to the *top right panel* detected within the innervation zone

Fig. 7 MUAP shapes produced by one MU detected by a linear array of 16 point electrodes

sampled with 2000 Hz sampling frequency and corrupted by Gaussian zero-mean noise with SNR of 20 dB.

3.3 Examples of model application

The signals utilized shown in Fig. 8 were decomposed using our KmCKC method [25] and multi-channel MUAP shapes were estimated using the spike-triggered method [26] and shown in the Fig. 9a. It can be seen that the original location of the innervation zone agrees with the decomposition result. Hence, it indicates that this simulation model can be used to test the decomposability of multi-channel SEMG signals. Suppose the delay time of each IPT obtained via decomposition between the two adjacent electrodes along the fibers is τ_{di} , then the conduction velocity of the i -th MUAP can be estimated as $cv_i = d_{ie}/\tau_{di}$, where d_{ie} is the inter-electrode distance. To simplify the simulation process, the conduction velocity of fibers was set to 4 m/s. The averaged results of five trials for estimating the conduction velocity [27] are shown in Fig. 9b.

Fig. 8 MUAP trains and the synthetic signal in one channel. **a** A segment of 10 MUAP trains. **b** A segment of SEMG signals composed by the 10 MUAP trains. **c** The entire SEMG signals. **d** The frequency spectrum of the entire SEMG signals

Fig. 9 Applications of simulated SEMG. **a** Multi-channel MUAP shapes estimated by spike-triggered averaging of simulated signals. The location of the innervation zone (black circles), and propagation

of MUAPs (grey lines) are indicated. The z-x plane in Cartesian Coordinates is shown in the figure. **b** Average conduction velocity of action potentials of 10 MUs estimated by decomposing the signals

4 Discussion

In this paper, multi-channel SEMG signals were successfully simulated for the first time using the Gaussian functions. The proposed new simulation model is simple, easy to implement and efficient since it does not involve complex mathematical operations such as the integration, differentiation and Fourier transform, etc. The entire simulation process can be completed within seconds. Simulation results demonstrated that the proposed new simulation model can resemble the real SEMG signals with the relevant parameters selected properly. The monopolar and single differential SFAP can also be simulated by precisely adjusting the parameters of Gaussian function. The effects of the fiber depth, localization of the electrodes and conduction velocity of SFAP on the simulated SEMG signals were successfully investigated. However, similar to the already existing models, the present model also has limitations. For example, the length of each fiber is assumed to be same, the different fibers generate the same SFAP shapes, the fibers of a motor unit are assumed to be parallel and straight to each other.

In reality, the SFAP shapes detected by the electrodes will be influenced by the parameters including the depth of MUs (y_0), localization of the electrodes (x, z), conduction velocity of SFAP (cv) and inclination angle of the electrode array (α), etc. These influences were simulated by adjusting the amplitude and width of the shapes of the Gaussian functions (Fig. 5). Note that the change of inclination angle of the electrode array can be viewed as the change of localization of the electrodes. In addition, because the SFAPs propagate along the opposite direction within the innervation zone, thus the amplitude of MUAP is smaller; on the other hand, the amplitude of MUAP will become larger if the SFAPs propagate along the same direction outside the innervation zone (Figs. 6, 9). It consists with the real case. In the simulation process, the amplitude of MUAP train is smaller when the size of MU is smaller or the depth of MU is shallower; on the contrary, the amplitude of MUAP train will become larger when the size of MU is larger or the depth of MU is deeper (Fig. 8a), which also consists with the real situation. In order to verify the applicability of the simulation model, the simulated signal was decomposed by CKC method, and the conduction velocity of MUAP was also estimated. Because of the sampling frequency, there may exist a certain degree of quantization errors when the conduction velocity was estimated. However, the satisfactory results can still be obtained.

5 Conclusions

In conclusion, a simple and effective SEMG simulation model is developed in this study to simulate multi-channel SEMG signals. The simulation is achieved by adjusting the

parameters of the Gaussian functions to imitate the variances of MUAP waveform. The proposed model is able to reflect the actual process of changes in MU shapes under different situations in a simply and efficient way.

Acknowledgements This work was supported in part by National Natural Science Foundation of China 51677171, Zhejiang Provincial Natural Science Foundation of China LY17C100001, Department of Education of Zhejiang Province Y201533132, Guangdong Provincial Work Injury Rehabilitation Center, and the University of Houston.

Compliance with ethical standards

Conflict of interest Y. Ning declares that he has no conflict of interest in relation to the work in this article. Y. Zhang declares that he has no conflict of interest in relation to the work in this article.

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