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Functional Muscle Network in Post-stroke Patients during Quiet Standing*

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***Abstract*—The overall muscle activation of post-stroke patients during standing has not been well understood. Functional muscle network provides a tool to quantify the functional synchronization across a large number of muscles. In order to investigating the functional muscle network of stroke survivors during quiet standing, we recruited 8 post-stroke hemiplegic patients and required them to stand still for 30 s with eyes open and closed. Surface electromyography signals were recorded from 16 muscles in abdomen, buttocks and lower limbs. The functional muscle networks of paretic side and healthy side were built by multiplex recurrence network approach. The topological characteristics of functional muscle network was quantified by parameters of multiplex network and weighted network. The results showed that the dynamical similarities of muscles on paretic side were reduced, and the dynamical connections of muscles on paretic side were weakened. Without visual feedback, the muscles activated in a more similar mode. The stroke led to lower synchronization of the muscle activation, and decreased efficiency of information transmission between muscles. When subjects stood with eyes closed, the muscles activated in a more deterministic pattern. The research opens new horizons to detect the overall muscle activation when stroke patients stand quietly, and can provide a theoretical basis for understanding the motor dysfunction caused by stroke.**

I. INTRODUCTION

As an acute cerebrovascular disease with high prevalence, stroke often leads to motor dysfunction [1]. One of the most common motor deficits in post-stroke patients is impaired standing balance, which is specifically manifested as weight-bearing asymmetry on lower limbs and increased body sway [2]. The abnormal muscle activation in hemiparetic stroke survivors is the direct cause of motor dysfunction. Not only the dystonia, but also the abnormal muscle synergy patterns would appear after stroke [3].

The muscle synergies reflect the efforts of central nervous system (CNS) to reduce the redundancy of musculoskeletal system. Abnormal muscle synergies often correlate with the motor impairment of patients. However, muscle synergies cannot effectively quantify the functional synchronization among multi-muscles. The functional muscle network, which is originated from graph theory, provides us with a tool to quantify the functional synchronization across a large number of muscles [4]. It is valuable to research whether and how the muscle network alters in post-stroke patients, especially during quiet standing.

The recurrence network (RN), which constructs a network according to the recurrence structure of the time series, could detect subtle dynamical transitions of complex system, and has be applied in many fields such as neuroscience, bioinformatics and meteorology [5, 6]. On the basis of RN, Deniz Eroglu et al proposed multiplex recurrence network approach, offering possibilities to assess dynamical synchronization across multi-muscles [7].

This study intends to apply multiplex recurrence network approach to quantify the topologies of muscle networks on healthy and paretic sides in post-stroke patients. It was hypothesized that functional connectivity between muscles of two sides in stroke survivors would be significantly different.

II. METHODS

A. Participants

Eight post-stroke hemiplegic patients were recruited in this experiment. All patients had been clinically diagnosed with first-ever stroke and had the ability to stand independently. The individuals who had a history of lower extremity injuries, severe lumbar diseases, dizziness or vestibular system diseases, cognitive disorder and serious vision defects, were excluded from the experiment. The Ethical Committee of Nanjing Medical University approved this experiment according to the Declaration of Helsinki. Subjects participated with signed informed consent. The characteristics of subjects were exhibited in Table 1.

Table 1. The characteristics of subjects.

Number	Sex	Age (y)	Height (cm)	Weight (kg)	Time post-stroke (month)	Paretic side
1	Male	56	163	75	10	Right
2	Male	45	170	70	4	Right
3	Male	58	175	74	7	Right
4	Male	45	168	86	10	Right
5	Male	39	168	82	4	Right
6	Male	16	174	55	5	Left
7	Male	41	173	80	7	Right
8	Male	52	170	70	5	Right
Mean		44.0	170.1	74.0	6.5	
SD		13.2	3.9	9.5	2.4	

B. Experimental Design

Sixteen wireless surface electromyography (sEMG) electrodes (Delsys Inc., Natick, MA, USA) were applied to collect the muscle signals of obliquus externus abdominis (OE), longissimus (LO), gluteus maximu (GMA), gluteus medius (GME), rectus femoris (RF), biceps femoris (BF),

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tibialis anterior (TA) and gastrocnemius caput mediale (GM) on paretic and healthy sides. The sampling frequency of sEMG system was set to 1926 Hz.

Subjects were required to stand upon the center of force plate. For the trial with visual-feedback, subjects maintained their body upright and stared at a "marker" on the wall 1.5 m ahead for 30 s. For the trial without visual-feedback, subjects put on the blindfold and maintained the upright posture for 30 s. Three trials were performed for each visual condition. The eyes open (EO) test and eyes closed (EC) test were performed alternately. Subjects had 1-min sit break between two trials.

C. Data Analysis and Statistical Analysis

The MATLAB R2020a (The Mathworks, Natick, MA, USA) was applied to process the pre-processing and analysis of recorded sEMG signals. For data pre-processing, the sEMG signals were band-pass fileted (20 to 500 Hz). Only signals of middle 20 s were left in each trial for future analysis.

For data analysis, each sEMG time series was reconstructed as a trajectory in high-dimensional phase space according to Taken's time delay theory. According to the mutual information and false nearest neighbors, the time delay was set to 5 samples and the embedding dimension was set to 4 for phase-space reconstruction. By comparing the distance between any two points of the new constructed trajectory with the 80% of the maxim phase space radius, a binary adjacency matrix for a sEMG time series could be obtained. Considering the adjacency matrix as a RN, the links between the nodes of RN can be represented by the values of adjacency matrix (1 represents there is a connection, and 0 represents there is no connection).

The RN can only reflect subtle dynamical transitions of single muscle activation. If we want to explore the functional connection of multi-channel sEMG signals, we need to build multiplex network (MN) and weighted network (WN) based on RN. Supposing there are m time series, they can construct m RNs. The m-layer MN can be created by m RNs, where a single RN forms one layer of m-layers in MN. The layers are connected each other with corresponding time points. The structural characteristics of MN can be quantitatively described by average interlayer mutual information (I) and average edge overlap (ω). The interlayer mutual information between layer α and β is derived as:

$$I_{\alpha,\ \beta}=\sum_{k^{[\alpha]}}\sum_{k^{[\beta]}}P\left(k^{[\alpha]},k^{[\beta]}\right)\log\frac{P\left(k^{[\alpha]},k^{[\beta]}\right)}{P\left(k^{[\alpha]}\right)P\left(k^{[\beta]}\right)} \tag{1}$$

where $P\left(k^{[\alpha]}\right)$ and $P\left(k^{[\beta]}\right)$ are the degree distribution probabilities of layer α and β respectively. The $P\left(k^{[\alpha]},k^{[\beta]}\right)$ is the joint degree distribution probability of layer α finding $k^{[\alpha]}$ degree and layer β finding $k^{[\beta]}$ degree. The I is the average value of interlayer mutual information between all possible inter-layer pairs in MN, measuring the similarity of degree distributions of the RNs.

The average number of identical edges over m-layers of MN is measured by ω , whose calculation formula is as follows:

$$\omega=\frac{\sum_i\sum_{j>i}\sum_k a_{ij}^{[k]}}{m\sum_i\sum_{j>i}\left(1-\delta_{0,\sum_k a_{ij}^{[k]}}\right)} \tag{2}$$

where $\delta_{x,y}$ is the Kronecker delta symbol (if $x=y$, $\delta_{x,y}$=1; others, $\delta_{x,y}$=0). The higher ω is, the more similar the dynamical structure of signals is.

Taking each layer in the MN as a node, the interlayer mutual information of two layers as the weight edge of two nodes, a m-node WN can be constructed. The structural characteristics of WN can be quantitatively described by related parameters, including clustering coefficient (C) and average shortest path length (L). The C is given by:

$$C=\frac{1}{m}\sum_{\kappa}\frac{1}{k_\kappa\left(k_\kappa-1\right)}\sum_{\gamma}\sum_{\beta}\left(I_{\kappa,\gamma}I_{\kappa,\beta}I_{\gamma,\beta}\right)^{\frac{1}{3}} \tag{3}$$

where k_κ is the degree of node κ. The L is calculated as follows:

$$L=\sum_{\alpha,\beta\in V}\frac{d\left(\alpha,\beta\right)}{m\left(m-1\right)} \tag{4}$$

where V is the set of all nodes of WN, $d\left(\alpha,\beta\right)$ is the shortest path length between nodes α and β. The C and L determine the small-world characteristics of WN. If the overall muscle activation is tighter, the functional muscle network will show larger C and smaller L.

A window with 1000 sample points and an overlap of 250 sample points was applied on the multi-channel signals to quantify the characteristics of MN and WN. The mean values of all the windows were calculated for each subject.

The SPSS 26.0 (SPSS Inc., Chicago, USA) was applied to perform statistical analyses. A two-way repeated measures ANOVA was applied to examine the differences of the functional muscle network parameters with the side (paretic vs. healthy) and the vision (EO vs. EC). A *p*-value less than 0.05 was considered statistically significant.

III. Results

A. MN

The statistical results of MN parameters are depicted in Fig. 1. The structure of MN was significantly different between healthy and paretic sides. The values of I and ω on paretic side were significantly lower than those of healthy side (Fig. 1, $p < 0.05$). The absence of visual information had a significant impact on functional muscle network. When subjects stood without visual feedback, the parameters of MN had significantly increase (Fig. 1, $p < 0.05$).

B. WN

The Fig. 2(a) shows the topological connection of WN. Compared with the connection of muscles on paretic side, the links between nodes of muscle network on healthy side were more weighted. Results were exhibited more obviously in Fig.

2(b). For the WN on paretic side, there were very few edges whose weight was greater than 0.45.

The statistical results of WN are displayed in Fig. 3. Effects of side were only observed in L, rather than C. The L on healthy side were significantly lower than corresponding values on paretic side (Fig. 3(b), $p < 0.05$). The topological connection of WN was significantly changed when visual feedback was removed. While C was significantly increased (Fig. 3(a), $p < 0.05$), the L was significantly decreased of both sides in stroke patients under the condition of EC (Fig. 3(b), $p < 0.05$).

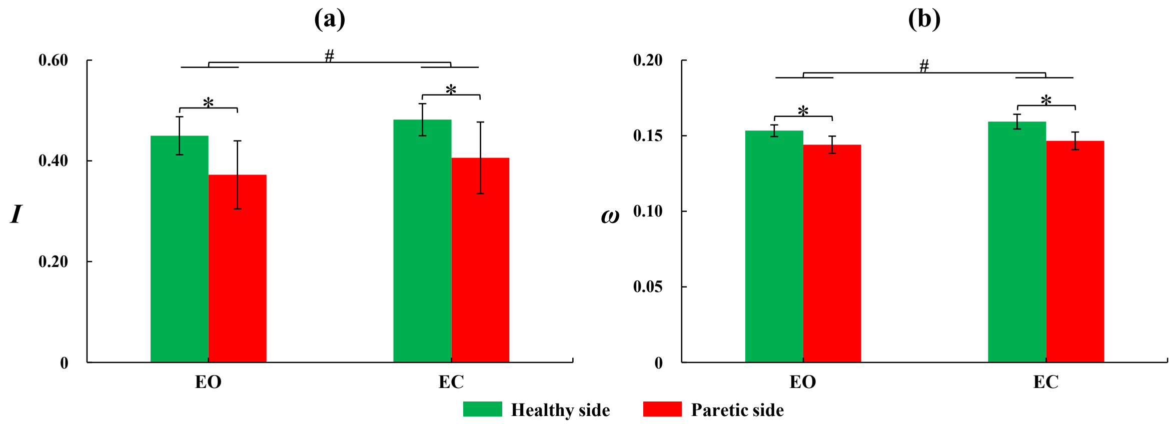

Figure 1. Statistical results of MN parameters.

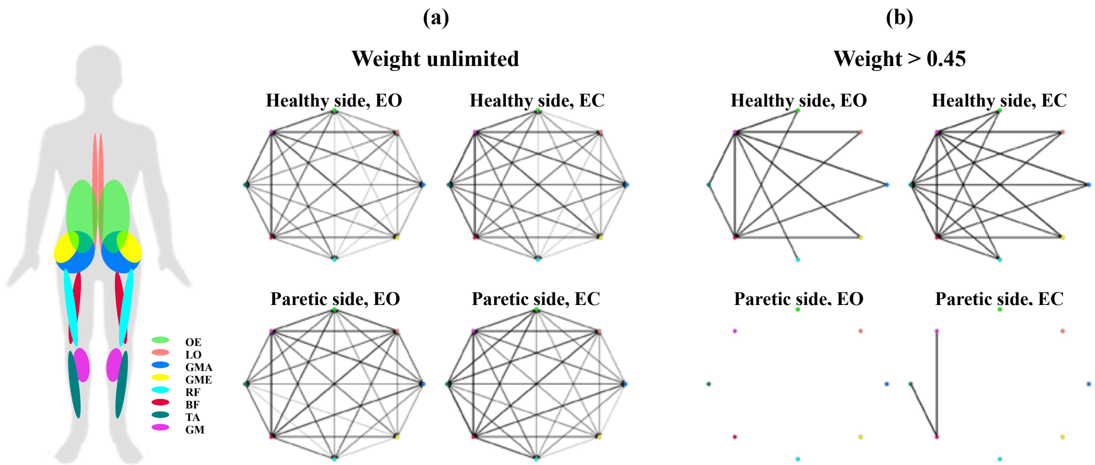

Figure 2. The topological connection of the WN. The line width represents the weight between two nodes. The wider the line is, the higher the weight is.

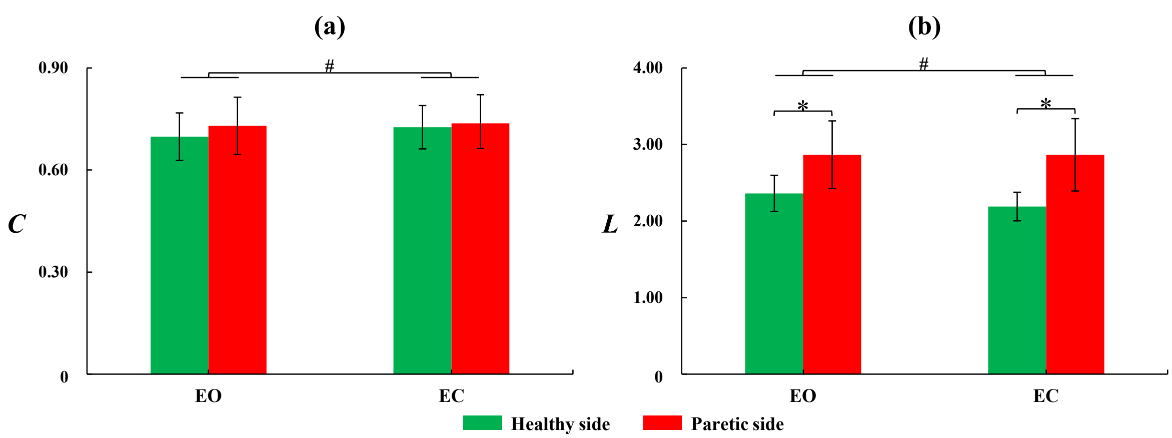

Figure 3. Statistical results of WN parameters.

IV. Discussions

This study investigated the effects of stroke on functional muscle network on paretic and healthy sides during quiet standing by MN and WN. The topological characteristics of MN were quantified by I and ω, while the topological characteristics of WN were quantified by C and L.

Stroke significantly reduced the dynamical similarity of muscle activation. Compared with the healthy side, the paretic side showed decreased I and ω of MN in stroke survivors. The smaller the parameters of MN are, the less similar the recurrent states of muscle activation are. Due to the damage to the CNS generated by stroke, there are synchronization lag in neural activity between brain regions [8]. Not only the abilities to integrate sensory information, but also the abilities of CNS to issue suitable motor commands are impaired. The patients with stroke would act with loss or reduction of motor unit synchronization [9]. This may be the reason why the parameters of MN were significantly lower on paretic side. The existence of synchronization lag changed the recurrent states of muscle activation, resulting in lower similarity in dynamical connection of muscles on paretic side.

When looking at the WN, the higher strength edges were more likely to exist on healthy side. There were very few edges with a weight greater than 0.45 on paretic side (Fig. 2(b)). It is evident that the dynamical connections of muscles on paretic side were weakened. The statistical results of WN also confirmed this. The WN of paretic side had longer path length, meaning that the functional connection of overall muscle activation was looser. This may be due to the lower-level synchronization of the overall muscle activation on paretic side. Besides, the shortest path makes an important contribution to fast information transfer within a network. Longer path length would result in lower information transmission efficiency [10]. The problem of information transmission may be one of the causes of motor dysfunction in stroke patients.

Visual feedback had significant effects on functional muscle network in stroke patients. When subjects stood without visual feedback, the dynamical structures of muscle activation were more similar and the functional connections were tighter. This may be because subtle dynamical transitions of muscle activation were more recurrent. When patients stood with EO, the visual feedback information would assist the CNS in real-time motor control. Cutting off the pathway of visual feedback, the CNS decreased the capacity of online motor adjustment and would rely on a larger proportion of feedforward control strategy to maintain balance [11]. The muscles would activate in a more deterministic pattern, resulting in more recurrent states of dynamical structure [11].

V. Conclusion

This study confirmed the effects of stroke on functional muscle connections by MN and WN. The stroke led to lower synchronization of the muscle activation, and decreased efficiency of information transmission between muscles. Muscles would activate in a more deterministic pattern without visual feedback. The research opens new horizons to detect the overall muscle activation when stroke patients stand quietly, and can provide a theoretical basis for understanding the motor dysfunction caused by stroke.

Acknowledgments

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References

[1] R. Bonita and R. Beaglehole, "Recovery of motor function after stroke," *Stroke,* vol. 19, no. 12, pp. 1497-500, 1988.

[2] W. Wang, Y. Xiao, S. Yue, N. Wei, and K. Li, "Analysis of center of mass acceleration and muscle activation in hemiplegic paralysis during quiet standing," *PLOS ONE,* vol. 14, no. 12, p. e0226944, 2019.

[3] N. Yang *et al.*, "Temporal Features of Muscle Synergies in Sit-to-Stand Motion Reflect the Motor Impairment of Post-Stroke Patients," *IEEE Transactions on Neural Systems and Rehabilitation Engineering,* vol. 27, no. 10, pp. 2118-2127, 2019.

[4] T. W. Boonstra, A. Danna-Dos-Santos, H.-B. Xie, M. Roerdink, J. F. Stins, and M. Breakspear, "Muscle networks: Connectivity analysis of EMG activity during postural control," *Scientific Reports,* vol. 5, no. 1, p. 17830, 2015.

[5] N. Marwan, J. F. Donges, Y. Zou, R. V. Donner, and J. Kurths, "Complex network approach for recurrence analysis of time series," *Physics Letters A,* vol. 373, no. 46, pp. 4246-4254, 2009.

[6] N. Zhang, N. Wei, S. Yue, and K. Li, "Analysis of Muscle Synergy for Grip and Pinch Based on Recurrence Networks," in *2019 IEEE International Conference on Real-time Computing and Robotics (RCAR)*, pp. 814-817, 2019.

[7] D. Eroglu, N. Marwan, M. Stebich, and J. Kurths, "Multiplex recurrence networks," *Physical Review E,* vol. 97, no. 1, p. 012312, 2018.

[8] X. Wang, C. Seguin, A. Zalesky, W.-w. Wong, W. C.-w. Chu, and R. K.-y. Tong, "Synchronization lag in post stroke: relation to motor function and structural connectivity," *Network Neuroscience,* vol. 3, no. 4, pp. 1121-1140, 2019.

[9] S. F. Farmer, M. Swash, D. A. Ingram, and J. A. Stephens, "Changes in motor unit synchronization following central nervous lesions in man," *The Journal of Physiology,* vol. 463, no. 1, pp. 83-105, 1993.

[10] S. Boccaletti, V. Latora, Y. Moreno, M. Chavez, and D. U. Hwang, "Complex networks: Structure and dynamics," *Physics Reports,* vol. 424, no. 4, pp. 175-308, 2006.

[11] J. Li, N. Wei, S. Yue, and K. Li, "Multidimensional Recurrence Quantification Analysis of Multi-muscle Synergy in Elderly during Standing on Slopes," in *2020 42nd Annual International Conference of the IEEE Engineering in Medicine & Biology Society (EMBC)*, pp. 3114-3117, 2020.