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Electrodes Adaptive Model in Estimating the Depth of Motor Unit: A Motor Unit Action Potential Based Approach

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Abstract— **High-density surface electromyography (EMG) has been proposed to overcome the lower selectivity with respect to needle EMG and to provide information on a wide area over the considered muscle. Motor units decomposed from surface EMG signal of different depths differ in the distribution of action potentials detected in the skin surface. We propose a noninvasive model for estimating the depth of motor unit. We find that the depth of motor unit is linearly related to the Gaussian RMS width fitted by data points extracted from motor unit action potential. Simulated and experimental signals are used to evaluate the model performance. The correlation coefficient between reference depth and estimated depth is 0.92 ± 0.01 for simulated motor unit action potentials. Due to the symmetric nature of our model, no significant decrease is detected during the electrode selection procedure. We further checked the estimation results from decomposed motor units, the correlation coefficient between reference depth and estimated depth is 0.82 ± 0.07. For experimental signals, high discrimination of estimated depth vector is detected across gestures among trials. These results show the potential for a straightforward assessment of depth of motor units inside muscles. We discuss the potential of a non-invasive way for the location of decomposed motor units.**

I. INTRODUCTION

Localization of active motor units in a muscle is of interest in several research areas including neurology, muscle synergy and prosthetic control. Some studies have been proposed to locate the active muscle regions and motor units [1]–[4]. The amplitude of motor unit action potential (MUAP) is dependent on its location, size and the position of the recording electrodes [5], [6]. It is often regarded as solving an inverse problem to estimate the location of motor unit based on MUAP [7], [8]. Specifically, when estimating the depth of motor units, a few methods are proposed to learn the relative depth for different motor units [8], [9]. It has been shown that changing the position of the recording electrode in the muscle fiber direction causes minor changes in the MUAP amplitude. In contrast, when the electrode position is changed over the skin surface in the transverse direction, a rapid decrease in recorded amplitude can be observed. Models are proposed by considering that the decay of the potential in the transverse direction with respect to the fibers is slower when the motor unit is deeper [10]–[12]. These studies assume the electrode which detects the maximum peak amplitude is placed directly above the motor unit. And the depth is only related to two detection points. But electrodes are often placed randomly around the muscle section with inter-electrode distance. It can't be ensured that the detected maximum amplitude is the theoretical maximum amplitude for the motor unit action potential. These models are therefore not adaptive in practice. Besides, the array of all the electrodes placed in the transverse direction contains a large amount of information that can be used. In the present paper, an alternative method to estimate the depth of motor unit from extracted parameters of MUAP is proposed and evaluated.

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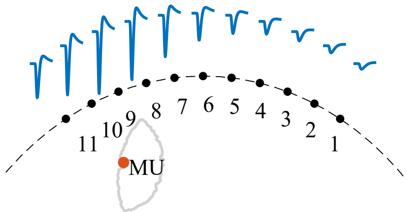
II. METHOD

A. Depth model

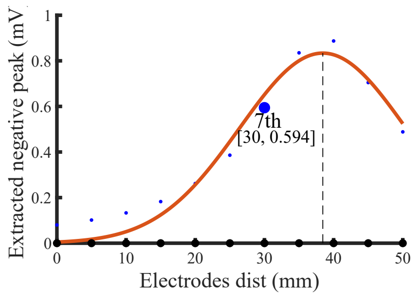
We extracted the detection distances in the transverse direction and the peak amplitude from the motor unit action potential, then fitted them to a Gaussian curve in Equation 1. The detection distance from the jth electrode's was denoted by $la(j)$, the negative peak amplitude was denoted by $N(j)$. We assume the depth of motor unit was linearly correlated to the Gaussian RMS width: σ. By curve fitting, we could give a reasonable estimate of the depth.

$$N(j) = \alpha e^{-\frac{[la(j)-\beta]^2}{2\sigma^2}} \tag{1}$$

Specifically, three steps were implemented: Firstly, we located the electrodes row whose action potentials had the maximum negative peak amplitude and set this row of electrodes as our interest region. This row must be perpendicular to muscle fibers (Fig. 1(a)); Secondly, all the negative peak amplitude $N(j)$ from each action potential were extracted. We numbered all the detection electrodes counterclockwise and the relative detection distance $la(j)$ was the arc length from the jth electrode to the $1st$ electrode; Lastly, all the extracted data points were fitted to a Gaussian curve (Fig. 1(b)). For example, every point in the x-axis was separated by inter-electrode distance (5 mm) in Fig. 1(b). The blue point denoted the 7th electrode in Fig. 1(a). The distance from the 1st electrode to the 7th electrode was 30 mm, the negative peak amplitude detected by the 7th electrode was 0.594 mV. The centerline predicted the theoretical detection point for the maximum peak amplitude using a monopolar electrode in Fig. 1(b). The Gaussian curve width σ was used for further analysis.



(a)



(b)

Fig. 1. Depth modeling process. (a), Motor unit territory and its action potentials detected from the skin surface (dotted curve): the reference depth was calculated from its center (red dot). Muscle fibers were perpendicular to the figure (not shown here). (b), Blue dots were the data points ($la(j)$, $N(j)$) used to fit the red Gaussian curve.

B. Simulated signal

1) Volume conductor: Two hundred motor units were simulated based on an anatomical model that consisted of a cylindrical volume conductor with an anisotropic muscle layer, and isotropic bone, subcutaneous, and skin layers [13]–[15]. The simulation parameters were reported in Table I. The muscle had an elliptical shape, and the motor-unit territories were circular and distributed randomly. The simulated signals were detected with circular electrodes (diameter 1mm), arranged in a grid with 17 rows and 11 columns (17 × 11 electrodes) with 5 mm inter-electrode distance (IED).

TABLE I

Model parameters	
Tissue Thickness	
Skin	1 or 5 mm
Muscle	25mm
Muscle properties	
Total number of motor units	200
Total number of fibers	119,634
Fiber properties	
Number of fibers in a motor unit	15-1500
Muscle fiber length	120mm
Conduction velocity	4m/s
Electrode configuration	
Circular(diameter)	1mm
Inter-electrode distance	5mm
Grid	11 x 17
Spatial filter	Monopolar

Reference depth of motor unit referred to the radial distance from every territory's center to the skin surface. With an arm radius of 50 mm, the depth range of reference motor units was 0 - 30 mm. The MUAP peak to peak amplitude distribution associated with size and depth of motor unit was consistent with the experimental result [5], [6]. Simulated MUAPs were used as model input. Besides, MUAP can not be directly obtained under experimental conditions. The firings of motor units were firstly decomposed from surface EMG and then used to trigger the MUAPs. To reproduce this process, we also simulated surface EMG using the MUAPs simulated from the volume conductor. The simulation was set at five different constant activation levels (10%, 30%, 50%, 70%, 100%) in Table II. Each signal was the summation result from a designated number of randomly selected motor units.

2) Decomposition: Simulated surface EMG signals were decomposed by convolution kernel compensation (CKC) algorithm [16]. The detailed decomposition results were shown in Table II. For example, during 10% of maximum voluntary contraction, 105 out of 200 motor units were activated to synthesize the surface EMG signal. Twenty-four motor units were decomposed. Spike triggered average was used to get the MUAPs for decomposed motor units. All the decomposed firing trains of motor units were compared to the reference to validate our depth calculation result. Motor unit pairs with $RoA > 0.8$ (rate of agreement [17]) were considered a successful match. For example, during 10% of maximum voluntary contraction, nineteen motor units were matched to the reference firing train using RoA-match method. Among all the matched motor units, the deepest one had a depth of 17.4 mm, and a size of 277 muscle fibers.

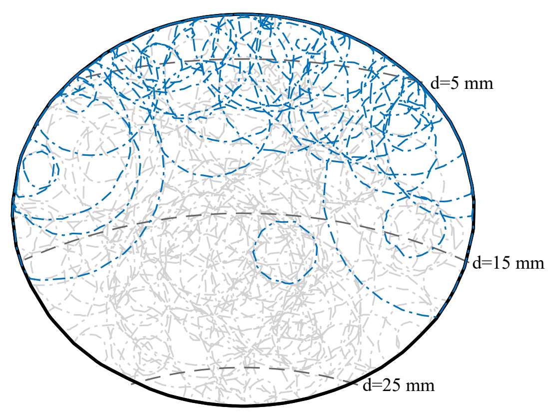


Fig. 2. Motor unit territories inside the cross-section of an elliptical muscle shape. Each motor unit was represented by a dot-dash circle inside the muscle with its radius representing different muscle fiber numbers. All of the plotted motor units were activated, the blue ones were decomposed by the surface EMG signal. The dash lines (depth: d) were parallel to the theoretical skin surface (not shown here).

All of the active motor units were plotted with known location and territories from the reference motor units in Fig. 2. The blue circles represented the decomposed motor units that were RoA-matched to the referenced active motor units. The light grey line indicated three different radial depths from the skin surface (5mm, 15mm, 25mm). Although only 12% of the active reference motor units were decomposed, 80% of the decomposed motor units could be matched to the reference. This indicated high reliability of decomposition, and we could further implement our method to experimental signals.

TABLE II

CONSTANT (%MVF)	Number of motor units		RoA matched	Depth (mm)	Number of muscle fibers
	Activated	Decomposed			
10%	105	24	19	17.4	277
30%	169	23	20	10.2	1220
50%	200	19	15	11.4	2387
70%	200	19	13	16.0	2387
100%	200	27	15	11.5	2387

C. Experimental signal

1) Experiment protocol: Experimental high density (192 channels) surface EMG signals were recorded in one subjects' forearm during three hand gestures (Hand open, Radius deviation, Ulnar deviation), each motion was repeated for eight trials [18]. Three electrode grids were placed along muscle fiber direction covering the forearm's primary flexor and extensor muscles to detect motor units from different depths. Surface EMG signals were sampled at 2048 Hz, band-pass filtered at 9-900 Hz. The subject was asked to perform each hand gesture for 10 seconds, with a rest time of 5 seconds in between. Only the middle 8 seconds of data were used for further analysis. The experiments were in compliance with the Declaration of Helsinki and approved by the local ethical committee of Shanghai Jiao Tong University.

2) Decomposition: A total of 1316 motor units were decomposed using CKC method [16], and the decomposed numbers for each grid and PNR (pulse-to-noise-ratio [19]) were listed in Table III. MUAPs for each grid were spike-triggered averaged separately.

TABLE III

	Number of decomposed motor units			
	Grid 1	Grid 2	Grid 3	PNR (dB)
Hand open	21±3	24±2	15±3	29.3±5.5
Radius deviation	18±3	14±2	16±6	29.6±5.8
Ulnar deviation	16±3	24±3	15±3	29.2±5.5

D. Correlation analysis

The Pearson correlation coefficient was used to evaluate the model performance. The model estimated depth was compared to the reference depth mentioned above. All the decompositions and analyses were implemented in MATLAB 2021b (Matlab Inc. USA).

E. Model adaptability analysis

To examine our model's adaptability to electrodes, we designed an electrode selection procedure. A total of k (k = 1,2,3) detection points were randomly removed, the data points in the removed electrodes were set to blank in Fig. 1(b) before fitting to the model. The procedure was repeated ten times for different k.

III. RESULT

With a large number of simulated motor units, we were able to examine the model performance. It was often very challenging to acquire this scale of data in experimental conditions [11]. There were two groups of simulated MUAPs

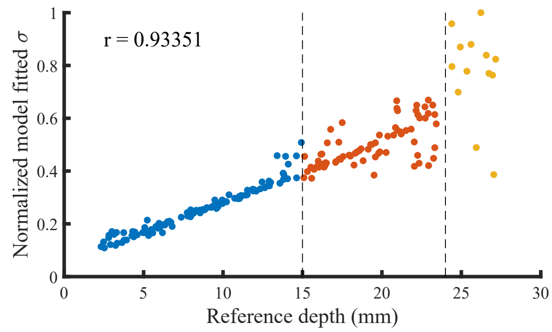


Fig. 3. Pearson correlation coefficient between reference depth (mm) and normalized model fitted σ. Two dotted lines separated the scatter plot into three depth levels.

as our model input: simulated surface MUAPs (group 1) and spike-triggered averaged MUAPs (group 2) after decomposition of the simulated surface EMG signals. The correlation coefficient between reference depth of motor unit and model fitted σ was 0.93 for group 1 in the scatter plot of Fig. 3. We divided the scatter plot into three different depth levels. The correlation between reference depth and model fitted σ was 0.97 for motor units with depths not exceeding 15 mm. When the depth increased from 15 mm to 24 mm, the correlation dropped to 0.68. The overall correlation coefficient was 0.92 ± 0.01 within electrode selection procedure in Fig. 4. Besides, the correlation coefficient dropped a little when the number of removed electrodes reached three. For group 2 in Fig. 2, the correlation coefficient between reference depth of the matched motor units and model fitted σ was 0.82 ± 0.07.

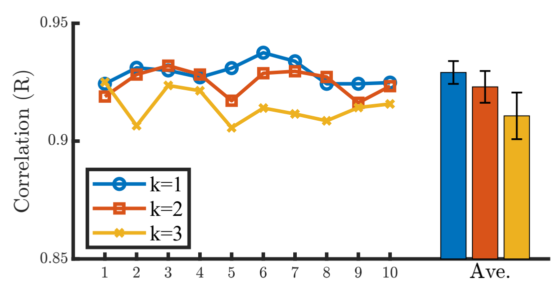


Fig. 4. Pearson correlation coefficient after randomly removing k electrodes (k = 1,2,3). The x-axis represented ten different random results.

Fig. 5 showed an example of the estimated depth of motor units decomposed during the experiment of different hand gestures. Because there was no actual depth, the depth information was normalized here. Each point in Fig. 5 represented one relative depth of one particular motor unit. This example indicated that the depth distribution of motor units from different hand gestures was not the same.

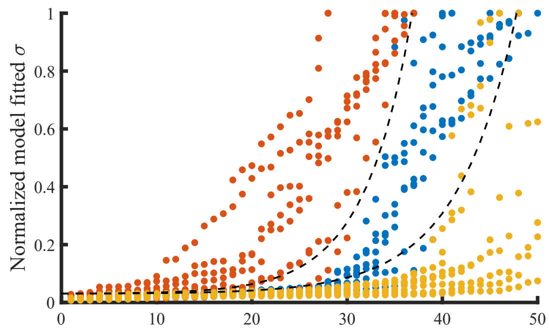


Fig. 5. Scatter plot of sorted depth vector after normalization, the x-axis corresponded to the number of decomposed motor units. Different gesture was denoted in different colors.

IV. DISCUSSION

Motor unit action potential is one of the representative features in discriminating motor units. It is used extensively in tracking the same motor unit across sessions [20], [21]. It is triggered from the surface EMG signal collected from different detection points, which means the displacement of electrodes would cause a significant difference to it, especially in the muscle's transverse direction. The model we propose is able to compensate for the displacement of electrodes in the transverse direction. We have proved the depth of motor unit is linearly related to the Gaussian RMS width during the electrode selection process.

In order to learn the limitation of depth estimated from motor unit action potential, we reproduce the entire process by simulation, including the setting of muscle activation levels, the acquisition of surface EMG, the decomposition of firing trains, the spike-triggered average for MUAP, and the depth estimation. The superimposition of action potentials has made it hard to decompose for more and deeper motor units. This explains the correlation decrease in Fig. 3 on different depth levels. In the practical experiment, electrode placement is often guided by the fiber direction of the superficial muscle. However, for a deeper muscle with an intersection angle, the MUAP triggered by the decomposed firing trains is arranged in either fiber or transverse direction. In this case, more variables will be introduced. Consequently, in our analysis for experimental gesture signals, part of our estimated result deteriorates more than expected. A reasonable guess is that all depth values that exceed a certain threshold may come from deeper muscles. Nevertheless, our work shows a possible discriminant feature vector among hand gestures.

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