Hand Functional Impairment in Stroke Survivors Using Coherence Analysis

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***Abstract*— Individuals with a stroke may experience varying degrees of nervous system damage leading to motor impairments, especially hand functional impairment. Precise assistive robot therapy has proven effective for motor rehabilitation of stroke survivors. To ensure its effectiveness, understanding the origins and assessing the severity of these impairments are crucial. In this preliminary study, we conducted the coherence analysis on high-density electromyographic (HD-EMG) signals to extract information on motor unit (MU) spike trains. Five stroke subjects and five age-matched neurologically intact control subjects participated in the experiment. A motor unit decomposition approach was used to obtain a group of concurrently active motor units across muscle groups and muscle compartments. The shared input across muscle groups or muscle compartments was quantified by a discharge-timing coherence analysis. The coherence at different frequency bandwidths with well-defined physiological origins allowed us to distinguish the different origins of diffused input in the central nervous system. Our results revealed varying degrees of increased coherence in the alpha (8-12Hz), beta (15-30Hz), and gamma (30-60Hz) bands between flexor digitorum superficialis (FDS) compartments, extensor digitorum (ED) compartments, and different intrinsic muscles on the affected sides, in comparison to the contralateral sides and intact control subjects. These findings indicate an increased shared synaptic input to the motor neuron pool on the affected sides, originating from different levels, including spinal and supraspinal pathways. Our study verifies the feasibility of using coherence analysis to better understand the origins and severity of motor impairment, thus contributing to the development of assistive robot therapy for stroke survivors.**

Keywords—coherence, hand functional impairment, electromyography, motor unit, stroke

I. Introduction

The cerebral stroke is a common neurological disease. In stroke survivors, their nervous system undergoes certain changes that lead to abnormal muscle activation patterns, resulting in varying degrees of motor impairment. Assistive robot therapy is considered to be an effective approach for motor rehabilitation in stroke survivors. These robots, equipped with motors, enable precise control over limb movements and aid stroke survivors in their rehabilitation therapy[1]. However, potentially different impairment mechanisms may contribute to heterogeneous responses to a particular treatment strategy across the stroke population. A comprehensive understanding of the factors contributing to the impairment and an accurate assessment of its severity are essential prerequisites for the development of a targeted and effective assistive robot therapy program.

The coherence of motor unit (MU) spike trains represents the common synaptic input to the motor neuron pool, which can serve as a valuable indicator of the relation between motor neuron pool and spinal or supraspinal network [2-4]. When individuals experience a stroke, certain motor neurons may become impaired, preventing the corresponding muscle fibers from receiving accurate neural input signals. Instead, these muscles may be triggered by other motor neurons within the motor neuron pool, resulting in an increased coherence of MU spike trains. The increase of coherence can lead to abnormal muscle activation patterns, such as co-activation, for some motor neuron corresponding with multiple muscles. Quantifying the coherence of MU spike trains provides a means to assess the severity of the stroke related impairment.

The coherence analysis is an approach for achieving the quantification. The analysis depicts the cross-correlation of MU spike trains in frequency domain, with distinct frequency bands representing varying levels of control. Previous studies have identified that most of neural control information is contained in the frequency band under 60Hz[5–7]. For instance, alpha band (5-12Hz) is associated with the muscle spindle activity originating from the spinal reflex loop[8, 9]. The beta band (15-30Hz) reflects cortical and subcortical processes[10, 11]. The gamma band (30-60Hz) represents cortical activities as well, especially during dynamically changing muscle contractions[11]. The coherence at different frequency bandwidths with well-defined physiological origins allowed us to distinguish the different origins of diffused input in the central nervous system.

In this study, we have undertaken the coherence analysis as a means of assessing the severity of stroke related hand impairment, particularly on the impaired control of individualized activation of finger muscles, which can contribute to the loss of hand dexterity. This analysis, in turn, offers valuable guidance for implementing precise and effective assistive robot therapies.

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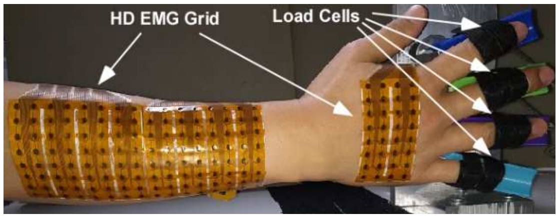

Fig. 1: EMG and finger force recording setup.

II. Methods

A. Subjects

We recruited 5 stroke subjects with the following inclusion criteria: (1) Individuals with a single hemispheric stroke incurred at least 6 months prior to enrollment; (2) Unilateral impairment of hand function (Stage of Hand 2-6 on the Chedoke-McMaster Stroke Assessment); (3) No marked increase in muscle spasticity (modified Ashworth scale < 2), and muscle tone with resting flexion force at neutral position < 20 N; (4) Passive range of motion to at least a neutral position; (5) No hand deficits prior to the stroke. We also recruited 5 age-matched neurologically intact control subjects. All participants received and signed consent forms with the study protocol approved by our local institutional review board.

B. Experimental Protocol

The participants were placed in an upright position in a chair, with their wrists in a 0° (radial/ulnar) deviation and their forearms lying neutrally on a table. Through the use of a finger strap, the distal and intermediate phalanges of each finger were connected to load cells (SM-100, Interface, Inc.), which measured the flexion and extension forces of each finger. The load cells were then coupled to a specially designed holder that was fastened to the table (**Fig. 1**). To lessen force pollution from the wrist, a U-shaped wooden block that was fastened to the table was positioned between the palmer and dorsal sides of the hand and padded. To better illustrate the EMG electrodes on the hand, the U-shaped block is not shown in **Fig. 1**. The force signals underwent amplification and were sampled at a frequency of 1 kHz. For measurement of extrinsic finger muscles, two HD-EMG grids were utilized, each comprising 8×16 channels with recording electrodes of 3 mm diameter and an inter-electrode spacing of 10 mm. These grids were positioned over the anterior and posterior sides of the right forearm, aligning with multiple bony landmarks (refer to **Fig. 1**). Additionally, two 8×4 channel grids were positioned on the palmar and dorsal surfaces of the hand to record intrinsic finger muscle activities. Using the EMG-USB2+ acquisition equipment (OT Bioelettronia, Inc), the monopolar EMG signals were amplified at a bandwidth of 10-900 Hz with a gain of 1000 and sampled at 2048 Hz. We made an effort to have consistent electrode placement between arms of the same subject.

The stroke participants underwent two lab visits in a week, during which they followed the same experimental protocol twice—once for each hand. To counteract any potential order impact, the order of the hand tests was randomized for each individual. The protocol was carried out once by the control participants using their dominant hands. Before the test, participants were instructed to flex and extend one or all of their fingers isometrically for three seconds, which is known as a maximum voluntary contraction (MVC).

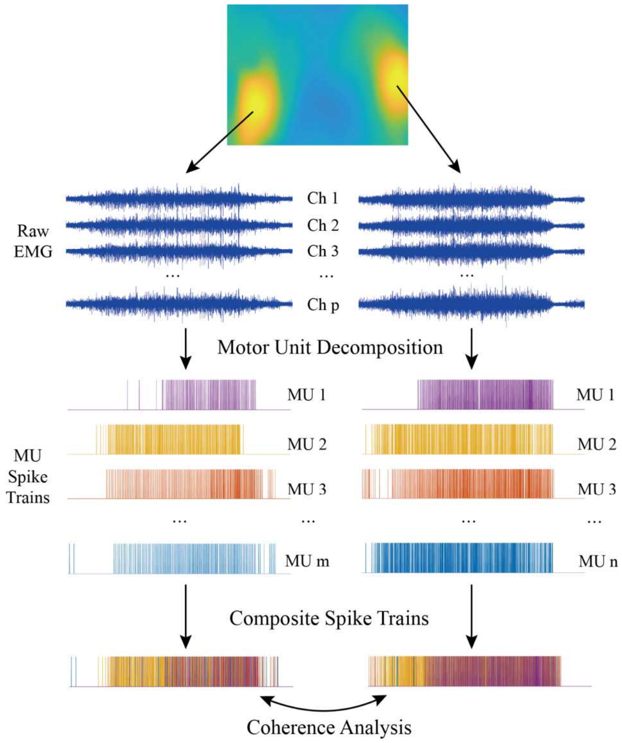

Fig. 2: Illustration of motor unit decomposition, and coherence analysis of composite spike trains.

The primary procedure for the experiment was the individual performing a series of isometric voluntary contractions while keeping track of computer-displayed trapezoidal force trajectories, which are force profiles or patterns that follow a trapezoidal shape over time. The trapezoid's peak force amplitudes were calibrated to represent percentages of the MVC. All four finger forces were recorded for future study, but the forces acting on the instructed fingers were shown. In random order, two steady state force levels (20% and 50% MVC) were put to the test. An 8-second steady state contraction was employed. In the experiment, participants were asked to flex/extend their single finger against the load cells isometrically while reducing the pressures applied by other fingers, and these trials were termed 'single-finger trials'. The participants simultaneously flex/extend all four of their fingers in the experiments as well, which were termed 'all-finger trials'. In all the tested conditions, the subjects were instructed to minimize wrist motion, and they were asked to repeat the movement when wrist motion was observed, or wrist muscle activation was evident from the EMG map. The participants performed the identical activity five times, pausing between contractions for 60 seconds. If needed, extended rest intervals were given to reduce muscle fatigue.

C. Data Analysis

Fig. 2 illustrates the data analysis in this study. For all-finger trials, multiple active regions are observed, as shown in the 2D heatmap in **Fig. 2**. These regions may represent different compartments or different muscles. We extracted the active EMG channels for each region and performed motor unit decomposition to obtain MU spike trains. Subsequently, we pooled the MU spike trains together to create composite spike trains. Coherence analysis was then conducted on these composite spike trains. The specific procedure details of motor unit decomposition and coherence analysis are as follows.

Motor Unit Decomposition: Because the HD-EMG grid covered the majority regions of the finger muscles, we performed a channel refinement procedure to isolate individual MUs from different fingers. The HD-EMG signals after channel refinement of the single-finger trials were decomposed into motor unit activities using a previously developed blind source separation algorithm [12-14]. The motor unit pool of each finger was then further refined [15, 16] to remove motor units of other fingers due to possible co-activation. The refined separation matrixes were then applied to the all-finger trials to extract finger-specific motor unit firing activities. Only the motor unit data from the all-finger trials were used for subsequent analysis.

Coherence Analysis: The decomposed motor unit spike trains of each finger/muscle compartment were pooled to form a composite spike train. To ensure fair comparison across different conditions, an equal number of motor units needs to be used for the composite spike train. Based on earlier studies [17-19], 6 motor units in each composite spike train can lead to reliable coherence estimations. For trials that contained more than 6 motor units for that subject, 6 motor units were selected randomly from the pool. The cross-coherence $C_{xy}(f)$ between the two composite spike trains were calculated as:

$$\boldsymbol{C_{xy}(f)} = \frac{|\boldsymbol{P_{xy}(f)}|^2}{\boldsymbol{P_{xx}(f)P_{yy}(f)}} \quad (1)$$

where $P_{xy}(f)$, $P_{xx}(f)$ and $P_{yy}(f)$ are the average cross-spectrum of two composite spike trains and their auto-spectrum densities, respectively (**Fig. 2**). The phase relation was not considered here because the inputs are discrete event trains, and the amplitude of the coherence already represents the event locking from two spike trains. Three frequency bandwidths: alpha band (5-12Hz), beta band (15-30Hz), and gamma band (30-60 Hz) were analyzed separately.

III. Results

Two exemplary coherence profiles (0.1 to 60 Hz range) between the index and middle compartments of the flexor digitorum superficialis (FDS) and extensor digitorum (ED) of a stroke survivor are shown in **Fig. 3**. Increased coherence in

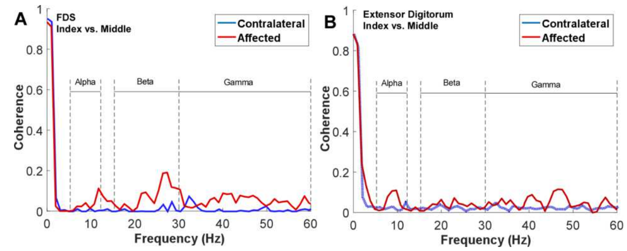

Fig. 3: Cross-compartment coherence. (A): Coherence between index and middle compartments of FDS. (B): Coherence between index and middle compartments of extensor digitorum.

the alpha and gamma bands was evident for both muscles in the affected hand. An increased beta-band coherence was only observed in the FDS.

Based on the preliminary results of 5 stroke subjects, and 5 unimpaired controls, the average coherence between compartments or muscle groups are shown in **Fig. 4**. The cross-compartment alpha-band coherence tended to be higher on the affected FDS and ED muscles, indicating that there was an increased common input that originates from the spinal afferent input of one compartment to the other. The cross-compartment beta-band coherence was higher on the affected FDS, but not on the ED muscle, thus providing evidence of increased common input from brainstem (e.g., possible reticulospinal input) across FDS compartments. Increased gamma-band coherence was also observed in both FDS and ED muscles, thereby indicating generally diffused cortical input. The coherence between the two intrinsic muscles, first dorsal interosseous (FDI) vs. hypothenar, (**Fig. 4C**) was higher in the beta and gamma bands, but not in the alpha band for the affected hand.

IV. Discussion

In this preliminary study, we assessed the degree of diffused input from spinal and supraspinal pathways for stroke survivors affected sides, compared with contralateral sides and unimpaired controls. Our approach employed the coherence analysis to shed light on this complex phenomenon. The results reveal that for the affected FDS muscles, there is an increase on the cross-compartment coherence in alpha, beta and gamma bands. For the affected ED muscles, the cross-compartment coherence in alpha and gamma bands are higher than contralateral sides and intact controls. The beta-band and gamma-band coherence between FDI and hypothenar increases in affected hand as well. The heightened coherence suggests a notable increase in shared synaptic input to the

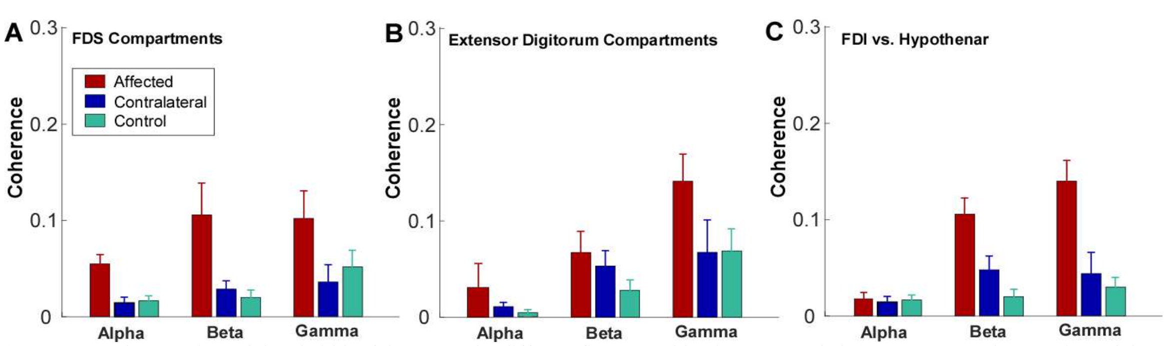

Fig. 4: (A): Average coherence in each bandwidth of the FDS. The different finger combinations are pooled. (B): Average coherence in each bandwidth of the extensor digitorum. The different finger combinations are pooled during averaging. (C): Average coherence in each bandwidth of the FDI vs. hypothenar muscles.

motor neuron pool. The diffused input across different levels can lead to synchronized activations across muscle groups and muscle compartments, thereby limiting finger dexterity. The diffused input from specific levels of the nerves system tends to be muscle specific, with different muscle groups or muscle compartments showing distinct patterns.

Furthermore, our analysis identified a remarkable degree of variability in coherence amplitude across stroke survivors, as evidenced by the wide error bars in our data. This suggests that the origins of deficits among stroke survivors may differ significantly from one individual to another. This observation underscores the highly personalized nature of stroke-related impairments.

In a previous study [20], coherence analysis was applied to EMG signals of the extensor digitorum communis in neurologically intact controls, revealing that cross-compartment coherence in the alpha, beta, and gamma bands exhibited low to moderate levels. Another study [18] focused on assessing coherence within the first dorsal interosseous muscle on both the affected and contralateral sides of stroke survivors, demonstrating a significant increase in alpha and beta band coherence on the affected side. In our present study, we departed from previous methods [18, 20] by utilizing HD-EMG arrays for data collection, allowing for the capture of more comprehensive information. Our analysis evaluated coherence across muscles and muscle compartments in both the affected and contralateral sides of stroke survivors, alongside neurologically intact controls for comparative purposes.

Significantly, our study confirms the utility of coherence analysis as a valuable tool for assessing the severity of impairments related to stroke. This not only enhances our comprehension of the condition but also opens new possibilities for the development of assistive robot therapy, providing hope for more effective and targeted rehabilitation strategies.

Nevertheless, the study does possess certain limitations. One notable limitation is the relatively small sample size, which hinders our ability to conduct comprehensive statistical analyses for a clearer interpretation of the results. To address this limitation in future research, we plan to augment our dataset by collecting additional HD-EMG samples from both stroke survivors and intact controls. This expanded dataset will contribute to a more robust and substantiated conclusion.

V. Conclusion

We conducted the coherence analysis on the specific muscle groups in stroke survivors and intact controls, using HD-EMG. We observed the increase of cross-coherence in stroke affected side in specific frequency band originates from different level. The results provide the information of origins and severity of motor impairment in stroke survivors, contributing to the development of assistive robot therapy.

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