Concurrent Prediction of Dexterous Finger Flexion and Extension Force via Deep Forest

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***Abstract*— Neuromuscular injuries can impair hand function and profoundly impacting the quality of life. This has motivated the development of advanced assistive robotic hands. However, the current neural decoder systems are limited in their ability to provide dexterous control of these robotic hands. In this study, we propose a novel method for predicting the extension and flexion force of three individual fingers concurrently using high-density electromyogram (HD-EMG) signals. Our method employs two deep forest models, the flexor decoder and the extensor decoder, to extract relevant representations from the EMG amplitude features. The outputs of the two decoders are integrated through linear regression to predict the forces of the three fingers. The proposed method was evaluated on data from three subjects and the results showed that it consistently outperforms the conventional EMG amplitude-based approach in terms of prediction error and robustness across both target and non-target fingers. This work presents a promising neural decoding approach for intuitive and dexterous control of the fingertip forces of assistive robotic hands.**

I. Introduction

To restore impaired or lost hand function for people with neuromuscular impairments, the design of assistive devices, such as prosthetic hands and exoskeleton gloves, has advanced to imitate movements of the human biological hand [1], [2], [3]. However, the clinical translation of these robotic devices has been limited by the lack of a robust neural-machine interface that can reliably decode the user's intent into executable control commands for the devices.

Surface electromyogram (sEMG) signals are commonly used as the source of neural control for robotic hands. While pattern recognition has advanced in identifying a finite set of intended movements from sEMG features [4], [5], it falls short in providing continuous and proportional control of finger kinetics. One possible solution is to extend the control strategies by using a regressor between the EMG amplitudes and the kinetic variables, however, the performance of this approach is often unsatisfactory and prone to interference. This is due to the limitations of the regressor in establishing complex muscle-force mapping when dealing with a large number of features, as well as the co-activation between fingers that affects the pattern of amplitude features, making it difficult to accurately estimate individual finger forces.

**This study was supported in part by the National Science Foundation (CBET-1847319, IIS-2106747) and the Department of Defense (W81XWH2110185).

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To address these challenges, this study proposes a deep forest-based neural decoding approach to concurrently predict the extension and flexion force of three individual fingers (index, middle, and ring-pinky) from sEMG amplitude features. The approach uses two deep forests [6] to extract prominent representations from the sEMG amplitude features that are highly relevant to the finger flexion and extension force. The outputs of the two deep forests are integrated through linear regression to predict the forces of the three fingers. This establishes the mapping between the sEMG amplitude and the finger kinetic variables. The proposed approach was evaluated on data from three subjects and showed improved accuracy in predicting fingertip forces compared to the conventional sEMG amplitude approach. Overall, the proposed neural decoding approach presents a promising solution for the dexterous control of finger force, providing insightful perspectives into the feasibility of using deep forest-based neural decoding for assistive robotic hand control.

II. METHODS

A. Experimental setup

Three neurologically intact participants were recruited in the study. All subjects gave informed consent with protocols approved by the Institutional Review Board of the University of North Carolina at Chapel Hill.

Two 8×16 electrode arrays with a 3-mm single-electrode diameter and a 10-mm inter-electrode distance covered the anterior and posterior sides of the forearm to record EMG signals from the finger flexor (FDS) and extensor (extensor digitorum communis (EDC)), respectively (Fig. 1 (A)). The placement of the electrode was determined by palpating the finger flexor or extensor when the subjects flexed or extended fingers. The EMG-USB2+(OT Bioelettronica) system was used to amplify and sample the monopolar EMG signals with a gain of 1000, a pass band of 10-900 Hz and a sampling rate of 2048 Hz. The reference was placed at the wrist. The index, middle, ring, and pinky fingers were individually secured to four miniature load cells (SM-200N, Interface), to measure the flexion and extension forces of individual fingers at 1000 Hz. The forearm was supported at the neutral position with the wrist fixed by two stiff foam pads. Before each trial, the offsets of individual load cells were removed such that a positive force reading represented flexion and a negative reading represented extension.

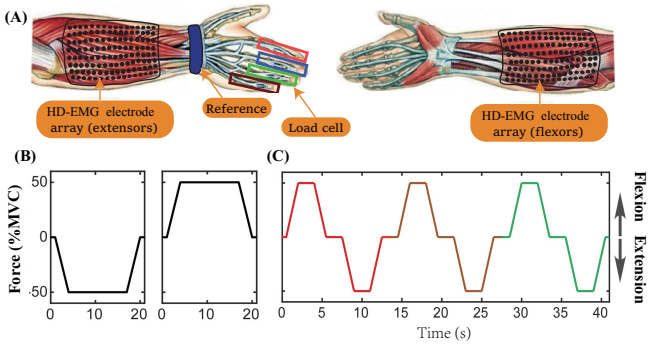

Fig. 1. The experiment settings. (A): Monopolar EMG signals were recorded from the finger extensor and flexor, respectively, with two 8×16 electrode arrays, and the flexion/extension forces of the index, middle, ring, and pinky fingers were recorded. Bottom: The trapezoidal force target from the single-finger extension and flexion trial (B) and the multi-finger trial (C). The force target of the multi-finger trial was shown with different colors to represent the three fingers, i.e. index (red), middle (brown), and ring-pinky (green) as the target finger, respectively.

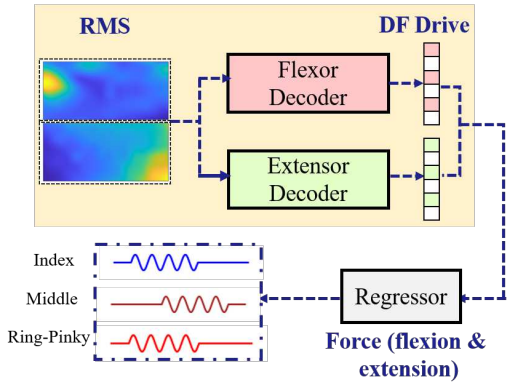

Fig. 2. Overview of the poposed method. The proposed method employs two deep forest-based decoders to predict the flexion and extension forces separately. The predicted force is obtained through a bivariate linear regression on the DF-drive information generated by the decoders.

B. Experiment procedure

The maximum voluntary contraction (MVC) force of each finger was measured for both flexion and extension. During the experiment, the subjects were asked to follow a predefined force target that had a repeated trapezoidal pattern with a maximum force of 50% MVC for each finger (Fig. 1 (B)). Due to high enslavement between ring and pinky fingers [7], the subjects were asked to extend or flex the two fingers simultaneously all the time. These two fingers were considered as one finger (ring-pinky finger) during the study. The MVC of the ring-pinky finger was the sum of the MVC of the ring and pinky fingers. The force measurements from the ring and pinky fingers were always added together and displayed to the subjects on the monitor.

This study involved two types of trials performed by the subjects. The first type was the single-finger trial, where the subjects were asked to flex or extend a single finger following a predefined single trapezoid while avoiding co-contraction of other fingers. The subjects performed four single-finger trials for each finger, both for flexion and extension, resulting in a total of eight single-finger trials per finger. The second type of trial was the multi-finger trial, where the subjects were asked to flex and extend at least two fingers sequentially. The force target in this trial contained multiple trapezoids, with the fingers flexing and extending in sequence (See in Fig.1 (C) as an example of three-finger trial). During a period , one finger was designated as the target finger and was asked to maintain the targeted force, while the other two fingers were allowed to co-activate. The order of the target fingers was randomized across the multi-finger trials, and each subject performed a total of 16 multi-finger trials.

C. Deep forest decoder

An overview of the proposed method is shown in Fig.2. The EMG signals were processed via a high pass filter (Butterworth zero-phase shift with an order of 4). The Root Mean Square (RMS) value was extracted as input features for training from each EMG channel within a window of 0.5 second and moving step of 0.1 second. The same window and overlap is also applied to the recorded force. To predict the concurrent flexion and extension force of the fingers in a dexterous manner, the proposed model uses two deep forests, the flexor decoder and the extensor decoder, to establish the relationship between the EMG features and the pattern of force (target finger, force direction, and the force strength). The flexor decoder is designed to learn the information related to finger flexion, while the extensor decoder is trained to identify the features that are highly relevant to finger extension. To enable the disentanglement of finger cross-talk, we embed the force information into a dense vector by discretizing the continuous values into different classes and assigning a different class to the force from different fingers. This technique, which we call *Force Embedding*, gives a comprehensive representation of the force information. The resulting outputs, termed DF-drive information, is obtained from both decoders and the finger force is predicted through bivariate linear regression with the ground truth force.

$$F_i = aD_f^i(X) + bD_e^i(X) \tag{1}$$

where F_i is the force of the i^{th}finger (one of index, middle, and ring-pinky), and $D_f^i(X)$ and $D_e^i(X)$ are the obtained DF-drive information of the i^{th} finger by the flexor and extensor decoders from input X, respectively. a and b are regression coefficients.

The parameters used in this study are as follows: for deep forest, two estimators in each layer were utilized, which consisted of both a random forest and a completely random forest. The model was trained incrementally, layer by layer. Early stopping was applied if adding a new layer did not result in an improvement in the validation performance on the training set. A Kalman filter was applied to the DF-drive information produced by the deep forest models.

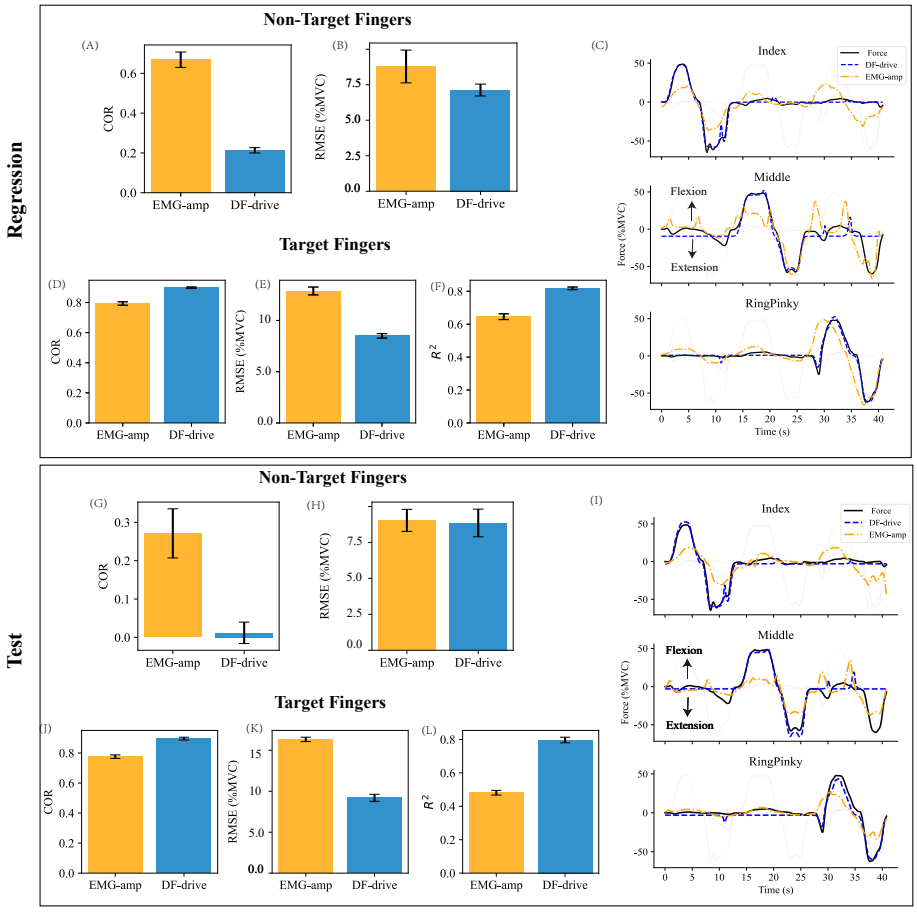

Fig. 3. Performance comparison between proposed and EMG-amp methods. The comparison includes both regression test results, where the regression is performed on a trial-by-trial basis, and near-online test results, where the regression coefficients are obtained over all training trials. The results for non-target fingers in regression test (A and B) and near-online test (G and H) are shown, as well as the results for target fingers in regression test (D, E, and F) and near-online test (J, K, and L). The results of force estimation on a representative three-finger trial in both regression test (C) and near-online test (I) is illustrated. Error bars represent the standard error.

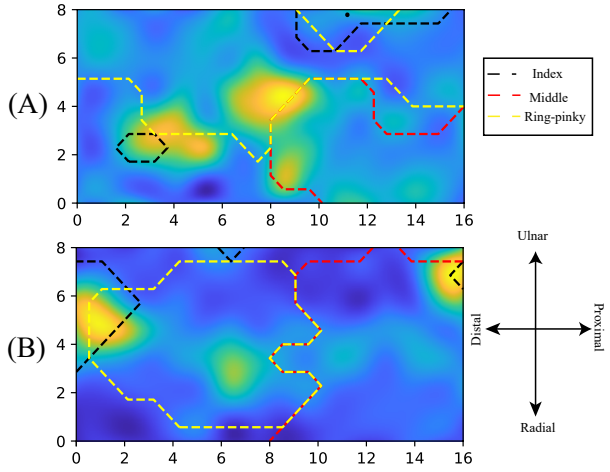

Fig. 4. The learned feature importance maps of the proposed decoder for a representative subject are shown. Specifically, the importance map of the flexor side of the flexor decoder (A) and the extensor side of the extensor decoder (B) are depicted. The channels refined by the EMG-amp method are highlighted by the encircled dashed lines.

D. Force prediction using EMG amplitude

The conventional EMG-amplitude method has been improved significantly through the refinement of the EMG channel set for each finger, demonstrating its potential for dexterous finger force control [8]. As such, it serves as the benchmark in this study. First, six sets of channels were defined for each finger's flexor and extensor muscles (i.e., index-flexor, index-extensor, middle-flexor, middle-extensor, ring-pinky-flexor, and ring-pinky-extensor), by selecting the top 60 channels with the highest Root Mean Square (RMS) values out of the 128 channels, averaged over all single-finger trials. Then, the channel sets were further refined by comparing the regression performance between the RMS values of each channel and the smoothed force of each finger. If the highest coefficient of determination (R^2) value was obtained for the force of the finger that matches the channel set's assignment, the channel was kept. Otherwise, it was removed from the pool of EMG channels. As a result, the most informative EMG channels that are strongly correlated with the force of each finger are selected. A bivariate linear regression is performed between the average RMS over the

optimized channels and the ground truth:

$$F_i = aA_f^i + bA_e^i \quad (2)$$

where F_i represents the force of the i^{th} finger (index, middle, or ring-pinky), and A_f^i and A_e^i denote the average RMS values calculated over the optimized flexor and extensor channels of the i^{th} finger, respectively.

E. Validation Protocol

For each subject, the proposed decoders were trained using only the single-trial data cross the experiments. The EMG-amp method, by contrast, requires multi-trial data for channel refinement. Therefore, we performed a 4-fold-cross-validation on all the multi-trial data by randomly selecting a quarter of trials for training while the hold-out trials for testing. The performance was evaluated in two ways. The first was a trial-by-trial regression test, where the regression was performed on each testing trial. The resulting R^2 and RMSE, as well as the Pearson correlation coefficient (COR) were reported. The second evaluation obtained the regression coefficients over all the training trials and testing the coefficients on the testing trials, which was considered a near-online test.

III. Results

The results of the force prediction performance comparison between the proposed DF-drive method and the EMG-amp method are shown in Fig. 3. The performance was evaluated using the RMSE, COR, and R^2 metrics averaged over all cross-validation folds and subjects. In the regression test, the proposed DF-drive method showed lower average estimation error on target fingers with a RMSE value of 8.50 ± 0.218 % MVC (mean $\pm$ standard error), compared to the EMG-amp method with a RMSE of 12.88 ± 0.38. Additionally, the DF-drive method exhibited a higher correlation with the recorded force with $R^2 = 0.82 \pm 0.01$ and $COR = 0.90 \pm 0.01$, compared to the EMG-amp method with $R^2 = 0.65 \pm 0.02$ and $COR = 0.79 \pm 0.01$. In the near-online test, the estimation error of the EMG-amp method increased to 16.33 ± 0.27, and the R^2 showed a significant drop ($R^2 = 0.48 \pm 0.01$). On the other hand, the performance of the proposed DF-drive method remained relatively stable, with only a slight degradation in estimation error and correlation metrics compared to the regression test (RMSE = 9.20 ± 0.43, $R^2 = 0.80 \pm 0.02$, $COR = 0.90 \pm 0.01$). For the non-target fingers, the DF-drive method showed a lower correlation with the recorded force in both the regression test and the near-online test, compared to the EMG-amp method.

The force predictions for a representative three-finger trial by both methods are shown in Fig. 3 (C) and 3 (I). The DF-drive method accurately fits the actual forces of the three fingers during both the regression test and the near-online test, with minimal error forces predicted for the non-target fingers. In contrast, the force prediction of the EMG-amp method showed large deviations from the actual forces throughout the trial, and these deviations increased when shifting from the regression test to the near-online test. One notable observation is that the DF-drive method tends to predict zero force for the non-target fingers, despite small forces being recorded.

Furthermore, the importance of the EMG features in predicting finger force and target fingers by the deep forest is visualized in Fig.4. The mean decrease impurity of the decision trees in both decoders are shown, with the refined channels of the EMG-amp method encircled by dashed lines. The results indicates that the most prominent features identified by the decoders are often located in the overlap region between different fingers, particularly in the extensor decoder. This information can provide valuable guidance for developing neural-interfaces with minimal channels.

IV. Conclusion

In this study, a novel neural decoder was proposed to predict the flexion and extension force of the index,middle and ring-pinky fingers concurrently. The proposed method, based on deep forest, was evaluated on data from three subjects and showed improved performance compared to the conventional EMG-amp method. The proposed method also shows robustness in near-online testing, making it a promising approach for dexterous finger force control. In addition, the feature importance map could potentially offer valuable insights into the explainability of the method, which might be useful for further improvement and development of the neural control. Future work should focus on exploring the generalizability of the proposed method on a larger subject population and long-term usability of such methods.

References

[1] C. Castellini, "Upper limb active prosthetic systems—overview," *Wearable Robotics*, pp. 365–376, 2020.

[2] X. Jiang, X. Liu, J. Fan, X. Ye, C. Dai, E. A. Clancy, M. Akay, and W. Chen, "Open access dataset, toolbox and benchmark processing results of high-density surface electromyogram recordings," *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 29, pp. 1035–1046, 2021.

[3] A. Waris, I. K. Niazi, M. Jamil, K. Englehart, W. Jensen, and E. N. Kamavuako, "Multiday evaluation of techniques for emg-based classification of hand motions," *IEEE Journal of Biomedical and Health Informatics*, vol. 23, no. 4, pp. 1526–1534, 2019.

[4] G. Li, A. E. Schultz, and T. A. Kuiken, "Quantifying pattern recognition—based myoelectric control of multifunctional transradial prostheses," *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 18, no. 2, pp. 185–192, 2010.

[5] X. Jiang, X. Liu, J. Fan, X. Ye, C. Dai, E. A. Clancy, M. Akay, and W. Chen, "Open access dataset, toolbox and benchmark processing results of high-density surface electromyogram recordings," *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 29, pp. 1035–1046, 2021.

[6] Z.-H. Zhou and J. Feng, "Deep forest: Towards an alternative to deep neural networks." in *IJCAI*, 2017, pp. 3553–3559.

[7] V. Zatsiorsky, Z. Li, and M. Latash, "Enslaving effects in multi-finger force production," *Experimental Brain Research*, vol. 131, no. 2, pp. 187–195, 2000.

[8] Y. Zheng and X. Hu, "Concurrent estimation of finger flexion and extension forces using motoneuron discharge information," *IEEE transactions on biomedical engineering*, vol. 68, no. 5, pp. 1638–1645, 2021.