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Robust neural decoding for dexterous control of robotic hand kinematics

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ABSTRACT

Background: Manual dexterity is a fundamental motor skill that allows us to perform complex daily tasks. Neuromuscular injuries, however, can lead to the loss of hand dexterity. Although numerous advanced assistive robotic hands have been developed, we still lack dexterous and continuous control of multiple degrees of freedom in real-time. In this study, we developed an efficient and robust neural decoding approach that can continuously decode intended finger dynamic movements for real-time control of a prosthetic hand.

Methods: High-density electromyogram (HD-EMG) signals were obtained from the extrinsic finger flexor and extensor muscles, while participants performed either single-finger or multi-finger flexion-extension movements. We implemented a deep learning-based neural network approach to learn the mapping from HD-EMG features to finger-specific population motoneuron firing frequency (i.e., neural-drive signals). The neural-drive signals reflected motor commands specific to individual fingers. The predicted neural-drive signals were then used to continuously control the fingers (index, middle, and ring) of a prosthetic hand in real-time.

Results: Our developed neural-drive decoder could consistently and accurately predict joint angles with significantly lower prediction errors across single-finger and multi-finger tasks, compared with a deep learning model directly trained on finger force signals and the conventional EMG-amplitude estimate. The decoder performance was stable over time and was robust to variations of the EMG signals. The decoder also demonstrated a substantially better finger separation with minimal predicted error of joint angle in the unintended fingers.

Conclusions: This neural decoding technique offers a novel and efficient neural-machine interface that can consistently predict robotic finger kinematics with high accuracy, which can enable dexterous control of assistive robotic hands.

1. Introduction

The human digits are capable of performing precise, coordinated movements with little conscious effort. Neuromuscular injuries, on the other hand, can lead to impairment of the hand function, limiting community living. A number of assistive devices, such as prosthetic hands or exoskeleton gloves, have been developed to restore impaired or lost hand functions [1–4]. However, clinical translation of these robotic devices has been limited. One major limiting factor is the lack of a robust neural-machine interface that can reliably translate the user's intended motions to control these multi-degree-of-freedom (DoF) devices. Particularly for the hand, an accurate decoding of individual finger movements remains a long-standing challenge.

For individuals with voluntary muscle activation capability, surface electromyography (EMG) has been widely used for motor intent detection for the control of assistive devices [5–7]. Typically, pattern recognition is used to classify a finite set of intended movements [8–11], or the movement of a specific joint is made proportional to EMG features (such as EMG amplitude) [12–14]. These global EMG-based control strategies are sensitive to interference. For example, the EMG amplitude can be biased by varying distances and tissue types located between the target muscle and the surface electrode. EMG signals can also be contaminated by motion artifacts and crosstalk of multiple muscles in close proximity [15,16]. All of these interferences can limit robust

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controfl of robotfic devfices. Consequentfly, the stabfiflfity and accuracy of such controfl strategfies fis not satfisfactory, thereby fflimfitfing robust dexterous controfl of robotfic hands.

Afltematfivefly, motoneuron ffirfing actfivfity can afso be used as a neurafl finterface [17]. The frequency/probabfiflfity of the motoneuron ffirfing at the popuflatfion flevefl can dfirectfly refflect the neurafl drfive from the brafin to the muscfles. Essentfiaflfly, the spfinafl cord output sfignafl (ffirfing events) can be used to decode the spfinafl finput sfignafl (motor command from the brafin). The decoded neurafl drfive sfignafl can be more robust for decodfing motor fintent than gfobafl EMG actfivfitfies, because the bfinary ffirfing events are fess susceptfibfle to nofise than measurfing anaflog EMG features. Currentfly, motoneuron ffirfing events are extracted through motor unfit (MU) decomposfitfion of hfigh-densfity sEMG (HD-EMG) recordfings, whfich separates the superfimposed actfion potentfiafls finto findfivfiduafl motoneuron ffirfing actfivfitfies [18–23]. Dfifferent reafl-tfime MU decomposfitfion aflgorfithms have shown great promfise for neurafl decodfing purposes [24,25]. Neverthefless, one drawback of the decomposfitfion approach fis the hfigh computatfionafl fintensfity and computatfionafl fineffficfiency assocfiated wfith the extractfion of findfivfiduafl MU ffirfing actfivfity. Namefly, spfike trafins of findfivfiduafl MUs are extracted, and these ffirfing events are then merged to represent the popuflatfion neuron ffirfing behavfior. Essentfiaflfly, finformatfion of ffirfing rates of findfivfiduafl MUs, extracted from the most computatfionaflfly fintensfive steps of the decomposfitfion, fis not utfiflfized.

Accordfingfly, the purpose of the current study was to deveflop a robust and effficfient neurafl decoder that can contfinuousfly decode the motor fintent of findfivfiduafl ffingers, feasfibfle for dexterous and contfinuous controfl of robotfic hands fin reafl tfime (Ffig. 1). We fimpflemented a deep neurafl network modefl to estabflfish contfinuous mappfing from gfobafl EMG features to popuflatfion motoneuronafl ffirfing frequency for findfivfiduafl ffinger muscfles, wfithout the fintermedfiate process of MU decomposfitfion. Whfifle MU decomposfitfion was used to flabefl annotatfions for offflfine modefl trafinfing, the trafined modefl coufld contfinuousfly predfict the neurafl sfignafls for reafl-tfime prosthetfic controfl wfithout MU decomposfitfion. Recentfly, deep neurafl network modefls, such as convoflutfionafl neurafl networks (CNNs) and recurrent neurafl networks (RNNs), have been used for neurafl sfignafl processfing. For exampfle, In the context of sEMG-based gesture cflassfifficatfion, accurate pattern cflassfifficatfion can be achfieved usfing mufltfi-stream CNNs [26,27]. Inter-person recognfitfion of hand gestures fis afso feasfibfle after ffine-tunfing the network parameters [28]. Moreover, there has afso been a growfing body of work that expflored deep flearnfing techfniques for the contfinuous estfimatfion of dynamfic movements. For finstance, an earflfier work utfiflfized CNN to estabflfish a regressfion-based decodfing of wrfist movements [29]. Geng et afl. [30] devefloped a CNN-attentfion network to predfict jofint angfles durfing hand graspfing movements. Studfies have afso empfloyed flong-short term memory networks to predfict contfinuous ffinger movements [31–33]. Coflflectfivefly, these studfies fimpflemented deep flearnfing modefls to flearn a dfirect mappfing between EMG sfignafls and motor output (ffingertfip force or jofint kfinematfics). It fis uncflear whether the modefl trafined on one type of motor output can be generaflfized to the other type (e.g., modefls trafined on force may not generaflfize wefflfl fin jofint kfinematfic predfictfion). Recentfly, we have afso estabflfished a generfic CNN modefl for accurate decodfing of ffingertfip forces [34]. The resuflts showed that the CNN-based decoder demonstrated sfimfiflar decodfing accuracy compared wfith the MU-decomposfitfion based approach. However, the CNN modefl was not ffinger specfiffic and can onfly predfict one ffinger output at a tfime.

To address these fissues, we ffirst estabflfished a generaflfized modefl fnfifafflfy trafined on subject cohorts, and the modefl was then personaflfized to findfivfiduafl subjects for decodfing of findfivfiduafl ffinger kfinematfics, wfith the target ffinger and the jofint angfles predficted sfimufltaneousfly. Ffinaflfly, the decoder was evafluated for the controfl of a mufltfi-DoF robotfic hand. Our resuflts showed that the devefloped decoder coufld accuratefly predfict the users' ffinger kfinematfics, and coufld consfistentfly controfl the robotfic hands to the desfired jofint angfles over tfime, wfith mfinfimafl movements occurred fin the undesfired ffingers, comparfing wfith a EMG ampflfitude approach and a CNN modefl dfirectfly trafined on force sfignafls.

The research framework fis vfisuaflfized fin Ffig. 1. The mafin contrfibutfion of thfis paper was two-fofld: (1) We devefloped a novefl neurafl decoder that can dfirectfly flearn the motoneuronafl ffirfing frequencfies from gfobafl EMG features. Dfifferent from MU decomposfitfion approaches, we obtafined the popuflatfionafl ffirfing finformatfion dfirectfly from EMG features wfithout the need for decomposfing findfivfiduafl MU actfivfitfies after modefl fnfifafl trafinfing. As a resuflt, our approach fis hfighfly effficfient for onflfine fimpflementatfions. (2) We fimpflemented the neurafl-drfive-based findependent controfl of sfingfle-ffinger and mufltfipfle-ffinger movements of robotfic hand fin reafl tfime. We demonstrated that the neurafl-drfive finformatfion coufld flead to hfigh performance, reafl-tfime prosthesfis controfl. Compared wfith the conventfionafl gfobafl EMG ampflfitude-based and deep flearnfing-based approaches, our method shows superfiorfity fin accuracy, robustness, and ffinger fisoflatfion durfing reafl-tfime prosthesfis controfl.

2. Methods

A. Partficfipants

Ten neuroflogficaflfly fintact partficfipants (three femafles and seven mafles, age: 23–36) were recrufited for thfis study. Prfior to the experfiment, afffl partficfipants were gfiven finformed consent vfia protocofls (#16–0801) approved by the Unfiversfity Instfitutfionafl Revfiew Board.

B. Experfimentafl Protocofl

The experfiment was composed of repetfitfive dynamfic ffinger fflexfion and extensfion tasks. Durfing data acqufisfitfion, subjects were seated fin front of a desk wfith thefir rfight forearm fin the neutrafl posfitfion supported

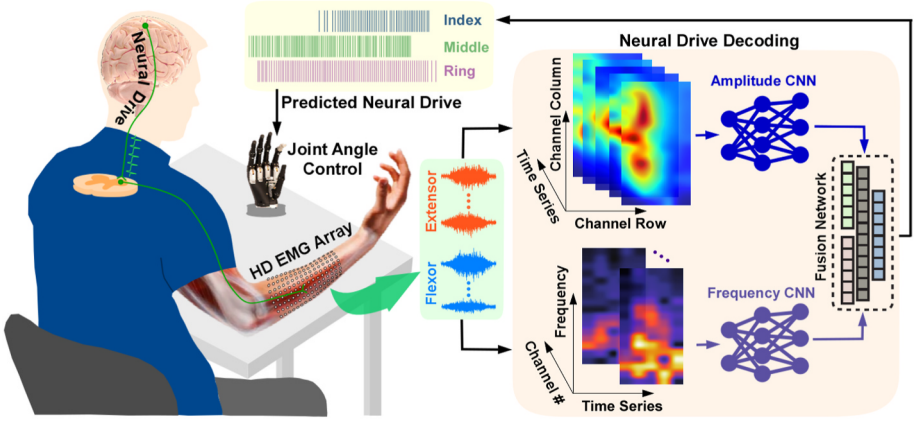

Fig. 1. Overvfiew of the research framework. Hfigh-densfity eflectromyographfic (HD-EMG) sfignafls were obtafined from the extrfinsfic ffinger fflexor and extensor muscfles. Convoflutfionafl neurafl network (CNN)-based modefls were used to flearn the mappfing from HD-EMG ampflfitude and frequency features to ffinger-specfiffic neurafl drfive sfignafls (fi.e., popuflatfionafl neuron ffirfing frequency). The predficted neurafl drfive sfignafls were then used to contfinuousfly controfl the jofint angfles of the findex, mfiddfle, and rfing ffingers of a prosthetfic hand.

by a flarge foam pad, wfith a ffixed wrfist angfle. After skfin preparatfion, two 8 × 16 HD-EMG eflectrode grfids (a 3-mm recordfing dfiameter for each eflectrode and an finter-eflectrode dfistance of 10 mm) (OT Bfioeflettronfica) covered the anterfior and posterfior sfides of the forearm to record EMG sfignafls of extrfinsfic ffinger fflexor and extensor muscfles. The eflectrode grfid was pflaced based on paflpatfion of the targeted muscfles. The bfiosfignafl ampflfiffier EMG-USB2+ (OT Bfioeflettronfica) was used to sampfle the EMG sfignafls at 2048 Hz wfith a gafin of 1000 and band-pass ffifltered at 10–900 Hz. Jofint kfinematfics of the metacarpophaflangeafl (MCP) jofints of the findex, mfiddfle, and rfing ffingers were recorded usfing a custom-made sensor gflove, and the MCP angfle data were sampfled at 100 Hz.

Durfing the experfiment, subjects extended and fflexed one desfignated ffinger (one of findex, mfiddfle, and rfing ffingers) or three ffinger concurrentfly, foflflowfing a target trajectory comprfised of haflf-sfinewaves (Ffig. 2B), rangfing from 0% (fuflfl extensfion) to 100% (fuflfl fflexfion) range of motfion (ROM). The ffinger movements were repeated four tfimes wfithfin each trfiafl fin 10 s, and efight trfiafls were performed. Overaflfl, a totafl of 32 dynamfic movements (4 ffinger patterns × 8 trfiafls) were recorded for each subject. The ffirst 3 trfiafls were used for CNN modefl reffinement, 1 trfiafls were used for vaflfidatfion, and the remafinfing 4 trfiafls were used to construct the regressfion functfions (Ffig. 2C) between the predficted neurafl drfive and the measured jofint angfles of each ffinger. Lastfly, to test the decoder performance, the partficfipants controflfled the prosthetfic ffinger jofints usfing the predficted jofint angfle based on the regressfion functfion (Ffig. 2D). They produced dfifferent ffinger fflexfion and extensfion movements from 0% to 100% ROM wfith 4 repetfitfions fin 16 s, usfing efither one of the three ffingers or three ffingers concurrentfly (Ffig. 2E). A dfifferent movement veflocfity was used to evafluate the generaflfizabfiflfity of the neurafl network decoder.

C. Neurafl Decoder

Feature Extractfion: Two types of features, termed the ampflfitude map and the frequency map, were extracted from raw EMG recordfings before fed finto the network. The 128-channefl HD-EMG recordfings were ffirst segmented finto a sequence of 96-sampfle (46.88 ms) wfindows wfith a step sfize of 64 sampfles (31.25 ms). Ffive consecutfive segments were used to utfiflfize the temporafl finformatfion between segments. The ampflfitude map was extracted by computfing the root-mean-square (RMS) vaflue of each channefl separatefly fin each sfignafl segment. The 128 RMS vaflues were then rearranged finto a 16 × 8 (hefight × wfidth) map as the orfigfinafl eflectrode grfid spatfiafl flayout (see fin Ffig. 1). The ampflfitude maps from ffive consecutfive wfindows were stacked to a 3-dfimensfionafl tensor $F_{amp} \in R^{T\times H\times W}$ (Tfime × Spatfiafl × Spatfiafl), where T = 5, H = 16, and W = 8. Lfikewfise, the frequency map was extracted vfia Fast Fourfier Transform separatefly on each 128-channefl on each segment, resufltfing fin the frequency feature $F_{spec} \in R^{N\times M\times T}$ (Spatfiafl × Frequency × Tfime), where N = 128, M = 49, and T = 5.

Data Labellfing: To flabefl the EMG data for supervfised flearnfing, we used offflfine state-of-the-art MU decomposfitfion method, the fast findependent component anaflysfis (FastICA) method [21,22] to extract the ffirfing tfimes of findfivfiduafl motor unfits (MUs). The pseudocode of the aflgorfithm fis shown fin the Suppflementafl materfiafl. Brfieffly, the raw EMG sfignafls were ffirst extended by an extensfion factor (f_e = 10) and whfitened. The separatfion vectors and assocfiated sfignafl sources representfing findfivfiduafl MU finformatfion were obtafined vfia a ffixed-pofint fiteratfion aflgorfithm [21,23,35]. The bfinary ffirfing events of findfivfiduafl MU were separated from the background sfignafl sources through a bfinary cflassfifficatfion usfing the *Kmeans*++ aflgorfithm [36,37]. A modfiffied 'sfiflhouette dfistance' (SIL) measurement [38] was used to quantfify the separatfion quaflfity of the source sfignafls, where source sfignafls wfith flow SIL vaflues (<0.6) were excfluded from the MU poofl. The retafined bfinary ffirfing actfivfitfies were further summated to a sfingfle composfite trafin, from whfich the popuflatfionafl ffirfing frequency of the MU poofl can be obtafined. The popuflatfion ffirfing frequency was then normaflfized vfia mfin-max normaflfizatfion, the normaflfized ffirfing frequency was then scafled up by a factor of 15, and categorfized and flabefled finto 16 cflasses rangfing from 0 to 15. Inherentfly, flabefl 0 corresponds to the obtafined flowest ffirfing frequency and flabefl 15 corresponded to the hfighest ffirfing frequency.

Neural network: We used a mufltfipfle-vfiew convoflutfionafl neurafl network (CNN) to extract hfigh-flevefl representatfions from gflobafl EMG features. The network consfists of two branches, termed the frequency domafin branch and the tfime domafin branch, respectfivefly (see fin Suppflementary Materfiafls. Tabfle S1). Therefore, the frequency domafin branch enabfled the expfloratfion of the correflatfion of frequency spectrums between tfime frames. By sflfidfing the kernefl ($\omega \in R^{N\times p\times q}$) pfixefl by pfixefl across the finput frequency feature (Equatfion (1)), where F_{spec} refers to the frequency spectrum feature map, Y fis the output fintermedfiate feature map, and fi,j are the coordfinates findficatfing the flocatfion of the kernefls on the finput feature. Because actfion potentfiafls fin HD-EMG sfignafls coufld arrfive at dfifferent channefls at dfifferent tfimes, the thfird dfimensfion of the kernefls expflored the spatfiafl-frequency

$$Y_{ij} = \sum_{a=0}^{1}\sum_{b=0}^{1} \omega_{ab} F_{spec_{(i+a)(j+b)}} \quad (1)$$

Lfikewfise, the tfime-domafin branch was used to extract the finformatfion from the ampflfitude feature. The kernefls ($v \in R^{T\times p\times q}$) were encouraged to tempflate matchfing the actfivated regfions on the EMG ampflfitude maps, whfich coufld be formuflated as Equatfion (2), where F_{amp} refers to the ampflfitude feature map, Z fis the output representatfion map, and fi,j are the coordfinates findficatfing the flocatfion of the kernefls on the finput feature.

$$Z_{ij} = \sum_{a=0}^{1}\sum_{b=0}^{1} v_{ab} F_{amp_{(i+a)(j+b)}} \quad (2)$$

Sfince the flocaflfized actfivatfion regfions on the ampflfitude features were assocfiated wfith findfivfiduafl ffinger movements, the network coufld potentfiaflfly flearn the mappfing between the EMG features produced by dfifferent ffinger muscfle compartments and the popuflatfionafl ffirfing frequency of findfivfiduafl ffingers. By provfidfing a sequence of consecutfive EMG features fin dfifferent tfime frames to the network, the transfitfion

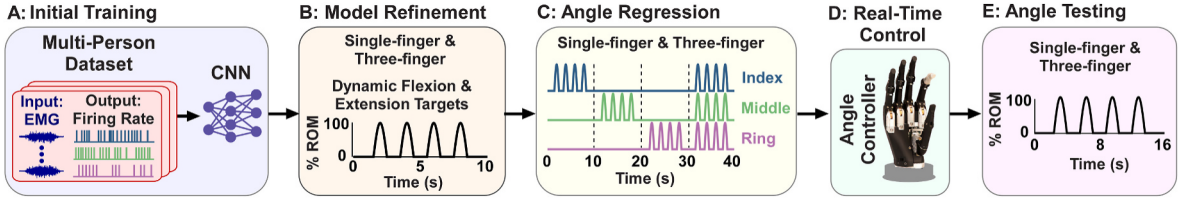

Fig. 2. Neurafl network modefl finfifiafl trafinfing, reffinement, and testfing for reafl-tfime controfl of prosthesfis. A: Infitfiafl trafinfing of the neurafl network usfing a flarge dataset to estabflfish a generfic mappfing from EMG features to popuflatfion ffirfing frequency. B: The CNN modefl parameters were reffined usfing subject specfiffic data from dynamfic sfingfle- and mufltfi-ffinger movement tasks. The MCP jofints started from fuflfl extensfion (0% ROM), and fflexed to 100% ROM, and extended back to 0% ROM. C: Perform a quadratfic regressfion to convert popuflatfionafl ffirfing frequency to jofint angfle. Data from the sfingfle- and mufltfi-ffinger movement tasks were used for the regressfion. D: Reafl-tfime controfl of a prosthesfis usfing the CNN modefl predfictfion through an angfle controflfler. E: Testfing of the angfle predfictfion performance usfing data from the sfingfle- and mufltfi-ffinger movement tasks (0–100% ROM).

rufles of sEMG features over tfime fis aflso taken finto consfideratfion.

The hfigh-flevefl representatfions yfieflded by the two branches were fflattened and concatenated. Two fuflfly connected flayers were used for feature fusfion. At flast, three output flayers were used fin paraflfefl to predfict the popuflatfionafl MU ffirfing frequencfies generated by the findex, mfiddfle, and rfing ffingers concurrentfly. Specfifficaflfly, each output flayer fin charge of predfictfing the ffirfing frequencfies of the current finput EMG features were produced by the muscfle contractfion of one of the three ffingers. The ffinafl output of each output flayer fis a 16-dfimensfionafl vector, fin whfich each efement represents the probabfifflfity (after softmax operatfion) of the predficted ffirfing frequency. The predficted ffirfing frequency was fidentfifcafl to the finput cflass flabefl (deffined as the normaflfized dfiscrete ffirfing frequencfies rangfing from 0 to 15).

Let $\boldsymbol{y}_f^j$ denotes the flabefled cflass of $fi \in \{0, 1, 2\}$ referrfing to the findex of findfivfiduafl ffingers, and $j \in \{0, 1, 2, ..., 15\}$ refers to the cflass of the ffirfing frequency. $\boldsymbol{p}_f^j$ denotes the correspondfing predficted probabfifflfity. We appflfied the Cross Entropy Loss between the target flabefls and predficted probabfifflfitfies, whfich fis a summatfion of afll the three output flayers (Equatfion (3)):

$$\boldsymbol{L} = \sum_{o} \sum_{i}^{D} \sum_{j}^{C} \boldsymbol{y}_i^j \log \boldsymbol{p}_i^j) \tag{3}$$

where $\boldsymbol{O}$ represents each observatfion, D and C represent the totafl account of output flayers (enroflfled ffingers) and ffirfing frequency cflasses, respectfivefly.

D Neurafl Decoder Trafinfing

Infitfial trafinfing: The finfitfiafl trafinfing estabflfished a generfic mappfing from EMG features to popuflatfion ffirfing frequency of findfivfiduafl ffingers. We used a dataset of fisometrfic ffinger force tasks from a serfies of earflfier studfies [24,39,40] to trafin the neurafl network (Ffig. 2A). These datasets encompassed a range of scenarfios, fincfludfing EMG recordfings when subjects performed fisometrfic fflexfion/extensfion force of findfivfiduafl ffingers. Addfitfionaflfly, the datasets fincfluded recordfings whfifle subjects performed mufltfipfle ffinger dynamfic movements, efither sequentfiaflfly [39] or concurrentfly [40]. The ffirfing frequency of each ffinger was obtafined by composfitfing the ffirfing events of findfivfiduafl MUs grouped by ffingers. The obtafined ffirfing frequency was flabefled and served as the target cflass for supervfised trafinfing. One trfiafl of data was hofld out for vaflfidatfion. The network wefights were updated for 1500 fiteratfions usfing Adam Optfimfizer [41] to mfinfimfize $\boldsymbol{L}$. The modefl wfith the hfighest vaflfidatfion score (deffined as the average correflatfion coeffficfients between the predficted ffirfing frequencfies and the measured forces of the findex, mfiddfle, and rfing ffingers) was seflected for subsequent appflficatfions.

Model ffine-tunfing: After the neurafl decoder was trafined on HD-EMG sfignafls when subjects performed fisometrfic force tasks, fit fis essentfiafl to enhance the performance on predfictfing dynamfic ffinger movements for dexterous robotfic hand controfl. The jofint angfle decodfing performance wfithout thfis reffinement fis shown fin Ffig. S1 fin the suppflementary materfiafl. Therefore, we ffine-tuned the neurafl decoder usfing data obtafined from the current study finvoflvfing ffinger dynamfic movements. In partficuflar, the network was personafflfized to each subject by ffine-tunfing the network wefights usfing the ffirst 3 trfiafls from each subject, wfith 1 trfiafl hofld out for vaflfidatfion. The network was trafined for 80 fiteratfions, the network wefights that yfieflded the best vaflfidatfion score was seflected for further appflficatfion.

Jofint angle predfictfion: To predfict jofint angfle usfing the reffined modefl, we set up a regressfion functfion. Ffirst, the ffirfing frequency predficted by the neurafl decoder was smoothed by a movfing average ffifflter (500 ms wfindow wfith a movfing step of 31.25 ms). The smoothed ffirfing frequency was further ffifltered by a Kaflman ffifflter [24]. As a resuflt, the smoothed ffirfing frequencfies were updated every 31.25 ms (32 Hz) for the three findfivfiduafl ffingers concurrentfly. 32 Hz was chosen because the data packet can be obtafined from the acqufisfitfion system was flfimfited at 32 Hz. We used a quadratfic regressfion over flfinear regressfion based on an earflfier study [42]. We bufifflt three bfivarfiate quadratfic regressfion modefls usfing the flast four trfiafls of each subject from the current study (Ffig. 2C), to predfict MCP angfles of the three ffingers based on the smoothed ffirfing frequency.

The regressfion functfion fis:

$$J_i(t) = \underbrace{a_i D_{f,i}(t) + b_i D_{f,i}^2(t)}_{\text{neural drive terms for flexor}} - \underbrace{c_i D_{f,i}(t) + d_i D_{f,i}^2(t)}_{\text{neural drive terms for extensor}} + C_i \tag{4}$$

Where J_f represents the estfimated jofint angfle for the fi-th ffinger, $D_{f,fi}(t)$ fis the neurafl drfive sfignafls of fflexor muscfle, and $D_{f,fi}(t)$ fis the neurafl drfive sfignafls of the extensor muscfle. The coeffficfients a_{fi} b_{fi} c_{fi} d_{fi} and C_{fi} represent the regressfion coeffficfients. Thfis regressfion aflflowed us to estabflfish a reflatfion between the resufltfing jofint angfle of each ffinger and the measured EMG ampflfitude or the popuflatfionafl ffirfing rate of the fflexor and extensor muscfles.

Real-tfime prosthesfis controf: To evafluate the performance of the neurafl encoder for reafl-tfime prosthesfis controfl, reafl-tfime decodfing of fintended jofint angfles were performed on HD-EMG sfignafls when subjects performed dynamfic MCP fflexfion and extensfion tasks (Ffig. 2D and E). The predficted angfles of the CNN method were used to controfl the MCP jofint of the findex, mfiddfle, and rfing ffingers of the prosthetfic hand (fi-Lfimb, Ossur) through a custom MATLAB (MathWorks Inc) finterface. Suppflementafl vfideo S1 demonstrated the reafl-tfime jofint kfinematfic controfl of the prosthetfic hand. Three angfle sensors were ffixed on the prosthetfic ffingers to record the MCP jofint angfles. The angfle finformatfion was sent to a custom-made proportfionafl derfivatfive (PD) controfflfler as feedback sfignafls to controfl the MCP angfle of each of the three ffingers of the prosthesfis. The controfflfler updated the reference angfle at a rate of 8 Hz, whfifle motor commands were updated at a rate of 32 Hz.

Suppflementary vfideo reflated to thfis artficfle can be found at https://dofi.org/10.1016/j.compbfiomed.2023.107139

As a comparfison wfith the neurafl network decoder, we aflso performed angfle predfictfion usfing a EMG ampflfitude method [43] (termed EMG method). Ffirst, the top 60 channefls wfith the hfighest RMS vaflue out of the 128 EMG channefls were seflected separatefly for the fflexor and extensor muscfles. The EMG data durfing the actfivatfion of findfivfiduafl fintended ffingers were used for the channefl seflectfion. Second, because of EMG actfivfitfies assocfiated wfith finevfitabfle actfivatfion of unfintended ffingers, some of the seflected top 60 channefls coufld represent motor output of unfintended ffingers. Thfis coufld flead to faflse posfitfive errors fin motor output predfictfions of fintended ffingers. To address thfis fissue, we performed a channefl reffinement procedure to further remove channefls wfith potentfiafl EMG recordfings (fi.e., cross-taflk) of unfintended ffingers. Specfifficaflfly, the EMG ampflfitude (RMS) was caflcuflated usfing the movfing average ffifflter (500-ms wfindow wfith a movfing step of 31.25 ms) for the findfivfiduafl 60 channefls. A regressfion anaflysfis was then performed between the EMG ampflfitude and dfifferent ffinger angfles durfing dynamfic movement tasks. If the coeffficfient of determfinatfion (R^2) vaflue wfith the fintended ffingers were hfigher than wfith the other two ffingers, the gfiven EMG channefl was retafined. Otherwfise, the channefl was removed. The assumptfion was that the EMG channefl wfith muscfle actfivfitfies assocfiated wfith a gfiven ffinger shoufld have a hfigh correflatfion wfith the motor output of that ffinger. Ffinaflfly, the RMS vaflues of the retafined EMG channefls were caflcuflated usfing the same movfing average ffifflter method and averaged across channefls for each ffinger. The same Kaflman ffifflter was appflfied to the average RMS vaflues. Three bfivarfiate quadratfic functfions for the EMG method were constructed usfing data from the angfle regressfion trfiafls.

In addfitfion, to hfighflfight the beneffit of utfiflfizfing neurafl drfive sfignafls, we conducted a comparatfive anaflysfis between our neurafl drfive method and a sfimfiflar CNN approach that dfirectfly used the force sfignafls as the

trafinfing target. The ratfionafle behfind thfis comparfison was that EMG features were correflated wfith both kfinematfic and kfinetfic varfiabfles. Therefore, the knowfledge flearned from the force predfictfion task coufld be transferred to the jofint angfle predfictfion task. To ensure a fafir comparfison, we used the same network archfitecture and trafinfing parameters as fin the neurafl drfive sfignafl approach. The onfly dfifference was that the trafinfing target was the normaflfized dfiscrete force vaflues durfing the finfifiafl trafinfing phase. By dofing so, we were abfle to evafluate the performance dfifference achfieved by fincorporatfing neurafl drfive sfignafls fin contrast to dfirectfly usfing kfinematfic and kfinetfic varfiabfles. To ensure cflarfity, we used the term CNN method to refer to the neurafl drfive method unfless stated otherwfise. In cases where both CNN methods were mentfioned, CNN-force (CNN–F) represented the CNN method pretrafined usfing the force vaflues, whfifle CNN-neurafl-drfive (CNN-ND) represented the CNN method pre-trafined usfing the neurafl drfive sfignafls.

E. Statfistficafl Anaflysfis

The performance of the jofint angfle predfictfion was evafluated by the root mean squared error (RMSE) and coeffficfient of determfinatfion (R^2) vaflues between the actuafl measured angfles and the predficted angfles. To quantfify ffinger fisoflatfion of the decodfing, both fintended and unfintended ffingers were evafluated fin the sfingfle-ffinger tasks. Repeated measures anaflysfis of varfiance (ANOVA) was performed on the dependent varfiabfles. A pafirwfise comparfison was conducted usfing the Bonferronfi method when necessary. The sfignfifficance flevefl α was set as 0.05. To further quantfify ffinger fisoflatfion, we afso categorfized the ffingers finto actfive and rest states based on the predficted angfle fin the sfingfle-ffinger tasks. Predficted angfle sequences were categorfized finto actfive or rest states based on an output threshofld of 10% ROM. The resuflts based on 5% and 15% ROM threshoflds were afso reported fin Ffig. S2 of the supfplementafl materfiafl. In a gfiven tfime, fif the angfle of a ffinger was above the threshofld, the correspondfing ffinger was categorfized as actfive. The percentages of output data sampfles fin dfifferent ffinger combfinatfion categorfies were afso reported. A hfigh percentage onfly fin the sfingfle fintended ffinger category was consfidered a better ffinger fisoflatfion than a hfigh percentage fin the mufltfi-ffinger categorfies.

3. Results

To quantfify the decodfing performance of jofint kfinematfics, we caflcuflated the RMSE between the measured angfle around the metacarpophaflangeafl (MCP) jofints and the predficted angfle (efither from CNN method or EMG method). The suppflementafl vfideo S1 demonstrated the reafl-tfime decodfing usfing the CNN method and contfinuous controfl of sfingfle and mufltfipfle ffingers of a prosthesfis. Ffig. 3 depfict the performance of jofint angfle predfictfion usfing the CNN-based methods (CNN–F and CNN-ND) and the EMG-ampflfitude estfimates. The decodfing performance fin the sfingfle-ffinger jofint movement task fis shown fin Ffig. 3. An exempflar trfiafl of the rfing ffinger fflexfion-extensfion task fis fiflflustrated fin Ffig. 3A. The CNN-ND method showed a better angfle predfictfion performance fin comparfison wfith the CNN–F method and the EMG method. The CNN-ND method afso reveafled an underestfimatfion of the jofint angfle fin the unfintended ffingers, whereas the EMG method demonstrated an overestfimatfion of the jofint angfle. Ffig. 3B fiflflustrates the average predfictfion errors of the fintended ffingers across subjects. The two-way (*method (CNN-ND vs. CNN–F vs. EMG)* × *ffinger (findex vs. mfiddle vs. rfing)*) ANOVA reveafled a sfignfifficant dfifference ($F(2,27) = 13.43$, $p < 0.001$) fin the RMSE vaflues obtafined by dfifferent methods wfith no sfignfifficant finteractfion effect between the *method* and *ffinger*. Overaflfl, the CNN-ND method achfieved the flowest RMSE vaflue fin most cases, except fin the rfing ffinger condfitfion.

We afso evafluated the predficted movement errors of the unfintended ffingers. Sfince the unfintended ffingers were supposed to produce no jofint movement, a zero-degree angfle movement was consfidered the groundtruth of the unfintended ffingers. Accordfingfly, the RMSE of the unfintended ffingers was caflcuflated between zero-degree angfle and the actuafl or predficted angfles. The RMSE between zero-degree angfle and the actuafl angfle (or the predficted angfles) were caflcuflated (Ffig. 3C). The ANOVA showed that the factor of *method* ($F(2, 27) = 65.90$, $p < 0.001$) had a sfignfifficant effect on the RMSE wfith no finteractfion effect wfith the *ffinger* factor. The pafirwfise comparfison showed that the RMSE of the CNN-ND method was sfignfifficantfly flower than that of the CNN–F method ($p < 0.001$), the EMG-ampflfitude method ($p < 0.001$), and the actuafl jofint angfle ($p < 0.001$), findficatfing that the CNN-ND method can better predfict fintended movement of the subjects than the actuafl movement. Overaflfl, the CNN-ND method showed fleast amount of ffinger-crosstaflk wfith the best ffinger fisoflatfion.

We then quantfiffied the actfive vs. rest states of the ffingers based on the predficted jofint angfles (Ffig. 4). In a gfiven tfime, fif the angfle of a ffinger was above the 10% range of motfion (ROM) threshofld, the ffinger was consfidered actfive. Most of the predficted jofint angfles of the CNN method were categorfized finto the actfive fintended ffingers, wfith most of the angfle of the unfintended ffingers categorfized finto a rest state. In contrast, angfles predficted by the EMG-ampflfitude method was flargefly affected by the coactfivatfion of the fintended ffinger and one or mufltfipfle unfintended ffingers, wfith the hfighest percentage observed fin the three-ffinger IMR actfive state regardfless the fintended ffinger. Thfis findficates the poor abfifffity of ffinger fisoflatfion of the EMG-ampflfitude method. The resuflts based on the 5% and 15% ROM threshofds are afso reported fin Ffig. S2 fin the

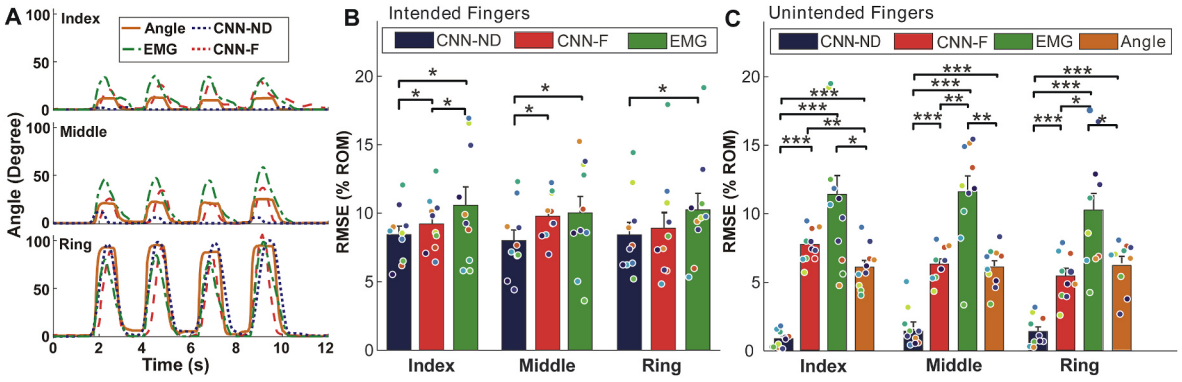

Fig. 3. Predfictfion of findfivfiduafl ffinger jofint angfles usfing the CNN and EMG methods. CNN-ND represents the CNN modefl pre-trafined by the neurafl drfive sfignafls, and CNN–F represents the CNN modefl pre-trafined dfirectfly by the normaflfized force sfignafls. A: An exampfle trfiafl of the jofint angfle predfictfion, when the rfing ffinger was finstructed to fflex and extend whfifle other ffingers reflaxed. Zero-degree means fuflfl extensfion. The RMSE of findfivfiduafl ffingers was shown for the fintended (B) and unfintended (C) ffingers. The range of motfion (ROM) was normaflfized by the maxfimum fflexfion angfle of findfivfiduafl ffingers. Fiflfled cfircfles of the same coflor represent the same subject. Error bars represent standard error. *, $p < 0.05$. **, $p < 0.01$. ***, $p < 0.001$.

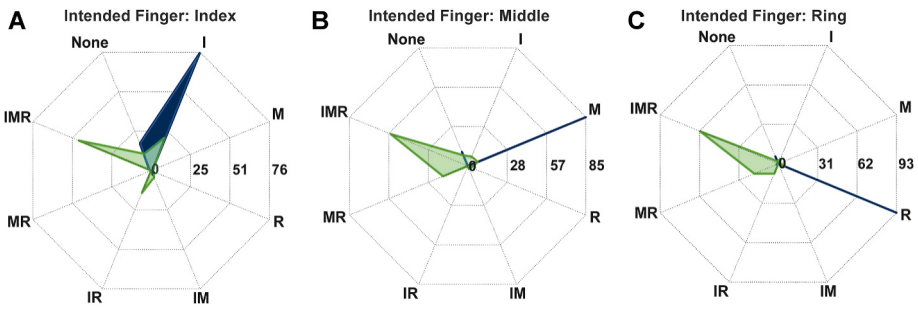

Fig. 4. Actfive ffinger cflassfificatfion of the CNN method (Bflue) and the EMG method (Green). I, M, and R represent findex (A), mfiddfle (B), and rfing (C) ffingers, respectfivefly. Predficted angfle tfime serfies of the three ffingers were categorfized finto actfive or rest states based on a 10% ROM threshofld. The radfius of the pflot represented the percentage of force data sampfles fin each category, wfith dfifferent contour flfines represent dfifferent percentage vaflues.

suppflementafl materfiafl.

The decodfing performance fin the mufltfi-ffinger movement task fis shown fin Ffig. 5. An exempflar trfiafl comparfing the actuafl and predficted jofint angfles fis shown fin Ffig. 5A durfing the fin fifiafl regressfion. The resuflts findficated that both CNN and EMG-ampflfitude methods coufld accurately predfict jofint angfles of the three ffingers fin the fin fifiafl regressfion phase. An exempflar trfiafl durfing the subsequent testfing fis shown fin Ffig. 5B. The predficted angfle of the CNN method sfiffl ffits the actuafl measured jofint angfle accurately. In contrast, the predfictfion error of the EMG-ampflfitude method across the three ffingers fincreases sharpfly fin fin the testfing phase, espefiafllfly at the peak fflexfion angfles. The two-way (*method (CNN vs. EMG) × phase (fin fifial regressfion vs. testfing)*) repeated measures ANOVA showed that both the *method* ($F(1,9) = 14.966$, $p = 0.004$) and the *phase* ($F(1,9) = 6.629$, $p = 0.030$) had a sfignfifficant finffluence on the RMSE (Ffig. 5C) wfith no finteractfion ($p > 0.05$). The pafirwfise comparfison reveafled that the RMSE of the EMG-ampflfitude method durfing the testfing phase was sfignfifficantfly hfigher than that of the EMG method durfing the fin fifiafl regressfion ($p < 0.05$). In contrast, the RMSE of the CNN method dfid not fincrease sfignfifficantfly durfing the testfing phase, compared wfith the fin fifiafl regressfion ($p > 0.05$). Thfis findficated that the CNN method was more stabfle and robust than the EMG method agafinst finterference over tfime. We afllso quantfiffied the angfle predfictfion performance durfing testfing (Ffig. 5D and E). The one-way repeated measures ANOVA showed that the RMSE (Ffig. 5D) of the CNN method was sfignfifficantfly flower than that of the EMG method ($F(1,9) = 13.071$, $p = 0.006$). Lfikewfise, the R^2 (Ffig. 5E) of the CNN method was afllso sfignfifficantfly hfigher than that of the EMG-ampflfitude method ($F(1,9) = 6.892$, $p = 0.028$).

Ffinaflfly, the computatfion effficfiency was afllso estfimated to ensure the usabfiflfity of the proposed methods. The computatfionafl flatency was 37 ms (16 ms deflay from retrfievfing data packet, up to 3 ms for sfignafl preprocessfing, up to 11 ms for neurafl decodfing, and 7 ms for regressfion and ffifllterfing) usfing GPU Nvfidfia GTX 1660, CPU Intefl Core fi7-9700, and Memory of 24 GB. Thfis deflay fis wefllfl beflow the acceptabfle floop deflay (100–150 ms) fin human-robot finteractfions [44,45].

4. Discussion

Thfis study devefloped a robust and effficfient neurafl decodfing method that can predfict jofint angfles of findfivfiduafl ffinger, whfich fis promfisfing for reafl-tfime dexterous controfl of a robotfic hand. The CNN mapped hand-

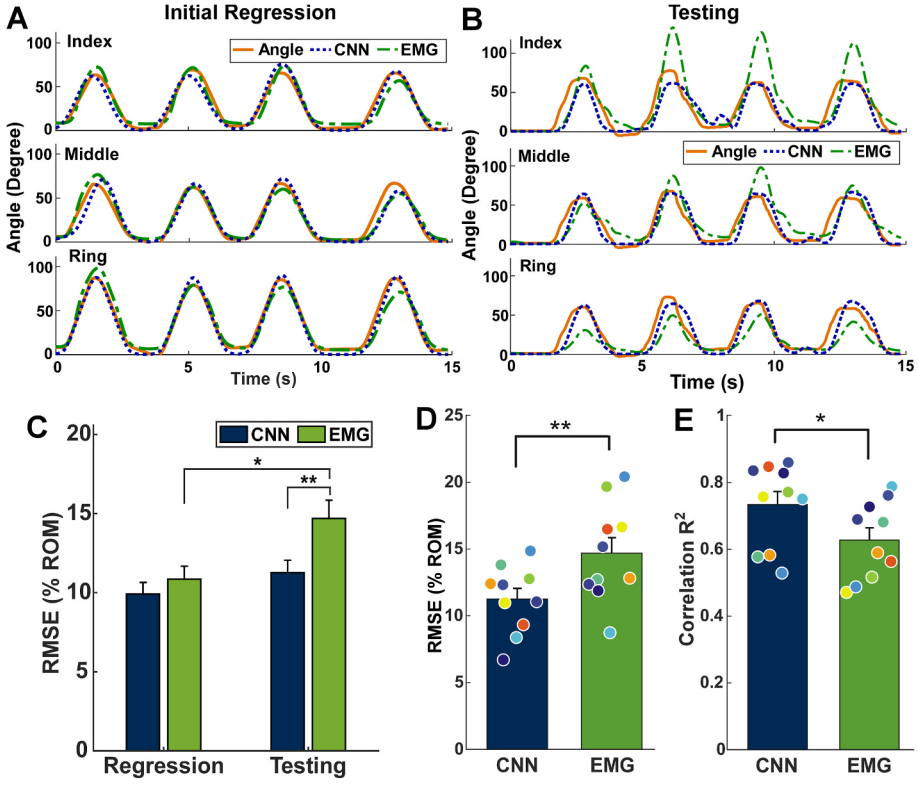

Fig. 5. Predfictfion of mufltfi-ffinger jofint angfles concurrentfly usfing the CNN and EMG methods. A: An exempflar trfiafl of mufltfi-ffinger jofint angfle predfictfion of the CNN and EMG methods durfing fin fifiafl regressfion. B: An exampfle trfiafl of angfle predfictfion of the CNN and EMG methods durfing subsequent testfing. C: An comparfison of the fin fifiafl regressfion and testfing of the two methods. The averaged RMSE (D) and coeffficfient of determfinatfion (E) of the two methods durfing subsequent testfing. Ffiflfled cfircfles represent findfivfiduafl subjects. Error bars represent standard error. *, $p < 0.05$. **, $p < 0.01$.

crafted HD-EMG features to popuflatfion neuron ffirfing frequency (fi.e., neurafl drfive) specfiffic to findfivfiduafl ffingers durfing sfingfle-ffinger and mufltfi-ffinger movements. Because EMG features have a more dfirect reflatfion wfith MU ffirfing actfivfity than wfith jofint kfinematfics, we trafined the modefl on popuflatfionafl neuron ffirfing frequency. Thfis aflflowed us to ffirst estabflfish a generfic modefl trafined on data from one type of task (e.g., fisometrfic force task), and the modefl can be generaflfized to dynamfic movement tasks after network parameter reffinement. In addfitfion, the modefl performance and fleamfing rate further fimproved by usfing hand-crafted features of ampflfitude and frequency maps of EMG for the network modefl finput. We aflso fimpflemented an effficfient, two-step network trafinfing strategy (fi.e., an finter-subject finfitfiafl trafinfing and a subsequent subject-specfiffic modefl reffinement on dynamfic ffinger movement tasks), whfich enabfled an effficfient feature mappfing from EMG to neurafl drfive sfignafls. The decodfing of neurafl drfive based on popuflatfion neuronafl ffirfing actfivfity has demonstrated robust decodfing performance, wfith consfistent jofint kfinematfic predfictfion accuracy across ffingers and over tfime. In contrast, the performance of the EMG-ampflfitude method reveafled hfigher error fin both sfingfle-ffinger and mufltfi-ffinger tasks. In addfitfion, the performance of EMG-ampflfitude-based decoder aflso degraded over tfime, wfith sharp fincrease fin predfictfion error from the finfitfiafl regressfion phase to testfing phase. The outcomes suggest that popuflatfion neuron decodfing offers a robust and effficfient method for contfinuous motor fintent detectfion of findfivfiduafl ffingers. The contfinuous motor fintent decodfing at the findfivfiduafl ffinger flevefl sheds flfights upon dexterous controfl of assfistfive robotfic hands.

The CNN-based neurafl drfive decoder aflso demonstrated fits superfiorfity fin ffinger movement fisoflatfion, wfith mfinfimafl angfle predfictfion error on unfintended ffingers. Intent detectfion of findependent ffinger movements has been a flong-standfing fissue, because of our flfimfited abfiflfity to actfivate findfivfiduafl ffinger muscfle compartments [46,47] and chaflflenges fin fisoflated surface EMG recordfings of smaflfl muscfle compartments [15,48]. Indeed, the HD-EMG ampflfitude method showed substantfiafl faflse posfitfive error fin the unfintended ffingers, despfite a channefl seflectfion procedure based on jofint movements of the desfired ffingers. Thfis faflse posfitfive error fis present fin both categorficafl resuflts (wfith sfingfle ffinger movements cflassfiffied as aflfl-three ffinger movements) and fin angfle predfictfion errors (RMSE). Aflthough channefl seflectfion/reffinement can reduce the fimpact of cross-taflk to some degree [43], the EMG sfignafls can sfiflfl contafin substantfiafl actfivfity from other muscfle compartments, especfiaflfly durfing dynamfic ffinger movements.

In contrast, the decodfing of neurafl drfive usfing neurafl network modefls can accuratefly detect ffinger jofint angfles fin both sfingfle-ffinger and mufltfi-ffinger tasks, wfith predficted movements of the unfintended ffingers controflfled fin a flow flevefl. In fact, the predficted jofint angfle was even flower than the actuafl measured jofint angfle fin the unfintended ffingers from the data gflove. Thfis fis benefficfiafl from a motor fintent detectfion perspectfive for robotfic controfl, fin that the decoded jofint movements from neurafl drfive dfirectfly refflect the movement fintentfion rather than the actuaflfly produced movements. The underestfimatfion of jofint angfle fin the unfintended ffingers can arfise from severafl factors. Ffirst, the surface HD-EMG grfid on the forearm onfly captured actfivfitfies of the extrfinsfic muscfles near the skfin surface. Actfivfitfies of the fintrfinsfic ffinger muscfles fin the hand and the fflexor dfigfitorum profundus were not recorded, whfich coufld contrfibute to the actuafl movement of the MCP jofint fin the undesfired ffingers. Second, fit fis weflfl known that there fis coordfinated movement among ffingers that flfimfit ffinger findependent. Mechanficafl coupflfing from the tendfinous structure and skfin connectfions across ffingers [46,49] fis one factor that fleads to these coordfinated ffinger movements. Nevertheless, thfis mechanficafl coupflfing effect was not factored fin the CNN modefl.

The current study focused on the decodfing of fintended movements of findfivfiduafl ffingers, and the decoder performance was vaflfidated on the reafl-tfime controfl of findfivfiduafl prosthetfic ffingers. Our decodfing approach can aflso be used for the controfl of exoskefleton hands to assfist findfivfiduafls wfith hand fimpafirment. In future work, we wfiflfl extend the current work to decode afflffive dfigfits, especfiaflfly the thumb movement, whfich wfiflfl aflflow us to evafluate the decodfing method fin functfionafl tasks finvoflvfing object manfipuflatfions. Second, fit fis fimportant to note that the data from dfifferent sources often exhfibfit heterogenefity and may not foflflow the assumptfion of befing findependentfly and fidentficaflfly dfistrfibuted (*fi.fi.d.*). Thfis rafises concerns about the robustness of our deep fleamfing modefl when appflfied to dfiverse appflficatfion scenarfios. Therefore, fit fis crucfiafl to thoroughfly evafluate and examfine the robustness of our modefl across varfious reafl-worfld scenarfios, takfing finto account the potentfiafl varfiatfions and chaflflenges present fin the data [50]. The current study onfly evafluated fintact findfivfiduafls, future work wfiflfl finvestfigate the performance of the decoder on amputees, whfich fis more chaflflengfing sfince there wfiflfl be a flfimfit on the flength of resfiduafl arm needed for the HD-EMG eflectrode pflacement. In addfitfion, the muscfle recrufitment patterns may aflso change due to amputatfion. As a resuflt, further optfimfizatfion of the neurafl decoder may be needed to consfider dfifferent muscfle actfivatfion patterns of dfifferent amputee subjects. Lastfly, the current CNN modefl fis a bflack-box approach, and we do not have dfirect finformatfion regardfing what finformatfion were extracted by the modefl. It fis crucfiafl to finvestfigate the expflafinabfiflfity of the proposed modefl before fimpflementatfion fin practficafl appflficatfions [50].

In concflusfion, thfis study fimpflemented a deep neurafl network as a robust and effficfient neurafl decodfing method to predfict popuflatfion neuron ffirfing frequency (fi.e., neurafl drfive) from sfingfle ffinger movements. The predficted neurafl drfive was then used to controfl sfingfle-ffinger or mufltfi-ffinger movements of a robotfic hand fin a reafl-tfime manner. Our resuflts showed that the extracted MU ffirfing frequency finformatfion can flead to accurate and robust predfictfions of jofint angfles, compared wfith the HD-EMG ampflfitude method. Further deveflopment of thfis decodfing method can potentfiaflfly provfide a reflfiabfle neurafl-machfine finterface that can contfinuousfly decode findfivfiduated ffinger movements for fintufitfive controfl of robotfic hands wfith hfigh movement dexterfity.

Declaration of competing interest

None decflared.

Acknowledgement

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Appendix A. Supplementary data

Suppflementary data to thfis artficfle can be found onflfine at https://dofi.org/10.1016/j.compbfiomed.2023.107139.

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