Multiplex Recurrence Network Analysis of Inter-Muscular Coordination During Sustained Grip and Pinch Contractions at Different Force Levels

Na Zhang, Ke Li, *Member, IEEE*, Guanglin Li, *Senior Member, IEEE*, Raviraj Nataraj, *Senior Member, IEEE*, and Na Wei

Abstract—Production of functional forces by human motor systems require coordination across multiple muscles. Grip and pinch are two prototypes for grasping force production. Each grasp plays a role in a range of hand functions and can provide an excellent paradigm for studying fine motor control. Despite previous investigations that have characterized muscle synergies during general force production, it is still unclear how intermuscular coordination differs between grip and pinch and across different force outputs. Traditional muscle synergy analyses, such as non-negative matrix factorization or principal component analysis, utilize dimensional reduction without consideration of nonlinear characteristics of muscle co-activations. In this study, we investigated the novel method of multiplex recurrence networks (MRN) to assess the inter-muscular coordination for both grip and pinch at different force levels. Unlike traditional methods, the MRN can leverage intrinsic similarities in muscle contraction dynamics and project its layers to the corresponding weighted network (WN) to better model muscle interactions. Twenty-four healthy volunteers were instructed to grip and pinch an apparatus with force production at 30%, 50%, and 70% of their respective maximal voluntary contraction (MVC). The surface electromyography (sEMG) signals were recorded from eight muscles, including intrinsic and extrinsic muscles spanning the hand and forearm. The sEMG signals were then analyzed using MRNs and WNs. Interlayer mutual information (I) and average edge overlap (ω) of MRNs and average shortest path length (L) of WNs were computed and compared across groups for *grasp types* (grip vs. pinch) and *force levels* (30%, 50% and 70% MVC). Results showed that the extrinsic, rather than the intrinsic muscles, had significant differences in network parameters between both *grasp types* ($p < 0.05$), and *force levels* ($p < 0.05$), and especially at higher force levels. Furthermore, I and ω were strengthened over time ($p < 0.05$) except with pinch at 30% MVC. Results suggest that the central nervous system (CNS) actively increases cortical oscillations over time in response to increasing force levels and changes in force production with different sustained grasping types. Muscle coupling in extrinsic muscles was higher than in intrinsic muscles for both grip and pinch. The MRNs may be a valuable tool to provide greater insights into inter-muscular coordination patterns of clinical populations, assess neuromuscular function, or stabilize force control in prosthetic hands.

Index Terms—Muscle coordination, multiplex recurrence network, surface electromyogram; grip force, pinch force.

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I. INTRODUCTION

THE dexterous use of the hand, including the precision modulation of grasping forces, is critical for activities of daily living. Production of functional forces requires coordination of multiple muscles under the control of the central nervous system (CNS) [1]. Several electromyogram (EMG) studies on musculo-muscular coupling [2]–[5] and muscle syn-

ergies [6], [7] have been done to characterize muscle coordination. However, the principles governing muscle coordination at varying *grasp types* and *force levels* remain unclear. Manual tasks can require varying force levels depending on the functional task. Determining how hand muscles coordinate their actions at varying force levels should promote our fundamental understanding of neuromuscular function during manual tasks. This knowledge may also serve as a template for formulating treatments and rehabilitation protocols for neuromuscular diseases [8] and for designing biomimetic robotic systems [9].

Whole-hand grip and two-digit pinch are two categories of human hand grasp commonly observed for physiological and functional assessments [10], [11]. During grip, all joints and muscles of the hand act to grasp an object within the palm. Stronger coupling of extrinsic muscles (forearm muscles) comprise the primary synergy during grip force production [3]–[5]. Pinch tasks typically require smaller forces and involve grasping an object with tip-to-tip opposition of the thumb and index finger. Pinch is used for precision hand tasks and mainly employs activation of intrinsic muscles of the hand. Intrinsic muscles typically exhibit less coupling so as to control digits more independently and execute dexterous manipulations [3]–[5]. Accurately characterizing coordination during grip and pinch may indicate generalizable muscle coordination principles across the spectrum of grasp. Coordination analyses can also indicate the dependence of muscular coupling on the varying grasp forces required. But few studies examined the muscle coordination for grip and pinch force control under the same framework.

The relationship between changes in required force levels and motor unit recruitment has been well established [12]. The CNS regulates motor unit recruitment and firing rate to produce the forces required for the given task. These force-activation dynamics result in uniquely emerging muscle synergies, or musculo-muscular couplings. D'Avella *et al.* demonstrated that the synchronous frequencies of synergistic muscle pairs move from beta to gamma activation bands with the larger force output [13]. Danion and Gallea showed the co-activation of antagonist muscles generally decreased as grip force increased [14]. However, detailed knowledge is still lacking about the changing characteristics in muscle synergies with systematic variations in force amplitude.

Time-series analyses of surface electromyogram (sEMG) signals can provide essential insights into the nature of dynamic changes in muscle synergies [7]–[9]. Traditional time- and frequency-domain approaches are limited in their ability to consider nonlinear characteristics of sEMG signals. Nonnegative matrix factorization (NNMF), principal component analysis (PCA), and other multivariate analysis methods cannot consider the multiple muscles as a whole. These methods often utilize dimensional reduction and limit the ability to consider nonlinear muscle characteristics or multiple muscles acting as a single unit [15], [16]. Complex network theory based on nonlinear time series analysis provides a powerful tool on identifying the structural and temporal characteristics of dynamic systems [17]. Furthermore, multilayer complex network theory has been established, which takes account of the multivariate time series simultaneously and

is capable of revealing the interactions of multiple dynamic subsystems [18], [19]. There are many types of multilayer networks, such as the multiplex visibility graph given by Lacasa *et al.* [19], the multiplex recurrence network (MRN) reported by Eroglu *et al.* [18], the construction of supra-Laplacian matrix proposed by Gómez *et al.* [20]. The MRN based on recurrence of a trajectory in its phase space is well suited for analyzing nonlinear, nonstationary, neurophysiological dynamics [21]–[23]. In this study, MRN was used to capture signature nuances in muscle activities from multidimensional, multivariate time series by the intrinsic similarity and synchronization in the dynamics of the different muscles [24], [25]. By jointing multivariate sEMG signals, the MRN can obtain both local (independent muscle) and global (multiple muscle) muscle synergy representations through quantitative analysis of its structure. Two key parameters of the MRN, the interlayer mutual information and the average edge overlap, can indicate inter-muscular similarity and synchronization at different movement paradigms. Furthermore, MRN can project its layers into a singular weighted network (WN) representation, thereby providing a visibility analog of functional networks [19]. Eroglu *et al.* reported that both MRN and WN can be used for large enough multidimensional systems [18]. Therefore, the WN would be an efficient method to quantify multidimensional muscular system and indicate the coupling of multiple muscle activations.

In this study, we propose a novel approach utilizing MRNs and WNs to investigate muscle coordination across the upper-limb muscles at different force levels during grip and pinch. With these advanced analytical tools, the tendency of muscle coordination over time could be examined during a short-term sustained force production. Three force levels at 30% (low), 50% (medium) and 70% (high) of maximum voluntary contraction (MVC) were selected for both the grip and pinch force production. The sEMG signals were recorded from eight muscles, including both intrinsic and extrinsic muscles that are highly implicated with hand grasp. These muscles were the brachioradialis (BR), flexor carpi ulnaris (FCU), flexor carpi radialis (FCR), flexor digitorum superficialis (FDS), extensor digitorum communis (EDC), abductor pollicis brevis (APB), first dorsal interosseous (FDI), and abductor digiti minimi (ADM). We hypothesized that compared to the intrinsic muscles, the extrinsic muscles during grip would exhibit higher MRN parameters and lower WN parameters with increasing force levels as well as duration of force maintenance.

II. METHODS

A. Subjects

Twenty-four healthy volunteers (mean age, 23, range, 21-28; 12 males and 12 females) participated in this experiment. All subjects were right-handed and have normal or corrected-to-normal vision. Participants were excluded if they self-reported any neurological or musculoskeletal disorders of the upper limbs. All subjects signed an informed consent form for this experiment approved by the Institutional Review Board of Shandong University Institutional Review Board of Shandong University (LL-201601007, 03/02/2016).
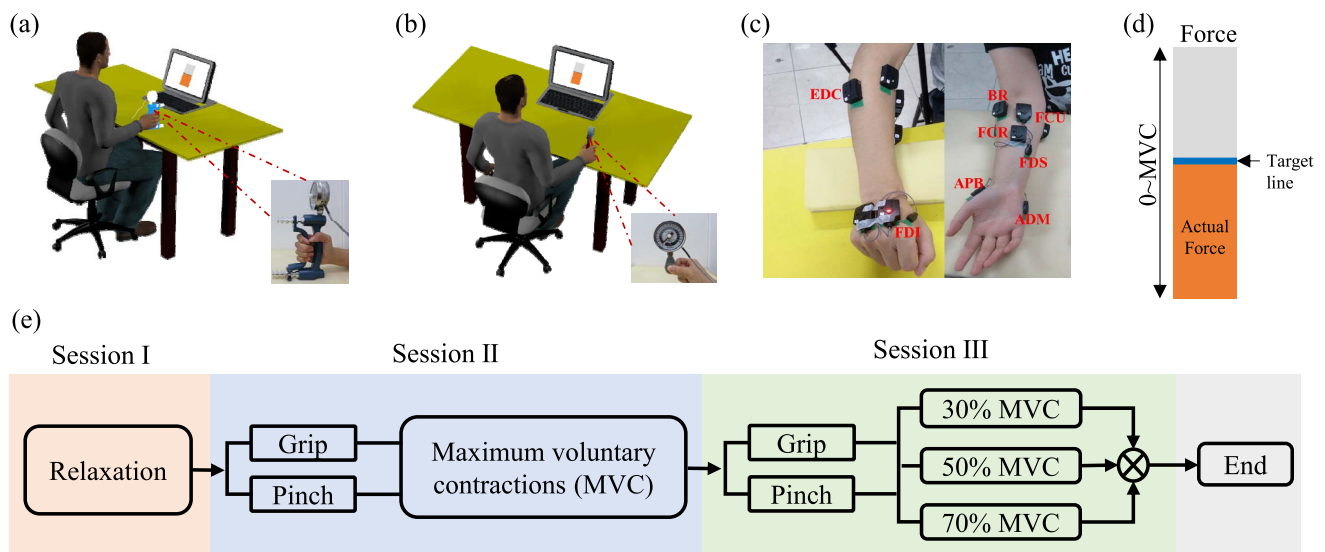
Fig. 1. Signal Acquisition and Experiment Paradigm. (a) MVC test of grip; (b) MVC test of pinch; (c) The placement of sEMG sensors; (d) Visual feedback for grasp task; (e) Experimental flow chart.

B. Experimental Set-Up

The grip force was measured using a hydraulic hand dynamometer (Baseline Evaluation Instruments, Fig 1a). The pinch force was measured using a hydraulic pinch gauge (Baseline Evaluation Instruments, Fig 1b). Analogue force data were digitized (National Instruments, USA) and recorded (Dell, USA) for real-time visual feedback using a custom program in LabView^{TM}(National Instruments, USA). The sEMG signals of the BR, FCU, FCR, EDC, FDS, APB, FDI and ADM were recorded using a wireless EMG system (Trigno^{TM}, Delsys, USA, Fig 1c), which uses silver-contact wireless bipolar bar electrodes with fixed 10 mm inter-electrode spacing. This parallel bar detection approach ensures reliability, robustness to cross-talk, ease-of-use and consistency across all data collection protocols. There was only one channel of sEMG applied for each muscle. The electrodes of sEMG were placed on the hand and forearm muscles according to the reference [26]. Specifically, for the BR it was positioned at 25% on the line from the elbow stripes outside to the radial styloid process; for the FCU it was positioned at 1/3 of the line between the styloid process of ulna and the internal epicondyle of femur; for the FCR it was placed at the midpoint of the line between the lteral head of biceps and pisiform bone; for the FDS it was attached at 1/4 of the line between the styloid process of ulna and the external epicondyle of femur; for the FDS it was placed on the line between the internal epicondyle of femur and the central wrist at 1/3 from the central wrist, for the APB it was placed on the slightly medial of the distal 1/4 of the first ossa metacarpalia; for the FDI it was placed parallel to the second metacarpal shaft, superficially, directly into the middle of the dorsal web space, for the ADM, it was attached at 50% between pisiform bone and the ulnar side of the pastern bone of the little finger. In addition, to improve the signal quality, the skin covering the muscles was washed with water and soap, shaved, and cleaned with alcohol. The electrodes were positioned above the muscle belly parallel to the muscle fibers. It was then fixed on the skin with adhesive elastic tape so that the quality of the sEMG could be guaranteed. All force data were recorded synchronously with the sEMG signals at 1000 Hz.

Subjects were seated with right arm comfortably placed on a testing table (Fig 1a and 1b), with their upper arm positioned vertically, their elbow flexed at 90°, and their forearm and wrist set in neutral positions as proposed by the American Society of Hand Therapists (ASHT) [27]. Subjects' right wrists were fixed in place with Velcro and wooden boards to mitigate differences in grasping postures during the experiment. The experiment protocol consisted of three blocks (Fig 1e). *Block I* - Relaxation. Each subject was asked to relax the arm flat onto the testing table while contacting the dynamometer without actively grasping for 1 min. Force and sEMG data collected during this block served as a reference baseline for the following grip and pinch blocks. *Block II* –MVC of grip and pinch forces. For each trial, subjects initially placed their digits onto the dynamometer without actively applying force. Upon hearing a 'go' cue, subjects were required to apply their maximum grasp force onto the dynamometer for a total of 5 s. The MVC of grip and pinch were determined from the mean of three such trials. *Block III* – Force levels. In this block, subjects were asked to produce grip or pinch force at 30%, 50% and 70% of MVC that have been frequently used in literature [28-30]. To accomplish this, subjects received visual feedback about their grasp force magnitude relative to the target force on a computer monitor. Subjects would observe their grasp force magnitude varying in direct proportion to the height of an orange bar (Fig 1d) in real time. Subjects were instructed to maintain the orange bar representing their actual force output surrounding the blue line representing the target force level to the best of their abilities for more than 10 s. In *Block III*, trials for grip versus pinch and each of the three force levels were randomized for each subject. To mitigate muscle fatigue effects, a 1-min rest interval was provided between two consecutive trials and a 3-min rest was provided
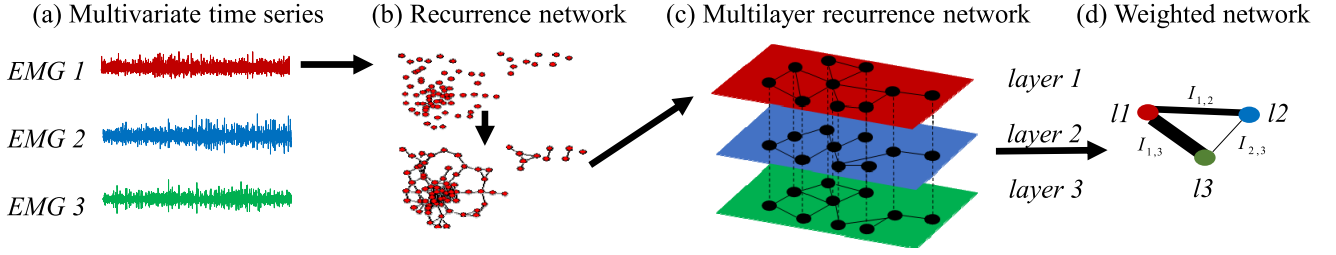
Fig. 2. Illustration of the procedure for constructing a multiplex recurrence network (MRN) and a weighted network (WN). Dashed lines between MRN's layers connect all layers. The WN is the projection of all layers of MRN: one layer as a node, the weights of WN's edges are the interlayer mutual information (similarity measure between two layers) of MRN.

between blocks [31]. The data of the experiment were saved on a public repository (DOI: 10.6084/m9.figshare.13643480).

C. Data Analysis

For each 10 s grasp trial, only the signal data during the middle 7 s were retained for the following analyses. Mean difference (MD) was used to examine the accuracy of the force production with respect to the target force. The MD was defined as:

$$\text{MD} = \frac{1}{N} \sum_{i=1}^{N} \left| \frac{\boldsymbol{F}_i - F_T}{F_T} \right| \qquad (1)$$

where N is the length of force signal, F_T is the target force, F_i is the applied force value at i^{th} sampling point. Then, we computed the magnitude of variability (MOV) as follows:

$$\text{MOV} = \sqrt{\frac{1}{N} \sum_{i=1}^{N} \left(\frac{\boldsymbol{F}_i - F_T - \tilde{F}}{F_T} \right)^2} \qquad (2)$$

where $\tilde{F}$ is the mean value of the difference between $\boldsymbol{F}_i$ and F_T.

The sEMG signals were band-pass filtered (2nd order Butterworth filter) at 20-450 Hz. For a N-length sEMG signal that can be reconstructed as a single trajectory of the dynamical system in its phase space by time delay and embedding dimension. The formula was defined as:

$$\boldsymbol{u}_i = \left(\boldsymbol{x}_i, \boldsymbol{x}_{i+t}, \ldots \boldsymbol{x}_{i+t(m-1)} \right) \qquad (3)$$

where m is the embedding dimension determined according to false nearest neighbor (FNN). The t is the embedding time delay determined from the mutual information (MI) method. The recurrence matrix was constructed as follows:

$$\boldsymbol{R}_{i,j} = \Theta \left(\varepsilon - \left\| \boldsymbol{u}_i - \boldsymbol{u}_j \right\| \right), \quad i, j = 1, \ldots N \qquad (4)$$

where $\Theta(\cdot)$ is the Heaviside function, $\| \; \|$ is the Euclidian norm, ε is an appropriate threshold value.

To specify an unweighted and undirected recurrence network (RN), the adjacency matrix was constructed according to the previous studies [18], [22], [32], as follows:

$$A_{i,j}(\varepsilon) = \boldsymbol{R}_{i,j}(\varepsilon) - \delta_{i,j}, \quad i, j = 1, \ldots N \qquad (5)$$

where the $\delta_{i,j}$ is the Kronecker delta symbol. For each RN, which has same number of nodes because of common sampling rate, embedding dimension m and time delay t.

The MRN was constructed by connecting the same time labeled nodes of RNs, which serve as the layers of MRN. For an example with three-dimensional sEMG signals, the procedure for constructing MRN are depicted in Fig 2. First, we reconstruct the phase space for each of three sEMG signals by Eqs. (3). Each RN is calculated by Eqs. (4)-(5) and then placed in to a layer of MRN [18]. Finally, the giant adjacency matrix of MRN is illustrated as follows:

$$\mathcal{A} = \begin{bmatrix} \boldsymbol{A}^{[1]} & I_N & \cdots & I_N \\ I_N & \boldsymbol{A}^{[2]} & \ddots & \vdots \\ \vdots & \ddots & \ddots & I_N \\ I_N & \cdots & I_N & \boldsymbol{A}^{[m]} \end{bmatrix} \qquad (6)$$

where I_N is the identity matrix of size N.

A number of features could be selected as indication of inter-muscular coordination. Similarity of and synchronization are two features that have been frequently examined for muscle coordination during skilled motions [33]–[36]. In this study we thus used similarity and synchronization as two features of inter-muscular coordination during force production. The similarity was calculated by the *interlayer mutual information* reflecting the topological structure differences in the phase space based on the recurrence matrix between the corresponding points of the degree series across layers. The similarity quantifies the information flow between the multiplex networks, indicating the differences of the behaviors of two systems [18], [19]. Given a pair of layers β and γ of m (the number of MRN layers), the *interlayer mutual information* between layers β and γ ($I_{\beta,\gamma}$) was defined as:

$$I_{\beta,\gamma} = \sum_{k^{[\beta]}} \sum_{k^{[\gamma]}} P \left(k^{[\beta]}, k^{[\gamma]} \right) \log \frac{P \left(k^{[\beta]}, k^{[\gamma]} \right)}{P \left(k^{[\beta]} \right) \left(k^{[\gamma]} \right)} \qquad (7)$$

where $P(k^{[\gamma]})$ and $P(k^{[\beta]})$ are the degree distributions of the MRN at the α and β layers, respectively. The $P(k^{[\beta]}, k^{[\gamma]})$ is the joint probability of the nodes with a degree $k^{[\beta]}$ at the layer β and with a degree $k^{[\gamma]}$ at the layer γ. The mutual information measures how much a system is similar to another. Therefore, the higher $I_{\beta,\gamma}$ the more correlated the degree distributions of the two layers [18], [19]. In this work, we used the average interlayer mutual information I, which is the mean of interlayer mutual information across every possible layer-pair in a MRN [18], [19], to capture the mean similarity between muscles' activities.

The synchronization was calculated by the average edge overlap (ω) that represents the average number of identical edges over all layers of the multiplex network. The ω was calculated as follows:

$$\omega = \frac{\sum_i \sum_{j>i} \sum_\gamma a_{ij}^{[\gamma]}}{m \sum_i \sum_{j>i} \left(1 - \delta_{0, \sum_\gamma a_{ij}^{[\gamma]}}\right)} \tag{8}$$

Note that ω can take value from $1/m$ to 1. At $\omega = 1/m$, the edge (i, j) exists in only different layers; if $\omega = 1$, the edge (i, j) exists in all layers. According to the theory of recurrence networks, an edge connecting two nodes of complex networks was established if the trajectories of the vectors fall into a neighbor in the common phase space, representing the two systems have synchronized states. The ω estimates the synchronization with averaged existence of overlapped links from nodes i to j between all layers, thereby indicating the synchronization of microscopic structures of multivariate sEMG signals. The motor-unit synchronization refers to the increased coincidence in the timing of action potentials discharged by motor neurons across muscles. The I indicating similarity and the ω showing synchronization served as hallmarks of the intermuscular coordination for grip and pinch force production.

To construct the WN, each layer was regarded as a node, and the weighted edges were represented by the interlayer mutual information between corresponding node pairs. The average shortest path length parameter (L) of WN was used to quantify the most efficient information flow among the involved muscles during collective contraction. The changes of L could reflect the transitions of stages during dynamical muscle coordination [18]. The L was defined as:

$$L = \frac{1}{N(N-1)} \sum_{i,j \notin N, i \neq j} d_{ij} \tag{9}$$

where N is the number of nodes in the weighted network, i.e. the layers of MRN. The L measures the mean of the weighted shortest path length d_{ij} between all node pairs (i,j). In other words, only the weighted shortest path length (maximum weights) between two nodes were used in the calculation of L, and only one parameter L could be calculated from one WN. For the WN, the shortest path length between two adjacent nodes i and j is $d_{ij} = 1/w_{ij}$, where w_{ij} is the weights between i and j, i.e. I_{ij} between two layers of MRN. Therefore, the L is inversely proportional to I, i.e. the lower L, the lower dynamical transition, the higher similarity of muscles states.

This study examined the coordination of the totally 8 muscles of the hand and forearms during sustained grip and pinch force production. The muscles were divided into the extrinsic muscles, including the BR, FCU, FCR, EDC and FDS, and intrinsic muscles, including the APB, FDI, ADM, according to their anatomical locations with respect to the wrist. A group including all the 8 muscles was also examined, which may reflect the overall activations and interactions of all the involved muscles during sustained force outputs. The

sEMG signals were segmented by a sliding window with size of 500 ms (500 points) and overlaps of 100 ms (100 points). Within each window the ω and I were calculated, and as the window shifts the trends of the ω and I presented. The ω or I value of all the sliding windows were averaged for statistical analyses. The cross-recurrence plot toolbox 5.1 of Matlab (The MathWorks, Natick, MA, USA) was used to calculated the recurrence matrixes. The network parameters were implemented with the Brain Connectivity Toolbox of Matlab.

D. Statistical Analysis

Statistical analyses were performed using SPSS 23.0 (SPSS Inc., USA). A Shapiro-Wilk (*S-W*) test was used to verify whether data were normally distributed. A two-way repeated measures ANOVA was employed to compare the differences in MD, MOV, I and ω of all the three muscle groups (intrinsic, extrinsic and all muscle groups) across the two factors of *grasp types* (grip vs. pinch) and *force levels* (30%, 50% and 70% MVC). The Huynh-Feldt correction was used when the assumption of sphericity was violated. Post hoc pairwise comparisons were performed using the Holm-Sidak test. A Spearman rank correlation coefficient test was used to verify existence of linear correlation between I or ω over time. A *p*-value of less than 0.05 was considered statistically significant.

III. RESULTS

A. Grip and Pinch Force

The mean MVCs of the grip and pinch forces were 295 ± 117 N and 50 ± 11 N, respectively. The MD and the MOV during grip and pinch at the three force levels are shown in Fig 3. No significant difference was found in either MD or MOV between grasp types (grip vs. pinch) or across the force levels (30%, 50% and 70% MVC).

B. Intermuscular Coordination by Network Analysis

Results quantifying feature parameters (I, ω) of MRNs during the grip and pinch at the three target force levels are shown in Fig 4. For the MRNs across all muscles, ANOVA showed significant differences between the grip and pinch on I ($F_{1,23} = 8.94$, $p = 0.007$) and ω ($F_{1,23} = 5.12$, $p = 0.033$) for all muscles (Fig 4a and 4d). The I and ω values were significantly higher during grip than during pinch at both 50% and 70% MVC ($p<0.05$). No significant differences were observed for I and ω values at 30% MVC between grip and pinch. No significant differences were observed across the three force levels for I or ω values during either grip or pinch.

For MRN parameters among the extrinsic muscles, ANOVA showed significant main effects on both *grasp type* (I: $F_{1,23} = 7.132$, $p = 0.014$; ω: $F_{1,23} = 6.930$, $p = 0.015$) and *force level* (I: $F_{2,46} = 5.715$, $p = 0.010$; ω: $F_{2,46} = 10.574$, $p = 0.001$) (Fig 4b and 4e). The I and ω values for the extrinsic muscles during grip were significantly higher than that during pinch at 50% and 70% MVC ($p<0.05$). Additionally, the I
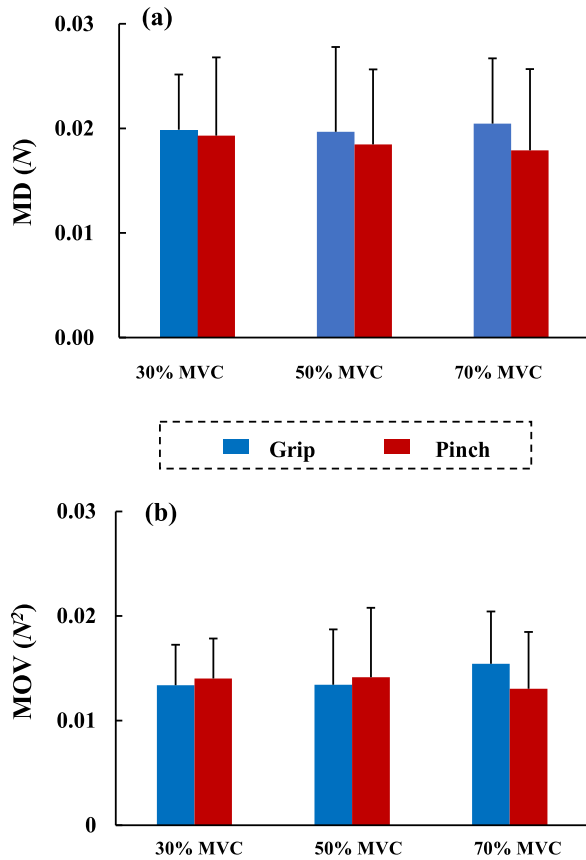
Fig. 3. The accuracy (MD) and variability (MOV) of three grip and pinch force levels. Results are shown as mean and standard deviations.

and ω values for extrinsic muscles at 30% MVC during grip were significantly lower than that at 50% and 70% MVC ($p<0.05$). For the extrinsic muscles during grip at 70% MVC, there was significantly higher ω values than that at 50% MVC ($p<0.05$). No significant force-level differences were present in the I value during pinch; however, the ω values for extrinsic muscles increased at 70% MVC during pinch compared with 30% MVC ($p<0.05$). For the intrinsic muscles, there were no significant differences in I and ω values either between the grip and pinch, or across the three force levels (Fig 4c and 4f). Fig 5 and Fig 6 demonstrates the variations of MRN parameters with time at each of the three force levels. For all muscles, both the I and ω values increased over time at all three force levels during grip ($p < 0.05$, Fig 5-6 a-c). The I and ω values showed positive trends at the 50% and 70% MVC during pinch. Conversely, the I and ω values at 30% MVC during pinch showed a negative trend over time ($p < 0.05$, Fig 5a and 6a) for all muscle sets tested. Similar correlations between I as well as ω values and duration of force production were also observed in extrinsic muscles group and intrinsic muscles group ($p < 0.05$, Fig 5 and Fig 6).

The visualizations of relative network weightings of the eight muscles at the three force levels during grip and pinch from one representative subject are depicted in Fig 7. There is greater thickness (weighting) in the nodal connectivity lines for the grip group WNs compared to the pinch group WNs.

These weightings also were apparently increased with higher force levels. Results for the L parameter of WNs for all tested muscle sets across the *grasp types* and *force levels* are shown in Fig 8. Repeated measures ANOVA showed a significant main effect on the *grasp types* ($F_{1,23} = 8.954$, $p = 0.007$) rather than on the *force levels* ($F_{2,46} = 1.913$, $p = 0.171$) for the WN parameters of all muscles group. The L values from the WNs during grip were significantly lower than that during pinch at 50% MVC and 70% MVC ($p<0.05$). The ANOVA also showed significant main effects on *grasp types* ($F_{1,23} = 7.59$, $p = 0.011$) and *force levels* ($F_{2,46} = 5.61$, $p = 0.011$) for L of the WNs with extrinsic muscles group during both grip and pinch. Significant differences in L were observed between grip and pinch at 50% MVC and 70% MVC, between 30% and 50% MVC during grip, and between 30% and 70% MVC during pinch ($p<0.05$). No significant difference in L was observed for intrinsic muscles across either *grasp types* or *force levels*.

IV. DISCUSSION

This study investigated the dynamical inter-muscular coordination at the 30%, 50% and 70% MVCs during grip and pinch using an advanced analytical tool - the MRN. The effects of *grasp type* and *force levels* on precision (MD), variability (MOV) of grip and pinch forces, and on the similarity (I), synchronization (ω) and transitions (L) of the muscle coordination were examined. Correlation analyses were used to identify dynamic changes in MRN parameters over time with different grip types, force levels, and muscle groups. We reported the following main findings: 1) similar precision and variability of grip and pinch forces at the relative force levels (Fig 3); 2) stronger synchronization and similarity of extrinsic muscles at higher force levels (50% and 70% MVC) were performed in grip than pinch (Fig 4, Fig 8); 3) during grip, the similarity (I) and transitions (L) of extrinsic muscles at lower force level (30% MVC) was inferior to that at higher force levels (50% and 70% MVC), but no significant difference was found between the 50% MVC and 70% MVC (Fig 4 and Fig 8). The synchronization (ω) of extrinsic muscles was augmented with the increased force levels; 4) the muscle coordination of the intrinsic, extrinsic and all muscle groups showed significant force-dependent trends (Fig 5, Fig 6). Specifically, the similarity and synchronization at the medium (50% MVC) and high (70% MVC) force levels showed growing trends with time, whereas the pinch at low force level (30% MVC) showed declined trends with time (Fig5a and 5d, Fig 6a, 6d and 6g).

In this study, we used MD and MOV to evaluate the relative force fluctuation during grip and pinch at each target force level. For MD and MOV, no significant difference was found either between grip and pinch or between force levels, which suggests similar precision and variability during pinch and grip at the relative target force levels.

In a previous study with coherence analysis, Erhard J *et al.* found stronger muscle synchronization for grip than for pinch [37]. Consistent with this finding, the current study found significantly greater similarity (I), transitions (L) and stronger synchronization (ω) for grip than for pinch at
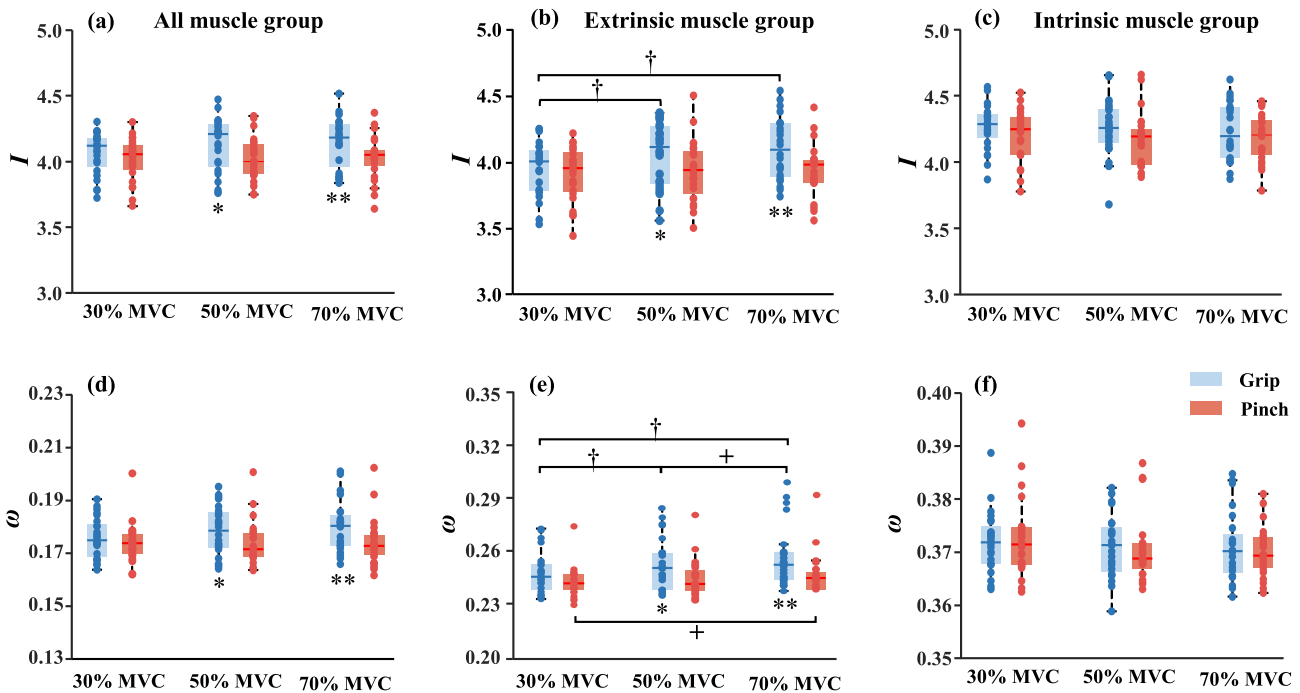
Fig. 4. Interlayer mutual information (I) and average edge overlap (ω) of MRNs for selected muscle groups (all muscles, extrinsic muscles, intrinsic muscles) across three force levels (30%, 50%, 70% MVC) and two grasp types (grip vs. pinch). Results are shown as mean and standard deviation values across all subjects. * ($p < 0.05$) and ** ($p < 0.01$) significant difference between the grip and pinch, + ($p < 0.05$) and †($p < 0.01$) significant difference across the force levels.
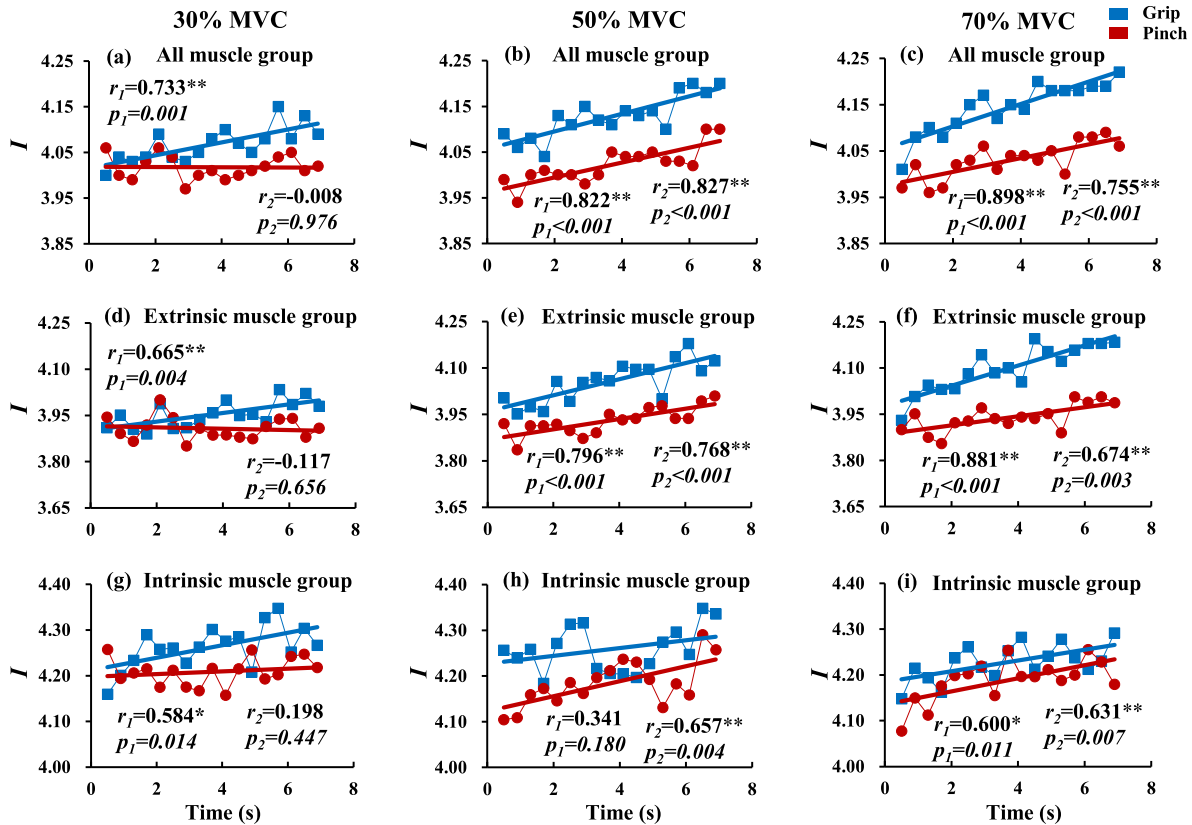
Fig. 5. Time-dependent trends of I values for MRNs of all muscles, extrinsic muscles and intrinsic muscles during sub-maximal grip and pinch contractions. The $r1$ and $r2$ indicate the linear correlations during grip and pinch, respectively. * denotes $p < 0.05$, ** denotes $p < 0.01$.

medium to high force levels (Fig 4a and 4d, Fig 8). Further study of muscle-location effects showed that the extrinsic muscles (Fig 4b and 4e, Fig 8) instead of intrinsic muscles (Fig 4c and 4f, Fig 8) played an important role for the difference between grip and pinch. Anatomical and experimental evidence indicates that intrinsic muscles differ from
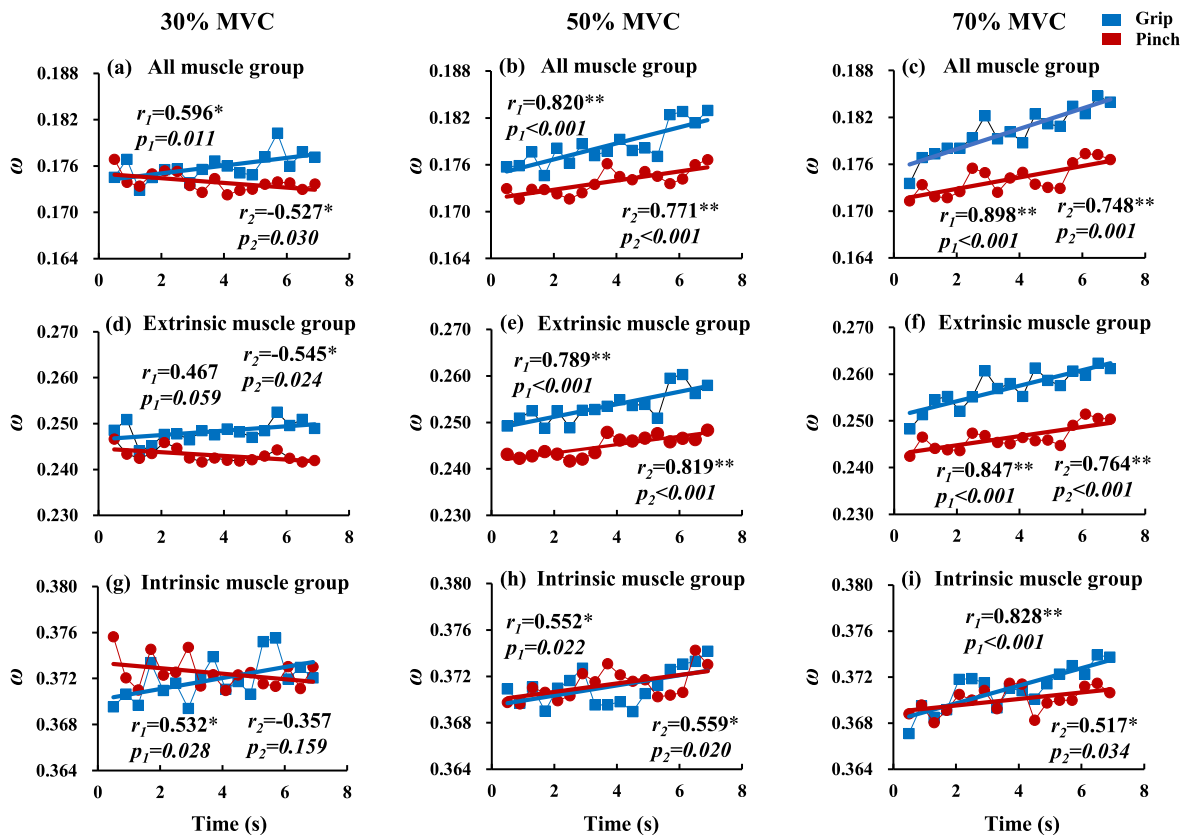
Fig. 6. Time-dependent trends of ω values for MRNs of all muscles, extrinsic muscles and intrinsic muscles during sub-maximal grip and pinch contractions. The r_1 and r_2 indicate the linear correlations during grip and pinch, respectively. * denotes $p < 0.05$, ** denotes $p < 0.01$.
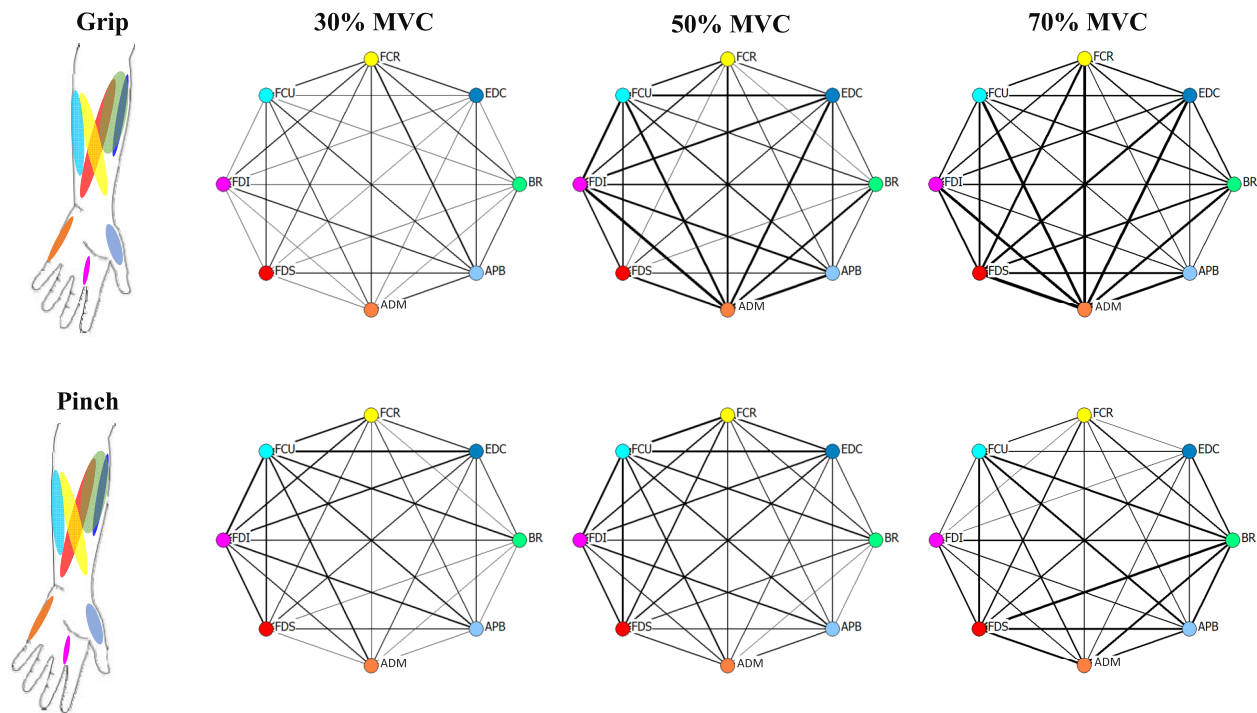
Fig. 7. The visualizations of relative network weightings (indicated by greater thickness) of eight muscles at the three force levels during grip (top) and pinch (bottom) from one representative subject.

extrinsic muscles in the innervations and the capacity of force production as well as in their functional roles. A number of the EMG-EMG coherence analyses found greater

motor-unit synchrony and coherence across extrinsic muscles than intrinsic muscles in either two-digit [5], three-digit [4] or five-digit grasping [38], [39]. Relative researches explained
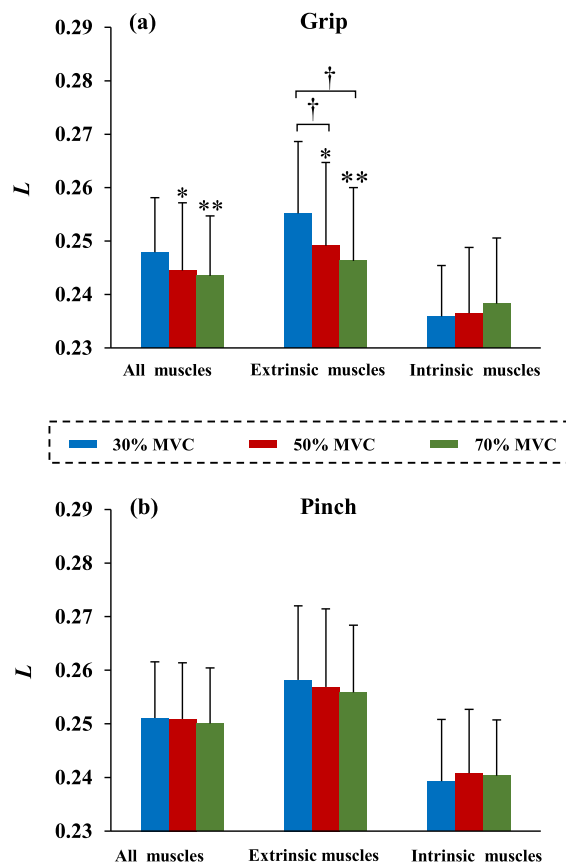
Fig. 8. Results shown for the *L* (average shortest path length) of the WNs for muscle groups (all, extrinsic and intrinsic muscles) and force levels (30%, 50%, 70% MVC) for grip (a) and pinch (b). Results are shown as mean and standard deviation values across all subjects. *(p < 0.05) and **(p < 0.01) significant difference between the grip and pinch, †significant difference across the force levels (p < 0.01).

this phenomenon as the difference of the spinal connectivity patterns of descending pathways in extrinsic and intrinsic muscles, which seem to be consistent with the functional roles of these muscle groups in grasping. Compared to the impendence and flexibility of smaller intrinsic muscles, the extrinsic muscles were larger as well as more concentrated and provided the major force of grasping. The more widespread terminations across motor nuclei supplying extrinsic muscles resulting in nearly synchronous or periodic modulation of the discharge of motor units contribute to synergistic force production, whereas highly independent pathways of intrinsic muscles are favorable to the interaction with an extensive range of objects of varying shapes and sizes [38]. Our results also showed that the extrinsic muscles had similar inter-muscle similarity (*I*), transitions (*L*) and synchronization (*ω*) between grip and pinch at lower force levels (Fig 4b and 4e, Fig 8), which may be interpreted in two alternative ways. The first interpretation is the extremely spatial inhomogeneous activation of muscles at lower force levels because of the nonrandom distribution of muscle fiber types [40]. The second interpretation is the similarity of brain activity during grip and pinch at light force [41]. The potential cross-talks could not be ruled out from the experiment, but it should not be the leading reason for the increased similarity, synchronization and transitions of

extrinsic muscles. When designing the experiment, the effects of cross-talk was controlled to prevent its interference with the results. For example, the electrodes we used to record the sEMG of the extrinsic and intrinsic muscles were the Trigno™sensors (Delsys, Int), which are wireless bipolar EMG sensors that are ideally suited for recording surface EMG on small and "difficult-to-isolate" muscles. The type of sensor used parallel bar detection approach ensuring reliability, robustness to cross-talk, ease-of-use and consistency across all data collection protocols. Moreover, the traditional methods (e.g. the cross-correlation analysis) that are based on the magnitude computation and can be easily tampered by cross-talks or additivity noise over the original sEMG waveforms were excluded. Instead, the multiplex recurrence network (MRN) was used as it has advantages in quantifying the dynamical interactions between muscles with robustness against nonstationary transients, model presumption, outliers, and noise. The application of MRN could further limit (but could not fully remove) the negative effects of cross-talk on the results.

For all the parameters, no significant difference was observed in the all muscle group or in the intrinsic muscle group across the force levels. Only the extrinsic muscles showed increased similarity, synchronization and transitions of muscular coordination with the force levels augmented. The EMG analyses showed that the amplitude and density of muscle activation have positive correlations with the force levels. The recruitment of various motor-unit types and its discharge rates may affect muscle force outputs. With stronger muscles contraction, the number of newly motor units and the firing rates of already recruited motor units are both increased. Previous studies have shown that at the high force levels, the larger number of active motor units and the higher firing rates may increase both the similarity between motor unit action potential shapes and the occurrence of superposition of motor unit action potentials [42]. Moreover, Schmied et al found common neural inputs and/or pre-synaptically correlated inputs could contribute to the increase in motoneurone drive and generate more synchronous firings [43] with increased force levels. According to our results, there is no significant difference in the similarity, synchronization and transitions of intrinsic muscles among three force levels. Similarly, Poston et al investigated the coordination of multiple hand muscles during three-digit grasping across a wide range (5%, 20%, 40%, 60%, and 80% MVC) of grasping forces, and found the forces did not affect the EMG–EMG coherence, which could be attributed to the force-independent distribution of neural drive for the intrinsic muscles [44]. Considering the anatomic and functional redundancy of finger musculature, consensus about the relationship between the hand muscle coordination patterns and the levels of force outputs has not been reached. Some studies suggested that different magnitudes of force outputs could affect the number of active muscles and further the inter-muscular coordination patterns [45], [46]. Others suggested that with different force outputs, it was the intensity of individual muscle's activations rather than the proportions of the involved muscles activations changed; therefore, the inter-muscular coordination patterns could remain the same

even with the changing force outputs during grip and pinch [1], [44]. The current study found that there were no significant differences of the similarity, synchronization and transitions of intrinsic muscles' coordination patterns with different force outputs during grip or pinch, which may support the viewpoint that a force-independent neural drives may play a role in controlling the intrinsic muscles. The force-independent neural drives could result in unchanging intermuscular coordination at different grip and pinch force levels.

The preliminary results of inter-muscular coordination using MRN during grip and pinch had been reported in our previous study [47]. The current study further investigated the accuracy and variability of grip and pinch forces, found the force-dependent trends of inter-muscular coordination, and the effects grasping types and forces levels on similarity, synchronization and transitions according to WRN and WN. It is noteworthy that the force outputs exhibited similar precision and variability, no matter the grasping types or the force levels; by contrast, the inter-muscular coordination was modulated by the grasp types and varied with force levels. Results showed that the muscle coordination of either extrinsic muscles or intrinsic muscle were increased over time during sustained grip and pinch force production, except for the pinch at 30% MVC (Fig 5 and 6), which is shown by a more regular organization of motor potentials in multiple muscles and a stronger inter-muscular coupling among muscles. Previous studies have reported that the motor cortex could be operating in a mode of increased oscillatory activity with efficient motoneurone recruitment during steady sustained contractions, and result in co-contraction pattern of muscular activity [48]. Besides, grasping is charged by a complex closed-loop feedback control mechanism. In the present study, the grip and pinch force production tasks required the continuous integration of visual and somatosensory inputs with the generated motor output to maintain the required target force. And the visual feedback during motor performance would increase complexity and adaptability of neural outputs [49]. It has been proposed that grip force production is characterized by the predominant coactivation of hand muscles that require more involvement of the premotor interneurons (PreM-IN) system. Conversely, pinch force control requires the fractionation of hand muscles as well as their coactivation, and thus might depend on cooperation of both the direct corticomotoneuronal (CM) and PreM-IN systems [50]. This could result in the differences of the I and ω between grip and pinch shown in Fig 5 and 6. This study also found an inconsistent trend of similarity and synchronization during pinch at 30% MVC (Fig 5a, 5d, 5g and Fig 6a, 6d, 6g). Previous studies found an upper limit of motor unit recruitment of intrinsic muscles at approximately $50 \sim 60\%$ MVC and $30\% \sim 40\%$ MVC is optimal because of minimal value of coefficient of variance for intermediate forces [51]. At the range of $30\% \sim 40\%$ MVC, the pinch force control dominates the movement-related muscles, and thus the muscle force can be readily adjusted by either varying the number of motor units, discharge frequency or motor unit substitution (i.e. newly recruited motor units replaced previously active units) [52]; whereas over this threshold, the increased pinch force could be resultant from the increased

motor unit firing rates, which could further lead to increased muscular similarity and synchronization [14], [44], [51].

A number of approaches are available to examine the inter-muscular coordination. Initially the inter-muscular coordination mainly referred to the relative time and magnitude of muscle activations. Analytical tools were developed accordingly, including the timings [53], [54] and root mean squares (RMS) [55], [56] of the muscle contractions. Although these classical approaches could help identify the sequences or intensity of the muscles' activations, other studies have found that observing only the timing and magnitudes is imprecise or impractical, particularly to describe the complex relationship between muscles. Some researchers believe that muscle coordination is a term that should be discussed in terms of the control of CNS. Therefore, muscle coordination would refer to the way that the CNS controls multiple muscles to work together. A term "synergy", which means a collection of relatively independent degrees of freedom that behave as a single functional unit, was proposed to describe the muscle coordination under the CNS control. Nonnegative matrix factorization (NNMF) and principal component analysis (PCA) are two of the most frequently used analytical tools for muscle synergy. At the same time, researcher also paid attention to the frequency or spectrum of the muscle contractions to examine the frequency components of the co-contracting muscles. Coherence analyses based on Fourier transforms or wavelet transforms have been extensively used in this case [4], [48]. However, approaches for both muscle synergy and the spectrum of co-contractions are limited in the ability to consider nonlinear dynamical characteristics during sustained muscle contractions. Muscle contractions naturally exhibit dynamical characteristics, which are reflected from highly complex, nonlinear, and nonstationary sEMG signals. Recently, more studies applied nonlinear dynamical analyses to similarly examine muscle coordination, including the sample entropy [57], fuzzy approximate entropy [58], empirical mode decomposition [59], fractal analysis [60], recurrence quantification analysis [61], [62] and cross-recurrence quantification analysis [21], [63]. Extended from these perspectives, the current study applied a novel method of multiplex recurrence networks (MRN) to assess the inter-muscular coordination for both grip and pinch at different force levels, and demonstrated that the MRN could explore the tiny changes of muscle coordination within a short time muscle contraction (e.g. less than 500 ms) compared with the traditional approaches, such as the PCA and NNMF. By this advantage, this study for the first time found regular trends in muscle coordination within short duration (7 s) at low (30% MVC) and medium (50% MVC) force levels. But few synergies were observed from the decomposition with the PCA and NNMF, nor any trends with sustained grip or pinch contractions. For more details, please see an example of muscle coordination analysis with PCA and NNMF at 50%MVC (see Appendix document). Therefore, the methodology developed by the current study would provide a more sensitive tool for analyzing inter-muscular coordination and may potentially facilitate evaluation for patients with neuromuscular disorders, such as stroke, Parkinson's and Huntington's diseases. Another application would be the force control of prosthetic hands.

The currently found that the coordination of extrinsic muscles would be more sensitive to force levels than the intrinsic or all muscles groups (Fig 4). In addition, the extrinsic muscles have similar force-dependent trend with grip or pinch contractions to the all muscle groups. These findings suggest that the extrinsic muscle coordination would provide more reliable information for grip and pinch force prediction even at low force levels. This would be particularly interesting in prosthetic hand control. Although multiple types of prosthetic hands have been developed, it is still a challenging issue how to the control the prosthetic hand for precise force outputs. For the amputees who lost their hands, it is debatable whether the prosthetic hand could be precisely controlled without references of intrinsic muscles. This study affirmed that extrinsic muscle would be a reliable source providing valuable information for precise force control, and thus could play a role in development of novel dexterous prosthetics.

V. CONCLUSION

This study investigated the dynamic muscles coordination patterns at the low, moderate and high force level during the sustained grip and pinch contraction with MRNs and MNs. Results showed that stronger synchronization, similarity and transitions of extrinsic muscles at higher force levels (50% and 70% MVC) were performed in grip than pinch. The similarity and synchronization of extrinsic muscles were enhanced with the force levels increased whereas the intrinsic muscles performed a force-independent trend. The inter-muscular coordination was increased over time during the sustained grip and pinch force productions. These results revealed that the CNS would increase the cortical oscillation inputs to adapt the increased of force level, changes of force production forms, as well as duration. The MRNs would be a sensitivity analytical tool for dynamic inter-muscular coordination with precision force outputs within short-term time series.

APPENDIX

The muscle synergy analyses based on our experimental paradigm have been performed using PCA and NNMF for the grip and pinch forces. An example of the PCA and NNMF synergetic analysis at 50% MVC has been demonstrated in document S1.

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