Concurrent Decoding of Finger Kinematic and Kinetic Variables based on Motor Unit Discharges

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***Abstract*— A reliable and functional neural interface is necessary to control individual finger movements of assistive robotic hands. Non-invasive surface electromyogram (sEMG) can be used to predict fingertip forces and joint kinematics continuously. However, concurrent prediction of kinematic and dynamic variables in a continuous manner remains a challenge. The purpose of this study was to develop a neural decoding algorithm capable of concurrent prediction of fingertip forces and finger dynamic movements. High-density electromyogram (HD-EMG) signal was collected during finger flexion tasks using either the index or middle finger: isometric, dynamic, and combined tasks. Based on the data obtained from the two first tasks, motor unit (MU) firing activities associated with individual fingers and tasks were derived using a blind source separation method. MUs assigned to the same tasks and fingers were pooled together to form MU pools. Twenty MUs were then refined using EMG data of a combined trial. The refined MUs were applied to a testing dataset of the combined task, and were divided into five groups based on the similarity of firing patterns, and the populational discharge frequency was determined for each group. Using the summated firing frequencies obtained from five groups of MUs in a multivariate linear regression model, fingertip forces and joint angles were derived concurrently. The decoding performance was compared to the conventional EMG amplitude-based approach. In both joint angles and fingertip forces, MU-based approach outperformed the EMG amplitude approach with a smaller prediction error (Force: 5.36±0.47 vs 6.89±0.39 %MVC, Joint Angle: 5.0±0.27° vs 12.76±0.40°) and a higher correlation (Force: 0.87±0.05 vs 0.73±0.1, Joint Angle: 0.92±0.05 vs 0.45±0.05) between the predicted and recorded motor output. The outcomes provide a functional and accurate neural interface for continuous control of assistive robotic hands.**

Keywords—Assistive robotic hand, neural decoding, finger force, finger joint angle, hand function

I. Introduction

Individuals with neural injuries tend to have hand impairments that severely limit their ability to live independently. Assistive robotic hands have the potential to alleviate the hand impairments. However, one critical barrier that limit wide clinical utility of these robotic devices is the lack of reliable neural decoding algorithms to control these robotic devices. Surface Electromyography (sEMG) [1, 2], which measures muscle activities composed of superimposing of hundreds of motor unit action potentials (MUAPs) from motor units (MUs), is widely used as reliable neural interface [3, 4]. Although a significant amount of success has been achieved in decoding several motor movements, including various upper-limb and hand activities, decoding individual finger movements still remains a considerable challenge [5]. To decode motor output from sEMG, two approaches are commonly used. One way is through pattern recognition, which involves recognizing a particular motion from a set of predefined patterns [6]. Although the method was successful at identifying a large number of patterns [7], the detected motions could only be used to control the assistive device in a discrete manner. An alternative is to use global EMG features such as EMG amplitude [8], which are capable of generating continuous control inputs. Although promising, EMG amplitude may be affected by a variety of interferences such as muscle fatigue, motion artifacts, and background noise. Since the control signal is directly related to the varying EMG amplitude, these interferences could result in deterioration of control performance over time [9].

As an alternative to global EMG features, decomposed signal sources as MU firing activities [2] was explored in estimating motor outputs. By using the MU discharge frequencies at the population level, neural-drive input to the muscles can be obtained, which can then be used for the movement estimation. It has been demonstrated that this approach is robust and efficient in estimating finger movements [10, 11], since it is less susceptible to intrinsic and extrinsic interferences. Both isometric finger force [10, 12] and dynamic joint angle [11, 13] were estimated more accurately using this approach than with the conventional EMG-amplitude method. In those studies, isometric finger force and dynamic joint angle estimation were performed separately, and the desired finger was involved only in a single task. Real-world scenarios may, however, involve a more complex movement of the fingers, requiring both isometric force and dynamic movements. In addition to developing efficient prediction models for concurrent and continuous estimation of isometric force and dynamic joint angle, keeping the complexity of those models to a minimum is also important to make them feasible for real-time implementation. In most prior studies [10, 12], the population firing frequencies of all the achieved MUs were determined and used in a linear regression model for the estimation. Due to the use of the summation of firing frequencies from all MUs, the prediction model had a minimum level of complexity; but details of individual MU firing activity were lost due to this process. In another study, ten motor units were selected and firing frequencies of individual MUs were used to estimate finger force and joint angle [11]. The inclusion of the firing rate of individual MUs increased the complexity of the prediction

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model. In addition, only a limited number of MUs were selected, and contributions of other MUs were not considered. Additionally, the computationally intensive process of MU decomposition makes implementing the neural-drive approach in real-time challenging. Previous studies have demonstrated that by performing the source separation process in advance using a small segment [14] or different trials of the data [11], the neural-drive approach can be implemented in-real time for estimating motor outputs based on the derived separation vectors. In this study, we aim to develop a neural interface that will, 1) estimate finger kinematics and kinetics concurrently from complex finger movements; 2) be efficient and low complexity, and 3) be able to use in real-time.

II. METHODS

A. **Participants.** The study recruited three healthy individuals (Age: 28±7 years) with no neurological disorders history. According to the protocols approved by the Institutional Review Board of the University of North Carolina protocol, all participants gave informed consent before the experiment.

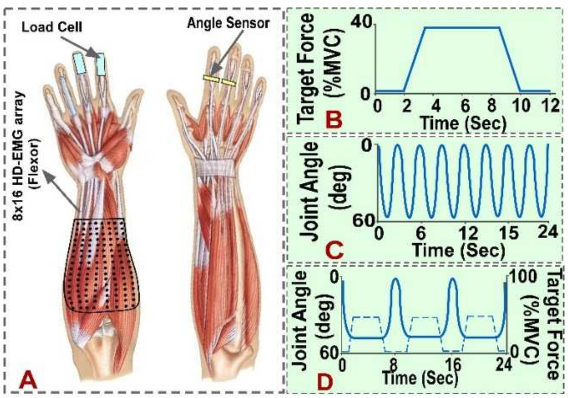

Fig 1. Experimental setup (A); Trajectory followed by the participant during Single-Isometric Task (B), Single-Dynamic task (C), Single-combined task (dash line represent force target, and solid line represent angle target) (D).

B. **Data Acquisition.** During the experiment, participants sat in a chair facing the testing desk and placed their right forearm on the desk in a neutral position supported by a soft foam pad. An electrode array of 8x16 was attached to the flexor side of the forearm overlying the flexor digitorum superficialis (FDS) muscle (Fig.1A) which was identified by palpating the participant's forearm. Each electrode in the array was 3 mm in diameter and 10 mm apart. Recordings of EMG data were performed at a sampling rate of 2048 Hz using an EMG USB2+ (OT Bioelettronica) data acquisition system, which amplified the signals with a gain of 1000 and a bandwidth of 10-900 Hz. Along with EMG, the experiment also included measuring the finger force involved in isometric motion and the joint angle related to the dynamic motion of the targeted finger. In order to accomplish this, two custom angle sensors were placed on the metacarpophalangeal (MCP) joints of the index and middle fingers (Fig.1A), and the fingers were aligned horizontally on a pair of miniature load cells embedded in the metal frame attached to the desk. The sampling rate for joint angle measurements was 100 Hz and 1 kHz for force measurements. The experiment consisted of three different tasks that each participant performed using their index or middle fingers at random. The same tasks were performed five times on each finger, with a minute gap between each trial. The Maximum Voluntary Contraction (MVC) of the index and middle fingers was measured before each participant began the actual task. As part of each task, a movement trajectory was displayed on the monitor, and the participant instructed to follow it with their fingers as shown in Fig. 1B, 1C, and 1D.

C. **Prediction through MU-discharge information.**

i. **MU extraction.** Single-isometric and Single-dynamic trials were processed for MU decomposition. Prior to that, the HD-EMG signals for each trial were pre-processed with the motion artifact removal method as described in [15], and then the Root Mean Square (RMS) was calculated for all 128 channels. RMS values across all trials associated with similar finger and task assignments were averaged and then sorted in descending order to determine the top 60 most active channels. A number of 60 was chosen based on the findings of earlier studies [10]. The MU decomposition method used in this study was similar to that described in [16, 17]. In brief, our procedure involved applying a fast independent component analysis (FastICA) based algorithm after extending the selected 60 channels by a factor (f=9) and whitening them, which resulted in a separation matrix of individual MUs through a fixed-point iteration procedure. Separation matrices obtained from different trials related to the same finger and task were merged together to form the 'MU pools' for each finger-task combination. From each MU pool, duplicate MUs and separation vectors with low Silhouette values (SIL < 0.5) were removed. The four MU pools were derived from the index and middle finger isometric and dynamic tasks: Index-Isometric (B_{II}), Middle-Isometric (B_{MI}), Index-Dynamic (B_{ID}), and Middle-Dynamic (B_{MD}).

ii. **MU Selection.** From each MU pool, we selected only 20 MUs that were strongly correlated to the assigned task of the given pool. Number 20 was selected based on our pilot testing. The MU selection was done by using a single-combined evaluation trial selected through five-fold cross-validation from the set of single-combined trials related to the same finger. All the remaining single-combined trials were used as testing trials for estimating motor outputs. For MU selection, MU pools generated through previous steps were applied to the evaluation trials; the obtained source signals were converted into binary firing event trains using a k-means algorithm (where, k = 2, MU discharges were set to 1 and background signals to 0), and firing rates of individual MUs were then calculated from them using a 0.5-sec moving average window (step size = 0.1-sec). A similar average window was used to process the measured finger force and joint angle of that trial. The firing rate of individual MUs of a selected pool and recorded motor output values related to the assigned task of that pool were fitted in linear regression (order = 1 for isometric and order = 2 for dynamic MU pools); the 20 MUs with the highest R^2 values were selected for further analysis.

iii. **Force & Joint angle estimation.** The isometric and dynamic MU pools associated with the same finger were directly applied to the EMG data of a single-combined testing trial of that finger separately. 20 MUs were divided into five groups based on similarity of firing patterns, and the populational discharge frequencies of each group were smoothed through a Kalman filter to remove isolated and sporadic fluctuations. In the force estimation process, the populational firing frequencies for five groups were fitted into a multivariate linear regression model (order = 1) with the recoded finger force of that trial (after processed through 0.5-sec average window of step size = 0.1) .

$$F_i(t) = \sum_{Gr=1}^{5} a_{Gr,i} S_{Gr,i}(t) + b_i \quad (1)$$

During the joint angle estimation process, the populational discharge frequencies for five groups were fitted into a multivariate linear regression model (order = 2) with the processed joint angle value.

$$JA_i(t) = \sum_{Gr=1}^{5} p_{Gr,i} S_{Gr,i}(t) + q_{Gr,i} S_{Gr,i}^2(t) + C_i \quad (2)$$

where, F_i and JA_i = Force and Joint angle of the i-th finger (i = index or middle); t = time; S=Population discharge freq. of four MUs; Gr = index of Groups; a, b, p, q and C =regression coefficients [18].

D. **Prediction through EMG-Amp.** For EMG-amplitude based estimation, we used the same 60 channels as for MU decomposition. For the combined testing trials, we calculated the average RMS values of the selected channels using a sliding window of 0.5 seconds (step size of 0.1) and then processed these values with the same Kalman filter we discussed earlier. In order to force estimation, we fitted the obtained values into a bivariate linear regression model (order = 1) along with the recorded finger force (after processing) of that trial.

$$F_i(t) = c_i A_i(t) + d_i \quad (3)$$

whereas, in order to estimate the joint angle, we fitted the obtained value into a bivariate linear regression model (order = 2) with the processed joint angle value.

$$JA_i(t) = x_i A_i^2(t) + y_i A_i(t) + z_i \quad (4)$$

where, F_i and JA_i = Force and Joint angle of the i-th finger (i = index or middle); A_i = RMS of EMG; c_i, d_i, x_i, y_i, *and* z_i = Regression coefficients.

III. RESULTS

The predicted force and joint angle estimation from an exemplary single-combined trial are illustrated in Fig. 2A and 2C. In these figures, the predicted motor estimations obtained from the MU discharge frequency-based method and the EMG amplitude-based method are compared with the measured values. As shown in figures, the predicted outputs obtained with the MU discharge frequencies are more accurate and closely match the measured outputs when compared with the EMG-amp-based method. In Fig. 2B and 2D, we also illustrate MU firing event trains used for neural-drive-based estimation. The firing event trains of the selected 20 MUs related to the isometric task are depicted in Fig. 2B, with a blue dashed curve representing the populational discharge frequencies of all the MUs. According to the figure, the MUs started firing as soon as the fingers exerted isometric force and continued until the fingers were retracted from the load cells. In the case of joint angle estimation, selected 20 MUs associated with the dynamic task started firing when the finger started flexing the MCP joint and were active until the finger started extending back to its original position. The black dashed curve represents the normalized populational firing frequency of all MUs.

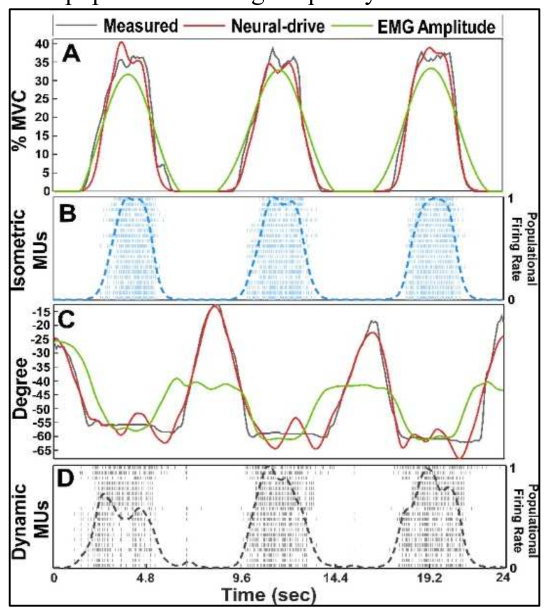

Fig 2: The concurrent estimation of force (A) and joint angle (C) from single-combined trial. MU firing event trains and populational firing frequency associated with the estimation of force (B) and joint angle (D).

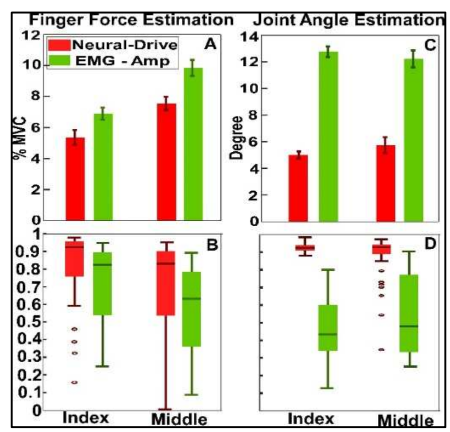

Figure 3: The RMSE (A & C) and the R^2 value (B & D) of the neural-drive and EMG-amp methods.

Further, a comparison was made between the performance of the neural-drive method and the EMG-amp method for force and joint angle prediction using RMSE and R^2 values. For each individual finger, RMSE values are illustrated in Fig. 3A and Fig. 3C for the average of all single-combined trials involving that finger. From Fig. 3A, it can be seen that the neural-drive method predicts forces with lower estimation errors than the EMG-amp method for both index (5.36±0.47 vs 6.89±0.39) and middle finger (7.54±0.43 vs 9.83±0.51). As a further demonstration, Fig. 3B shows a box plot illustrating the spread of R^2 values across the trials associated with a particular finger. By comparing the median values, it appears that the force output predicted with the neural drive method has a higher correlation (index: 0.92, middle: 0.82) with measured finger force compared to the EMG-amp method (index: 0.83, middle: 0.63). There is a similar type of observation for joint angle estimation also; as illustrated in Fig. 3C and 3D respectively, the joint angle estimations predicted by the neural drive approach have lower estimation error (index: 5.00±0.27 vs 12.76±0.40, middle: 5.74±0.59 vs 12.22±0.63) and higher correlation (index: 0.92 vs 0.45, middle: 0.93 vs 0.46) with the measured joint angle than the conventional EMG-amp method.

IV. Discussion

Our study investigated continuous and concurrent prediction of isometric finger force and dynamic joint movement. The motor outputs of the index and middle finger were estimated using MU discharge frequencies obtained through HD-EMG decomposition. A similar estimation was done with the EMG-amp approach in order to compare prediction performance. According to the results, the neural-drive had a lower estimation error (RMSE) and higher correlation (R^2) with the recorded force and joint angle values than the EMG-amp-based approach. The concurrent kinematic and kinetic prediction algorithm at single-finger levels can be applied to dexterous control of prosthetic hands by arm amputees. Compared with the pattern recognition approaches, the continuous decoding algorithm developed here could allow arm amputees to perform daily functional tasks in a more intuitive manner. In addition, the algorithms can be used to control assistive exoskeleton gloves for assisting finger movement in clinical populations such as stroke survivors.

Even though the MUs were decomposed from the single finger isometric and dynamic trials, it is possible the MU pools associated with each finger-task label may contain active MUs related to other fingers and tasks, which can lead to inaccurate predicted outcomes. Further, this study used MU pools generated from single-isometric and single-dynamic trials associated with a specific finger to estimate force and joint angle from single-combined testing trials. The number of MUs in the testing trials might be fewer than in the pools and using too many MUs might result in errors in estimation. Therefore, we selected only 20 MUs that were strongly correlated with the assigned task of a given pool in order to minimize the number of MUs and remove those that were associated with different fingers-task combinations. The selected MUs were divided into five groups, and the population discharge frequency of each group was fitted into a regression model.

As MU pools were formed from the isometric and dynamic trials conducted with index and middle fingers, they were specific to individual finger and task labels. The selected MUs from the desired MU pools were applied directly to combined trials for estimating force and joint angle. By making the time-consuming source separation process during initial calibration, the neural drive approach is feasible for real-time decoding. Since the selected MUs were specific to finger and task labels, in the future, the same set of MUs should be able to estimate motor outputs correctly when fingers are engaged in more complex tasks requiring a variety of finger movements and force levels. With further development, the developed neural decoding algorithm can lead to dexterous interaction of assistive robotic hands.

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