Estimation of Joint Kinematics and Fingertip Forces using Motoneuron Firing Activities: A Preliminary Report

Feng Xu, Yang Zheng, and Xiaogang Hu

Abstract—**A loss of individuated finger movement affects critical aspects of daily activities. There is a need to develop neural-machine interface techniques that can continuously decode single finger movements. In this preliminary study, we evaluated a novel decoding method that used finger-specific motoneuron firing frequency to estimate joint kinematics and fingertip forces. High-density electromyogram (EMG) signals were obtained during which index or middle fingers produced either dynamic flexion movements or isometric flexion forces. A source separation method was used to extract motor unit (MU) firing activities from a single trial. A separate validation trial was used to only retain the MUs associated with a particular finger. The finger-specific MU firing activities were then used to estimate individual finger joint angles and isometric forces in a third trial using a regression method. Our results showed that the MU firing based approach led to smaller prediction errors for both joint angles and forces compared with the conventional EMG amplitude based method. The outcomes can help develop intuitive neural-machine interface techniques that allow continuous single-finger level control of robotic hands. In addition, the previously obtained MU separation information was applied directly to new data, and it is therefore possible to enable online extraction of MU firing activities for real-time neural-machine interactions.**

I. Introduction

Individuated finger movement is essential for our daily activities. Advanced neural decoding techniques now allow us to control robotic hands in a dexterous manner, based on electroencephalogram (EEG) [1] or electromyography (EMG) [2]. Surface EMG (sEMG) is a promising neural-machine interface due to its non-invasiveness and versatile applications. Previously, pattern recognition approaches are commonly used to detect user intent when interacting with robotic devices [3]–[5]. Most pattern recognition approaches identify discrete states of user intent as a classification problem in gesture recognition. Different features, such as EMG mean absolute value, root-mean-square (RMS), and medium frequency, are extracted from sEMG signals and are fed into different classifiers such as support vector machine, linear discriminative analysis, and neural networks in order to estimate the gesture patterns [5]–[8]. The state-of-the-art classifiers on sEMG can reach a classification accuracy above 90% [9]. Certain algorithms can also be applied in a cross-subject manner with minimum intra-subject adjustments [10]–[12]. However, the available number of gestures is usually limited to a finite number of predefined gestures, and the actual neural control of robotic devices is also not continuous. As a result, these approaches are not intuitive, and hinder the natural ability of what the human hand is capable of doing.

To continuously drive a robotic device, an alternative approach is to produce the motor intent estimation based on the envelope of the EMG signal amplitude [13]. An initialized linear or quadratic regressor can associate the amplitude of EMG to fingertip forces or joint kinematics. However, the performance of this approach can deteriorate over time due to unstable EMG recordings arising from EMG amplitude drift [14] or electrode shift [15]. It is also sensitive to unavoidable random noise or movement artifact that can lead to abnormal and unstable estimation of EMG amplitude. Alternatively, since the EMG signals intrinsically comprise motor unit action potentials (MUAPs), the decomposed signal sources as motor unit (MU) firing activities can be used to estimate the neural command to the muscles, which can then be used to estimate finger isometric forces or joint kinematics using regression functions (termed neural drive method) [16], [17]. This method is based on neuron firing event (binary signal) frequency, and is less sensitive to the aforementioned interferences of EMG signals. The use of finger-labeled MU discharge information for individual finger isometric force estimation has recently been shown to be feasible [18], where a MU pool classification procedure was applied to validate whether MUs correspond to a specific finger across different trials. However, the feasibility of the classification of MUs in dynamic tasks is still unclear. In addition, source separation of high-density EMG (HD-EMG) signals, such as using independent component analysis [16], is computationally intensive, and thus it is not suitable for direct online deployment [19]. More efficient calculation is needed to enable real-time neural decoding.

To this end, we implemented the decomposition-validation-estimation method for finger joint angle estimation in a dynamic task, and also evaluated the performance of the same method on the finger isometric force estimation in this preliminary study. Our approach first extracted the MU firing activities from earlier trials in an offline manner, and the validated separation information was then directly applied to new HD-EMG signals. Since the second matrix operation process is computationally efficient, the source separation can be performed in an online manner, which allows real-time control of assistive devices. A conventional EMG amplitude-based method (termed EMG amp method) was also performed as a comparison. The results showed that the neural drive method using cross-trial separation matrix can estimate the

This study was supported by the National Science Foundation (Grant #: CBET-1847319). Xu, Zheng, and Hu are with the Joint Department of Biomedical Engineering at University of North Carolina-Chapel Hill and NC State University (correspondence e-mail: xiaogang@unc.edu). Zheng is now with Xi’an Jiaotong University.

joint angle or fingertip isometric flexion force more accurately than the EMG amp method.

II. Methods

A. Participants

Three subjects with no neurological diseases were recruited in the study. All participants gave informed consent via protocols approved by the Institutional Review Board of the University of North Carolina at Chapel Hill.

B. Data acquisition

The subjects were seated in front of a desk with their right arm supported by a large foam pad on the desk. They were instructed to adjust the height of the chair to avoid discomfort before the experiment. To record the index and middle finger forces, two miniature load cells (SM-200N, interface) were pre-installed to the desk held by a metal frame and horizontally aligned to these two fingers when the subject's forearm and hand were in the neutral position. The force recording was sampled at 1000 Hz. To record joint kinematics of the metacarpophalangeal joints of the index and middle fingers, subjects wore a custom-made sensor glove with two individual angle sensors, and the angle data were obtained at 100 Hz. An 8×16 HD-EMG electrode array (OT Bioelettronica) was attached to the flexor side of the subjects' forearm with double-sided adhesive pads (Figure 1 (A)). The HD-EMG electrode array has a 10 mm inter-electrode distance and 3 mm electrode diameter. The amplifier EMG-USB2+ (OT Bioelettronica) sampled the signals at 2048 Hz and band-passed at 10-900 Hz.

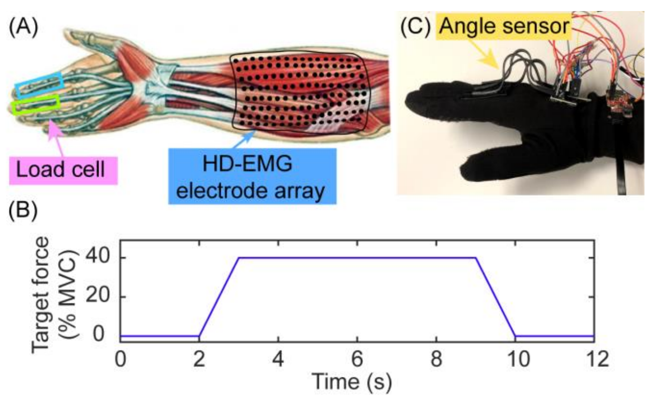

Figure 1: Experimental setup for the data acquisition. (A) The placement of the HD-EMG electrode array on the flexor muscles in the forearm and load cells for isometric finger flexion force measurements. (B) Trajectory for the isometric finger flexion task. (C) Custom-made sensor glove to record joint kinematics in the dynamic task.

Two tasks were performed by the subjects under the guidance of the experimenter. Prior to the main tasks, the maximum voluntary contraction (MVC) was recorded for each finger. First, the subjects followed a trapezoid trajectory (Figure 1 (B)) in the isometric finger flexion task using their index or middle fingers, respectively. The trapezoid trajectory started to rise at 2 seconds of the trial, ramped up linearly, and peaked at 40% MVC at 3 seconds. The plateau of 40% MVC was held for 8 seconds, and then ramped down to 0% MVC linearly. Each isometric trial lasted for 12 seconds, and was repeated three times. Then, the dynamic finger movement task was performed also using the index or middle finger, respectively. Aided by a 1 Hz metronome, the subjects repetitively flexed the finger (index or middle) from the neutral (maximum extension) position to the maximum range of motion and opened back to the neutral position until the end of the trial at 24 seconds. Each of the closing and opening movements lasted for 1 second, and the 24-second trial was repeated three times as well. The index and middle finger testing trials were randomized across subjects.

C. Motor unit extraction

The decomposition of motor units in this study was based on the fast independent component analysis (FastICA) algorithm [20]. Before performing the convolutive blind source separation on HD-EMG signals, motion artifact was removed using the method as described in [21]. The EMG decomposition procedure followed the procedure described in [16], [22]. In brief, the procedure comprises extending the raw EMG signal channels by a factor of f_e, whitening the extended channels, and obtaining the decomposed signal sources via a fixed-point iteration algorithm. The MUs were separated from the background signal sources using the $Kmeans{+}{+}$ algorithm by setting the number of clusters to be 2. The decomposed MUs were in the form of separation vectors which can be applied to different segments of EMG signals. This matrix multiplication resulted in the decomposed source signals, which were then used to derive the MU discharge events. For each trial, 60 channels with the highest RMS values in that trial were selected among the 128 HD-EMG signals for decomposition. The 60 channel number was based on our earlier work [23]. The separation matrices of each finger were applied to other trials to obtain new MU firing activities (termed cross-trial MUs).

D. Motor unit validation

In order to accurately estimate the finger kinematics or forces using cross-trial MUs, the MUs extracted from any trial were validated on a second validation trial before they were applied on the third testing trial. Specifically, the separation matrix derived via decomposition from the first trial (dynamic motion and isometric force trials) was applied on the second validation trial, resulting in an $M_i \times K_j$ spike trains array, where M is the length of EMG samples in the second trial and K is the number of spike trains (the number of the decomposed MUs) in the first trial. A moving average window (window size=0.5s, step size=0.1s) was applied to the individual spike trains to smooth the discharge frequency before a Kalman filter was applied on the smoothed firing frequency. The Kalman filter was used to remove sporadic and large-amplitude fluctuations [14]. A regression analysis was then performed between the filtered firing frequency and the measured joint angle or isometric force. The regression function was linear in the isometric trial, and was quadratic in the dynamic trial [17]. This process provided K_j number of R^2 values, indicating how well a specific MU estimated the motor output in the validation trials. Then, a cross-validation was performed, where the MUs from the second trial were validated on the first trial and resulting in an $M_j \times K_i$ spike train. Similarly, K_i number of R^2 values were provided in the second validation process. The MUs from the first trial and the second trial were concatenated together. The $K_i + K_j$ number of R^2 values were then sorted in a descending order, and the top N largest R^2 values' indexes were used to select N

MUs from the concatenated separation matrix for the third testing trial. Removal of duplicate MUs was conducted, given there were likely common MUs from the first two trials. The number N was empirically selected to be 10 as a reasonable choice based on our pilot testing. A three-fold validation was then performed. Namely, each trial was used as the testing trial and the other two trials of the same finger and same motion type (dynamic or isometric) were used for decomposition and validation.

E. Finger joint angle/force estimation

The estimation of individual finger forces or joint angles was derived from the extracted and validated MUs from two trials and applying on the third testing trial. The same moving window average and Kalman filter were used for smoothing the spike trains as in the validation. For the conventional EMG amp method as a comparison, the top 60 channels with the maximum amplitude were found using the training and validation trials, since the RMS distribution of the highest amplitude channels were unknown (blinded) for the testing trial. The average RMS across the 60 channels were calculated using a 0.5-second sliding window with a step size of 0.1 second. The same Kalman filter was applied to the RMS values. Regression analysis was performed for both the neural drive method and the EMG amp method, where the order of the regression was linear for the isometric force trials, and was quadratic for the dynamic trials. The root mean square error (RMSE) between the estimated values (force or angle) and the measured values were calculated to evaluate the estimation performance.

III. RESULTS

An example joint angle estimation and an example isometric force estimation are shown in Figure 2 The results showed that the neural drive method had a better estimation of both joint angle and isometric force, in comparison with the EMG amplitude method.

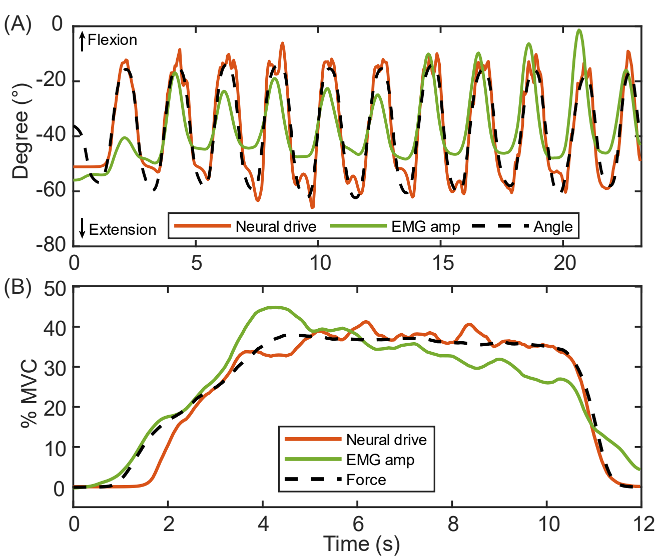

Figure 2: (A) An example trial of the estimation for the joint angle movement. (B) An example trial of the estimation for the isometric force.

To better illustrate the MU discharge information, an example of spike trains for neural drive estimation is shown in Figure 3. It showed that when the finger flexed (measured joint angle increased), the MUs of the flexor muscles were recruited.

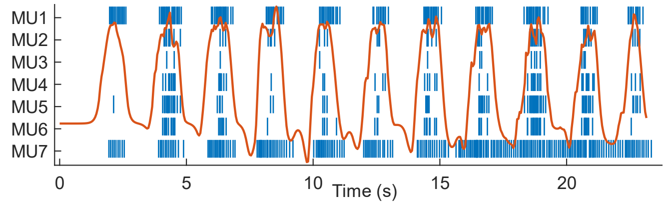

Figure 3: The spike trains in a dynamic validation trial using the MUs decomposed from two other trials after the validation procedure. The trace shows the estimated neural drive. The MUs were not ordered based on recruitment order.

The averaged RMSE values across the three subjects are shown in Figure 4. The preliminary results showed that the neural drive method was more accurate than the EMG amp method in both the dynamic task and the isometric task. The neural drive method revealed a smaller estimation error (RMSE=8.76 (°), standard error (SE)=0.87) than the EMG amp method (RMSE=19.56, SE=2.06) in the dynamic condition. Similarly, the neural drive method also showed a smaller estimation error (RMSE=3.05 (% MVC), SE=0.67) than the EMG amp method (RMSE=3.88, SE=0.32) in the isometric task.

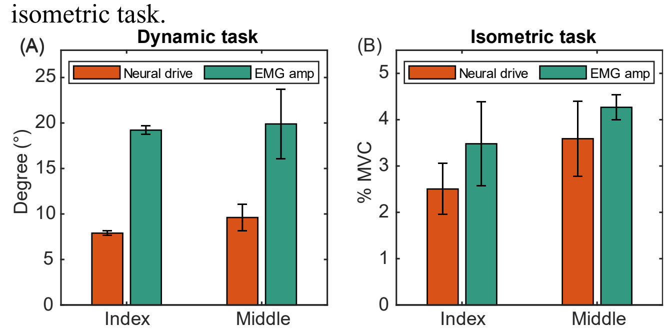

Figure 4: The RMSE for the neural drive method and the EMG amp method. The error bar represents standard error. (A) RMSE in the dynamic task. (B) RMSE in the isometric task.

IV. DISCUSSION

In the current study, we presented a preliminary investigation using cross-trial MUs (labeled to specific fingers) for the estimation of finger dynamic movements and isometric forces. We first performed offline MU decomposition on two trials separately. Then, we cross-validated the MUs between these two trials. We then retained the finger-specific MUs with strong associations with the motor output (joint angle or isometric force) of a particular finger. The retained MU information (separation matrix) was applied to the third trial for validation testing. We found that the cross-trial MUs can accurately estimate both dynamic movement and isometric force tasks. The estimation was more accurate than the conventional EMG amplitude method in terms of overall RMSE, across three subjects and finger-specific evaluations.

Since the decomposition of HD-EMG signals is computationally intensive, it is not feasible for real-time computation for human-robot interactions. One potential solution is to decompose the MUs during an offline initializing period of the trial, and since the actual source separation is time consuming, these calculation steps are performed offline. After the separation matrix is available, we can then apply the separation matrix to a new data set in a real-time manner [14]. This is based on the assumption that a common set of MUs are recruited across different muscle activation trials. The results showed that this approach can accurately estimate the dynamic and isometric finger tasks.

There is substantial estimation error (~ 20 degrees) in the EMG amp method during dynamic movements, compared with a smaller error (~7-8 degrees) in the neural drive method. The results indicate that the EMG amplitude during dynamic movement is not a reliable estimate of motor output. This finding is consistent with a previous study, where the estimation error of the EMG amp method is larger than the neural drive method in finger extension angle estimation [17]. It is potentially due to residual motion artifacts and muscle fiber shift beneath the electrodes, which could lead to variations of the EMG amplitude. As shown in Figure 2, the peak EMG amplitude drifted over time in the dynamic trial, and the EMG amplitude during the plateau segment also drifted over time in the isometric trial. The binary spike train of the neural drive method is less affected by those variations. Prior to the EMG amplitude calculation, potential motion artifact has been removed using a source separation method [21]. Without this removal method, we expect even larger estimation errors of the EMG amp method. Although the extraction of MUs during dynamic movement is more challenging than the isometric condition, we still found that the neural drive method during dynamic movement performed better than the EMG amp method.

The difference in estimation error between the neural drive and the EMG amp method is smaller in the isometric condition. A possible reason is that each isometric trial is merely 12 seconds, and the performance of the EMG amplitude usually degrades over time due to possible fatigue. An earlier study has shown that the EMG amp and neural drive methods exhibit similar performance in the first 200 s of contraction, but beyond that, the EMG amplitude tends to show a drift [14]. On the other hand, the neural drive is a more robust method since it does not rely on the amplitude of the EMG signals.

In future studies, the optimal number of selected MUs during validation can be further investigated to achieve a more accurate estimation. Only three subjects were recruited in this preliminary study, we plan to recruit more subjects to systematically evaluate the neural decoding performance in future work. Lastly, in the current study, MU decomposition was performed separately for the dynamic and isometric tasks. We plan to explore whether it is feasible to estimate neural drive (composite MU firing frequency) directly using neural network approaches [24] across tasks, which would be more efficient and could further facilitate real-time decoding.

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