Prediction of Individual Finger Forces Based on Decoded Motoneuron Activities

CHENYUN DAI,1,2 YIZHOU CAO,1,2,3 and XIAOGANG HU1,2

1Joint Department of Biomedical Engineering, University of North Carolina - Chapel Hill, 144 MacNider Hall, Chapel Hill, NC 27599, USA; 2North Carolina State University, Raleigh, NC, USA; and 3Medical College of Soochow University, Suzhou, Jiangsu, China

(Received 2 October 2018; accepted 28 February 2019)

Abstract—Accurate prediction of motor output based on neural signals is critical in human–machine interactions. The objective was to evaluate the performance of predicting individual finger forces through an estimation of the descending neural drive to the spinal motoneuron pool. High-density surface electromyogram (EMG) signals of the extensor digitorum communis muscle were obtained, and were then decomposed into individual motor unit discharge events. The frequency of the composite discharge events at the population level was used to derive the descending neural drive, which was then used to predict the finger forces. The global EMG-based approach was used as a control condition. Compared with the EMG-based approach, the experimental results show that the neural-drive-based approach can better predict the individual finger forces with higher $R^2$ values across different force levels and across different force trajectories (steady and varying forces). These findings indicate that the neural drive estimation based on motoneuron firing activities can be used as a reliable neural-machine interface signal involving individual fingers. However, real-time implementation of this approach is needed for future clinical translation.

Keywords—EMG signal processing, Motor unit decomposition, Finger force, Hand function, Muscle activity.

INTRODUCTION

Decoding the desired motor output is a key component in human–machine interactions. This decoded signal can allow individuals with neuromuscular disorders to interact with machines, such as exoskeletons, prostheses, or neural-stimulation systems, which can help restore lost or diminished motor functions. Recent advancement in neurally implantable micro-electrodes or thin-film electrode arrays have facilitated the ability to decode neural signals sent directly from the brain to the periphery. However, there is still considerable challenge in applying these techniques to humans, specifically in clinical populations, largely due to the invasive nature of the procedures and the lack of long-term stability of the system interface.

Alternatively, non-invasive muscle activity recordings, such as surface electromyogram (sEMG) signals, have been widely used as the neural control signals of human wearable robots or neuropaortheses. One common strategy uses the amplitude of sEMG as a proportional control input of different degrees of freedom of the machine. Another typical strategy uses different features/patterns of EMG to identify different preset movements involving multiple degrees of freedom. Nevertheless, these global EMG-based approaches have several limitations. First, the global sEMG sig-
nals consist of the summation of hundreds of motor unit action potentials (MUAPs) generated from motoneuron discharge events, it may not accurately reflect the cortical control of muscle activation. Namely, the measured EMG amplitude can be biased by intrinsic physiological factors, such as the cancellation of superimposed MUAPs\textsuperscript{20} and the natural variations of action potential amplitude from the complex conductive processes of different tissue layers.\textsuperscript{11} Second, EMG signals can be further deteriorated/corrupted by external interference during signal acquisition, such as changes in electrode–skin contact, the crosstalk of multi-channel EMG,\textsuperscript{10} motion artifacts, and the variation of baseline noise. All these factors can ultimately limit robust communications between humans and machines.

In contrast, recent studies have used motoneuron discharge timings as a promising neural control input for human–machine interactions.\textsuperscript{12,22} Instead of using the global sEMG signals, a decomposition step was performed on the multiple-channel sEMG signals to extract spinal motoneuron discharge events. Although individual motoneurons have distinct discharge properties that may not directly reflect the descending drive, the frequency/probability of the motoneuron discharge at the population level can directly reflect high level neural drive from the brain to the muscles. Essentially, the spinal cord output signal (motoneuron discharge spikes as a whole) is used to estimate/decode the spinal input signal (descending command from the brain). This decoded neural command based on the binary events can potentially overcome some of the disadvantages of the global EMG patterns. However, the feasibility of using this approach for fine motor control, such as involving individual finger movement has not been evaluated. In addition, the decoding accuracy of the neural-drive-based approach compared with the EMG-based method has not been fully investigated under different conditions (i.e., force level, signal quality, or signal stability). To overcome these limitations, the objective of this study was to evaluate the performance of the neural-drive-based approach in estimating the individual finger forces using both simulated and experimental data under different conditions, with a wide range of signal quality and muscle contraction levels.

**MATERIALS AND METHODS**

Both simulated and experimental data were obtained to verify the parameter selection and the accuracy of the methods. Figure 1 shows the process of the EMG-based (Fig. 1a) and the neural-drive-based (Fig. 1b) estimations.

---

**Simulated Data**

A classic EMG model\textsuperscript{22} was used to generate the EMG data, in order to evaluate the accuracy of the methods. The signal generation were described as follows:

First, the individual spike trains were generated from a widely accepted physiologically-based MU model.\textsuperscript{13} A progressive recruitment pattern with an exponential threshold function and a distributed discharge rate of MUs were modeled as described in the original study.\textsuperscript{13} The main parameters used were summarized in Table 1. Firing variations with a 10% Coefficient of Variation in the firing rate were added to the spike trains. In addition, a moderate level (10%) of MU discharge synchronization was added based on Yao et al.\textsuperscript{29}

Second, for each spike train, waveforms of HD MUAP was randomly selected from a HD MUAP pool. The MUAP pool was derived from earlier experimental data\textsuperscript{16} using OT Biolab (OT Bioelettronica, Torino, Italy). The EMG signals were first decomposed into constituent spike trains, and the corresponding waveforms of HD MUAPs were derived from a spike trigger average algorithm.\textsuperscript{16} In addition, a 10% amplitude variation was added to the MUAPs for each firing. The MUAP grid was also scaled by a coefficient from a uniformly distributed random number ranging from 0.1 to 2.

Third, each HD MUAP array was convolved with the corresponding spike train to generate an HD MUAP train grid. Then, the 8 × 8 noise free EMG was obtained by superimposing all the MUAP train grids from different MUs. Additional Gaussian noise (band-pass filtered at 10–900 Hz) with different signal-to-noise ratio (SNR = 5, 10 and 20 dB) was added.

Fourth, the twitch force of each MU was also simulated. The MU force and the resultant muscle force was subsequently calculated based on the excitation drive level and the MU discharge frequency using the force model described in the same MU model.\textsuperscript{13} The main parameters used for the force simulation was summarized in Table 2.

To match the conditions of experimental data, two excitatory drive levels (20% and 50%) were simulated. The variation of the drive level was similar to that of the experimental data, including both sine-wave and trapezoid. A total of 600 trials (two force levels × two trajectories × three SNRs × fifty repetitions) were simulated.

**Experimental Data**

**Participants**

Nine neurologically intact (with no known neurological injuries or disorders) subjects (six males, two females; aged 26.3 ± 4.9 years) were recruited. One
Finger Force Estimation from Motoneuron Activities

was excluded due to a short forearm length. Therefore, the experimental data were acquired from eight subjects. A power analysis was performed to ensure that eight subjects were not under powered. All subjects provided written informed consent approved by the Institutional Review Board at the University of North Carolina at Chapel Hill.

TABLE 1. The main parameters used for MU timing event train generation.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Total number of neurons in the pool</td>
<td>120</td>
</tr>
<tr>
<td>Range of recruitment threshold</td>
<td>30</td>
</tr>
<tr>
<td>Coefficient of recruitment threshold</td>
<td>ln 30/120</td>
</tr>
<tr>
<td>Minimum firing rate</td>
<td>5</td>
</tr>
<tr>
<td>Maximum firing rate of first MU</td>
<td>35</td>
</tr>
<tr>
<td>Maximum firing rate of last MU</td>
<td>20</td>
</tr>
</tbody>
</table>

TABLE 2. The main parameters used for the force generation.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Range of peak twitch force (RP)</td>
<td>100</td>
</tr>
<tr>
<td>Coefficient of peak twitch force</td>
<td>(ln RP)/120</td>
</tr>
<tr>
<td>Range of contraction time (RT)</td>
<td>3</td>
</tr>
<tr>
<td>Coefficient of contraction time</td>
<td>log_{10} RP</td>
</tr>
<tr>
<td>Longest duration rise time</td>
<td>90 ms</td>
</tr>
</tbody>
</table>

Experimental Setup

The subjects sat in a height-adjustable chair with their dominant forearm comfortably placed on the experimental table and the elbow supported on a foam pad. Given that a large electrode pad was placed on their forearm, also covering the wrist extensor, the...
subjects were asked to minimize the wrist extensor activation. To restrict the wrist movement, their wrist was immobilized within two padded wooden boards in a neutral pronation-supination position and zero degree flexion–extension. The four fingers (index, middle, ring and little) were comfortably abducted. Each finger was secured, using two Velcro straps (each at the proximal and middle phalanges) to one load cell (Interface, SM-200N, with a resolution of 0.01 N) which measured the finger forces with a 1 kHz sampling frequency. During the experiment, the subjects were asked to isometrically extend one designated finger in each trial. The maximum voluntary contraction (MVC) of each finger was separately measured. The average force of each finger during the contraction plateau of 2 s was calculated as the MVC.

During the main testing session, the subjects were provided with a target force trajectory shown on a screen. The finger force output was instantaneously displayed as a feedback to the subjects via a custom-built MATLAB program (MathWorks Inc). Only the designated finger force was displayed, but the forces from all the four fingers were recorded. They were asked to adjust the displayed muscle force of a designated finger to track the trajectory. Two force target trajectories, sine-wave and trapezoid, were tested. The sine-wave force trajectory allowed us to evaluate the force estimation performance of the EMG- and neural-drive-based approaches during varied level of contractions. Two contraction force levels (20% and 50% MVC) were used in each target. For the trapezoid force, the subject took 2 or 4 s (2 s for 20% or 4 s for 50%) to ramp up to the designated maximum effort, maintained the force for 10 s, and lastly used 2 or 4 s (2 s for 20% or 4 s for 50%) to ramp down to zero effort. For the sine-wave force, the subject took 2 or 4 s to ramp up to the designated effort, maintained for 5 s, then performed three repeated sine-wave oscillation forces either from 10 to 20% or from 25 to 50%, and finally used 2 or 4 s ramp down to zero effort. Three repeated trials were performed for each condition. The order of the different conditions were randomized during the experiment. A minimum of 2 min rest was provided between trials to reduce the influence of muscle fatigue. A total of 48 trials (four fingers × two force levels × two trajectories × three repetitions) were recorded for each subject.

**EMG Recordings**

Surface EMG signals were recorded over the extensor digitorum communis (EDC) muscle via an 8 × 16 channel high density (HD) EMG electrode array (see Fig. 1c) with 10 mm inter-electrode distance (OT Bioeletronica, Torino, Italy). Each electrode was filled with conductive gel to ensure high conductivity between the electrodes and the skin surface. Prior to the electrode placement, the skin surface was scrubbed with alcohol pad to improve the signal quality. To standardize the electrode placement location across subjects, the HD array was centered at the midway between the olecranon and the styloid process. The EMG signals were acquired from EMG_USB2+ (OT Bioeletronica, Torino, Italy), sampled at 2048 Hz with a gain of 1000 and a bandwidth of 10–900 Hz.

**EMG Analysis**

Channel selection was first performed based on several previous studies. EMG activities from only a localized region of the extensor muscle can be obtained during individual finger extension. Therefore, a large number of the EMG channels contained primarily baseline noise. To remove the channels with no EMG information, only the EMG channels (64 out of 128 channels) in proximity to the regions with EMG activities for individual fingers were selected for the analyses. Specifically, based on the muscle activation region of individual fingers, channels from row 1–8, 5–12, and 9–16 were used for index, middle, ring, and little fingers, respectively.

**EMG Decomposition and Neural-Drive-Based Estimation**

The EMG signals were decomposed into individual MU discharge spike trains using the fast independent component analysis (FastICA) method. Briefly, the algorithm includes four steps: (1) signal extension by adding eight delayed replicas of each original channel, (2) signal whitening, (3) FastICA-based deconvolution, and (4) action potential timing identification through peak detection and clustering. The details of the algorithm and the parameter selection are described by Negro et al. Lastly, the silhouette measure (SIL), a separation index in cluster analysis, was used to filter those MUs with low accuracy. Previous literature has shown that the decomposed MUs with larger SILs tended to have a higher accuracy. In the current study, MUs with SIL larger than 0.8 were accepted for further analysis.

During decomposition, the algorithm can converge to the same source signal multiple times. To remove the duplicated MUs, a post-processing step was performed. If a pair of MU firing trains had > 50% of synchronized firing events within ± 1 ms after adjusting the time delay, the MU firing train with a lower SIL was removed. All the processed firing events trains were then pooled into a composite train, and the discharge rate of the composite firing event train was calculated (Fig. 1c).
The EMG-amplitude-based feature is widely used for EMG-to-force prediction. The root-mean-square of EMG has also been verified as the best EMG-amplitude feature, especially at high effort levels (> 25% MVC). Therefore, the root-mean-square of EMG was used to estimate the force for experimental data as a control condition compared with the neural-drive-based estimation. Raw EMG signals were band-pass filtered to reduce the influence of motion artifacts and high frequency background noise (4th Butterworth and 2nd IIR filter at 60 Hz with a bandwidth of 1 Hz). The root-mean-square values of all the 8 × 8 processed EMG signals used for decomposition were calculated, and were then averaged across all the channels.

A 350 ms moving window with a moving step of 50 ms was used in both the neural-drive-based and EMG-based approaches. The force prediction was performed using a linear regression method. Specifically, a single trial from trapezoid condition was used to calculate the regression coefficients from the neural-drive-based or EMG-based estimate for each force level. The remaining trials were then used to evaluate the force prediction. A cross-validation was also performed such that any single trial was used for the estimation approach was evaluated by calculating the time to calculate the regression coefficient calculation, and the remaining trials were used for evaluation/testing. Only the evaluation results were reported. The performance of the two estimation approaches was evaluated by calculating the \( R^2 \) values between the estimated values (EMG-based or neural-drive-based approaches) and the actual force output. Prior to the \( R^2 \) calculation, the time series of the neural-drive-based or EMG-based estimations were adjusted with the force recordings to account for the neural-mechanical delays, using a cross-correlation analysis.

### Statistical Analysis

Standard errors were used for all the figures, and standard deviations of the data were used for all other data analyses. The performance differences were tested using a repeated measures analysis of variance (ANOVA) in SPSS 24 (IBM). Since the \( R^2 \) values were bounded at 1, an arcsine-square-root transformation was performed to satisfy the normal distribution assumption of the ANOVA and regression analysis.

For the simulated data, the performance of the neural-drive-based approach was examined on three factors [force level × trajectory × SNR]. For the experimental data, the evaluation was examined on four factors [force level × trajectory × finger × estimation method]. Post hoc pairwise comparisons with Bonferroni corrections were conducted when a significance was found. A significance level of \( p < 0.05 \) was used.

### RESULTS

#### Simulation Results

The overall decomposition results (both accuracy and number of MUs detected) are shown in Table 3. Overall, the decomposition accuracy and yield revealed similar pattern across force trajectory. As the force level increased and the SNR decreased, the decomposition accuracy decreased from 97.33 ± 0.27% (the least challenging condition: 20% trapezoid shape at 20 SNR) to 68.90 ± 0.76% (the most challenging condition: 50% trapezoid shape at 5 SNR). Similarly, the corresponding number of MUs detected also dropped from 19.00 ± 0.24 to 11.92 ± 0.21.

After decomposition, discharge events from all the MUs with SIL > 0.8 were pooled to estimate the neural drive. The sample time-series plots in Figs. 2a and 2b show that the estimated neural drive can largely match the variation of the simulated muscle force. The overall estimation results are summarized in Fig. 3. The \( R^2 \) values varied from 0.90 to 0.96 across different

### TABLE 3. The overall results of decomposition.

<table>
<thead>
<tr>
<th></th>
<th>5 SNR</th>
<th>10 SNR</th>
<th>20 SNR</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sine 20%</td>
<td>78.90 ± 0.82%</td>
<td>88.32 ± 0.60%</td>
<td>95.32 ± 0.37%</td>
</tr>
<tr>
<td></td>
<td>(15.14 ± 0.21)</td>
<td>(15.60 ± 0.19)</td>
<td>(18.90 ± 0.24)</td>
</tr>
<tr>
<td>Sine 50%</td>
<td>71.49 ± 0.83%</td>
<td>81.26 ± 0.64%</td>
<td>92.58 ± 0.43%</td>
</tr>
<tr>
<td></td>
<td>(11.92 ± 0.21)</td>
<td>(16.02 ± 0.20)</td>
<td>(18.86 ± 0.27)</td>
</tr>
<tr>
<td>Trapezoid 20%</td>
<td>79.06 ± 0.84%</td>
<td>89.25 ± 0.67%</td>
<td>97.27 ± 0.27%</td>
</tr>
<tr>
<td></td>
<td>(15.36 ± 0.23)</td>
<td>(15.66 ± 0.19)</td>
<td>(19.00 ± 0.24)</td>
</tr>
<tr>
<td>Trapezoid 50%</td>
<td>68.73 ± 0.78%</td>
<td>79.61 ± 0.63%</td>
<td>92.18 ± 0.40%</td>
</tr>
<tr>
<td></td>
<td>(12.40 ± 0.27)</td>
<td>(16.06 ± 0.20)</td>
<td>(18.80 ± 0.21)</td>
</tr>
</tbody>
</table>

The accuracy (mean ± standard error) are shown. The numbers of motor units (MUs) detected are shown in brackets.
373 conditions. A three-way repeated measures ANOVA [force level × trajectory × SNR] showed that all the three main factors ($p < 0.05$) had significant differences. Further post hoc comparisons revealed that the estimate became less accurate as the SNR decreased or the force level increased, largely due to a decline of the decomposition accuracy. In addition, the sine-wave trajectory and lower force level showed higher $R^2$ values.

379 To quantify the sensitivity of the $R^2$ to the decomposition performance, Fig. 4 illustrates the relation between the $R^2$ of the drive estimation and the decomposition performance (the accuracy and the number of MUs detected) after pooling all 600 simulated trials. The results indicated that a higher performance in both the accuracy and yield led to a higher $R^2$ value. The decomposition accuracy seemed to be more critical in that a small number of MUs can lead to an accurate neural drive estimation, as long as the discharge timings were accurate. In contrast, a large number of inaccurate discharge timings can still lead to relatively low $R^2$ values.

382 Experimental Results

384 A linear regression method was used to predict the muscle force. Figure 5 shows two representative examples of the time-series of EMG and neural drive,
in comparison with the force output. The neural-drive-based approach for both examples revealed better performance compared with the EMG-based estimation. The relation between the SNR and the $R^2$ was examined on both estimations across all the trials. A robust linear regression was performed to quantify the strength of the correlation (Fig. 6). Based on the regression results, the $R^2$ of the EMG-based approach tended to decline as SNR increased ($R = 0.32$, $p < 0.05$). However, the neural-drive-based approach showed a weaker association with SNR ($R = 0.19$, $p < 0.05$).

![Figure 3](image-url)  
**Figure 3.** The $R^2$ values of the simulation results in different conditions. The bars represent the standard errors. The asteroids represent significant differences ($p < 0.05$).

![Figure 4](image-url)  
**Figure 4.** The influence of the decomposition performance (accuracy and the number of MUs detected) on the $R^2$ of the neural-drive-based estimation. The color bar shows the values of $R^2$'s. Note: the map was interpolated linearly three times just for visual presentation.

Four separate two-way ($\text{finger} \times \text{estimation method}$) repeated measures ANOVAs were performed on each condition (each subplot in Figs. 7a–7d). The detailed statistical outcomes are summarized in Table 4. Most of the results showed that the estimation method was significant, except for trapezoid 50% condition ($p > 0.05$). The values of power analysis for the significant factors of the four two-way ANOVAs ranged from 0.80 to 0.95. Post hoc comparisons found that the neural-drive-based approach always had higher $R^2$ values than the EMG-based method for all the fingers.

Since no significant difference was observed in the finger factor and no interaction was found, the marginal mean values were calculated by averaging the $R^2$ values of four fingers for different conditions (trajectory, force level, and estimation method) as shown in Fig. 7e. The $R^2$ values ranged from 0.83 to 0.92 for the neural-drive-based estimation, and from 0.73 to 0.88 for the EMG-based estimation.

A three-way (trajectory $\times$ force level $\times$ estimation method) repeated measures ANOVA was performed on $R^2$ values. The results showed a significant difference for trajectory [$F(1,7) = 14.355, p < 0.05$], and a significant interaction [$F(1,7) = 19.287, p < 0.05$] between estimation method and force level. The values of power analysis of the three factors (trajectory, force level, and estimation method) are 0.92, 0.88, and 1, respectively. The sine-wave trajectory showed higher $R^2$ values than the trapezoid trajectory ($p < 0.05$). Further Post hoc analysis were tested between the two estimation methods and the two different force levels. For each force level, the neural-drive-based approach always had higher $R^2$ values than the EMG estimate ($p < 0.05$). For the EMG-based estimation method, 50% force level had higher $R^2$ values than the 20% force level ($p < 0.05$).

**DISCUSSION**

In this study, the feasibility of using motoneuron discharge events to estimate the individual finger forces was investigated. The simulation results showed that the decomposition accuracy was sensitive to the signal quality (SNR) and the number of active MUs in the signals (associated with the level of excitation), and that the decomposition yield was only sensitive to the signal quality. The experimental results showed that the neural-drive-based approach was consistently better than the EMG-based approach in estimating muscle forces across different conditions (individual finger, force level, and force trajectory). Overall, the superior performance of the neural-drive-based estimation of individual finger forces offers a promising neural interface signal for intuitive and robust control of rehabilitative/assistive techniques that can help restore individual finger movement.

**Implications of Simulation Results**

Given that the ground-truth of the neural drive (input) and MU firings (output) are known in the simulation, a direct evaluation on the performance of...
the neural-drive-based estimation in relation to the performance of the MU decomposition was performed. The descending neural drive can be estimated from the discharge frequency/probability of the MU pool. In order to reliably estimate the neural drive, accurate discharge timings from a certain number of MUs sampled from the MU pool are required to reflect the pool behavior. Based on the simulation results, both the accuracy and yield of the decomposition indeed affect the neural-drive-based estimation, in that a lower decomposition accuracy and yield can lead to inaccurate force estimations. However, the degree of influence of the decomposition accuracy and yield on neural drive estimation differs, with decomposition accuracy being the more sensitive variable. Specifically, if the decomposition accuracy is above approximately 85%, a large range of decomposition yield (as low as 8 MUs) can lead to an accurate estimation of the neural drive. In contrast, if the decomposition accuracy is low (below 80%), a large number of MUs (~15) would be needed to derive an accurate neural drive.

On the other hand, the performance showed improvement as the number of MUs increased. This effect can arise from several factors associated with the
nature of the decomposition errors. First, the neural drive estimate is based on the population firing behavior of composite spike trains from multiple MUs. Even though the timing of discharge in individual MUs may be inaccurate due to an incorrect random shift in discharge timings, a comparable number of false positive and false negative errors from individual MUs can be averaged out in the average window. Second, the decomposition error can also arise from incorrect assignment of the discharge events. For instance, the spike of a MU is incorrectly assigned to a different MU, which would lead to two errors. However, the errors are cancelled out in the composite spike train, and would not affect the neural drive estimations. Nevertheless, to ensure an accurate estimation of the neural drive, a high decomposition accuracy is necessary and can provide confidence on the neural drive estimations.

**FIGURE 6.** The relation between SNR and $R^2$ for both approaches. Each circle represents one individual trial.

**FIGURE 7.** (a)--(d) The mean values of the two estimates in different conditions. (e) The marginal mean values for the two estimates on different conditions after averaging across different fingers. The bars represent the standard errors. The asteroids represent significant differences ($p < 0.05$). The average SNR of the EMG signals in each condition are also shown.

**TABLE 4.** The summary of four two-way (finger $\times$ estimation method) repeated measures ANOVAs.

<table>
<thead>
<tr>
<th>Condition</th>
<th>Finger</th>
<th>Estimation method</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sine 20%</td>
<td>$F(3,21) = 0.095, p = 0.962$</td>
<td>$F(1,7) = 12.590, p = 0.009$</td>
</tr>
<tr>
<td>Sine 50%</td>
<td>$F(3,21) = 1.777, p = 0.182$</td>
<td>$F(1,7) = 10.677, p = 0.014$</td>
</tr>
<tr>
<td>Trapezoid 20%</td>
<td>$F(3,21) = 2.837, p = 0.063$</td>
<td>$F(1,7) = 17.733, p = 0.004$</td>
</tr>
<tr>
<td>Trapezoid 50%</td>
<td>$F(3,21) = 2.307, p = 0.106$</td>
<td>$F(1,7) = 2.823, p = 0.137$</td>
</tr>
</tbody>
</table>

The values are marked in bold when significance was found.
Consistent with earlier studies, the simulation results also showed that the SNR of the EMG signals and the force level (i.e., the number of MUs in the EMG signals) can affect the decomposition results. A large number of MUs can increase the degree of superposition and pose challenges to the source separation. The simulation results can provide a reference for the decomposition of experimental data. Namely, a high SNR and a low-to-moderate effort is desirable in order to ensure accurate decomposition results.

Implications of Experimental Results

The experimental results show that the neural-drive-based approach was consistently superior to the EMG-based approach for force estimation. The neural-drive-based approach is not affected by different MUAP features, such as amplitude, duration, or cancellation due to superposition, as in the EMG-based approach. For example, at low contraction levels, the EMG signals tend to be sparse, and the EMG-based approach has large estimation biases, which could be even more prominent in clinical populations, because the EMG signals are often sparse and unstable due to disordered control of MU activations. In addition, external factors, including high baseline noise or variations in electrode-skin contact, can further decrease the reliability of the EMG-based approach. Although the simulation results show that SNR can affect the estimation performance of the neural-drive-based approach to some degree, the EMG-based approach is more sensitive to SNR with high estimation errors at low SNR levels (Fig. 5).

These findings indicate that the neural-drive-based approach is more robust to low signal quality, compared with the EMG-based estimates. The less stringent requirement on the signal quality of the neural-drive-based approach can facilitate wide clinical applications for human-machine interactions, because the quality of the signals obtained from clinical populations tend to vary depending on pathology.

The force estimation showed comparable performance across individual fingers. These outcomes have critical implications for clinical applications involving human-machine interactions. First, assistive/rehabilitation strategies focusing on fine control of individual finger movement are still a challenge in the field. The ability to estimate individual finger forces reliably shown in this study can help improve the performance of human-machine interactions involving fine motor control of finger movement. Together with the development of advanced control frameworks, this approach can help better utilize the high degrees of freedom in exoskeletons or prosthetic hands, and further improve the functional outcomes for individuals with neuromuscular disorders. Second, the robust performance across different task conditions involving steady grip or dynamic force variations can also facilitate applications during daily activities. However, the varying forces were still produced in isometric conditions. Additional studies involving dynamic finger movements are needed to further evaluate the performance in different dynamic movements with muscle fibers shifting substantially beneath the recording electrodes. Nonetheless, these findings suggest that the neural-drive-based estimation on individual finger force can be a promising approach for robust control of hand exoskeletons, prosthetic hands, or neuroprostheses, which can help restore individual finger control and eventually could facilitate the utility of advanced devices in disabled individuals.

The signal conditions may affect the EMG- and neural-drive-based approaches in different ways. For the neural-drive-based approach, no significant difference was found across the two force levels. Although the signals from the 50% force level had a higher SNR than that from the 20% level, more superposition from more MUs is expected at higher forces. These two contrasting factors can balance out the effect on the decomposition performance. On the other hand, the EMG-based estimate showed a better performance at higher force level. The EMG envelop tended to be smoother at higher forces, which decreased the variation of EMG-based estimate. In addition, the trajectory also influenced the two estimations, largely because the small variation of force estimate during the steady contraction can potentially decrease the $R^2$ values. The overall $R^2$ of the neural-drive-based approach on simulation results exceeded the values shown in the experimental data. Because all the characteristics of EMG signals cannot be fully captured in the simulation, which can lead to higher decomposition errors. Specifically, the EMG signals obtained from experiments may have sporadic action potential variations in amplitude and/or duration, and external factors (shift of electrode locations or motion artifacts) can also alter the signal properties.

Limitations and Future Work

The current study has several limitations. First, the subjects were instructed to only extend the designated finger in each trial. However, the subjects may still inevitably perform co-contractions due to finger enslaving, especially for the ring finger extension. The EMG signals from muscle co-contraction can potentially bias the force estimations. Second, the finger activations were not classified. However, previous works have showed that the muscle activation of individual finger movement was localized and distin-
guishable for both finger extension or flexion using high-density EMG grid. The EMG activities of individual finger contraction can be separated using pattern recognition techniques. Third, the linear regression was performed using the steady contraction trial within each force level, but still exhibited a good performance when tested on the varying force trials. Since the mean firing rate of the decomposed MU pool at each force level is not linearly related with the force level, the regression was performed at individual force levels. Future work will investigate whether the regression performed on a single force level (e.g., close to the maximum force) can be generalized across different force levels. Fourth, this study does not allow us to dissect the specific levels of the central nervous system in contribution to the neural drive estimations. For example, different cortical regions, cerebellum, basal ganglia, and brainstem can all play a role for the neural drive estimation. Lastly, the force estimation is performed through post-processing, and the computation load is a factor during real-time estimation. The EMG-based approach is suitable for real-time estimation. The neural-drive-based approach, however, requires more computation time, largely at the EMG decomposition step. Real-time decomposition has been investigated previously.\textsuperscript{15} The strategy of online neural-drive-based approach is to obtain the separation matrix for the extraction of neural drive information using an initial batch (approximately 5-10 s). Then, the separation matrix can be multiplied to the incoming data to obtain the neural drive information in real-time. The separation matrix will need to be updated periodically during long-term use.

CONCLUSIONS

The current study shows that the neural-drive-based approach out-performances the EMG-based approach in predicting individual finger forces under different scenarios. The boundary conditions for reliable neural drive estimation were also provided. These findings can potentially provide an intuitive and robust neural interface for future studies that investigate the applications of rehabilitative or assistive devices for clinical populations, with a goal to promote their independence of living and enhance their quality of life. Future work focusing on the real-time implementation of this approach is needed for future clinical translation.

CONFLICT OF INTEREST

The authors have no financial relationships that may cause a conflict of interest.

REFERENCES


Publisher’s Note Springer Nature remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.