Abnormal Low-Frequency Corticokinematic Coherence in Stroke: An Electroencephalography and Acceleration Study

Ping Xie, Ying Wang, Jian Yu, Yan Lv, Shengcui Cheng, Yingying Hao, Xiaoling Chen, Tengyu Zhang, and Jie Chen

***Abstract*— Motor control is a complex process of coordination and information interaction among neural, motor, and sensory functions. Investigating the correlation between motor-physiological information helps to understand the human motor control mechanisms and is important for the assessment of motor function status. In this manuscript, we investigated the differences in the neuromotor coupling analysis between healthy controls and stroke patients in different movements. We applied the corticokinematic coherence (CKC) function between the electroencephalogram (EEG) and acceleration (ACC) data. First, we collected the EEG and ACC data from 10 healthy controls and 10 stroke patients under the task of movement execution (ear touch and knee touch) and movement maintenance (ear touch and knee touch). After the preprocessing of raw data, we used frequency domain coherence method to analyze the full-frequency EEG and ACC data, which could be concluded that the CKC intensity in the movement execution was higher than that in the movement maintenance. However, there was no significant difference between healthy subjects and stroke patients. Secondly, the coherence results in local frequency bands showed that low-frequency bands could better reflect the difference between movement execution and maintenance. The intensity of coherence in healthy subjects was significantly higher than that in other bands, but not in stroke patients. Further comparison of coherence results in local frequency bands showed that the intensity of theta band in healthy controls was significantly higher than other rhythms, especially in the knee touch phase. Therefore, we infer that neurodynamic coupling analysis based on EEG and ACC data can show the differences between healthy subjects and stroke patients. Such researches could add to the understanding of neuro-motor control mechanisms and provide new quantitative indicators on the motor function assessment.**

***Index Terms*— Motor function evaluation, corticokinematic coherence, EEG, ACC signal, stroke.**

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This work involved human subjects or animals in its research. Approval of all ethical and experimental procedures and protocols was granted by the Ethical Review Board of the Ethical Committee of the Rehabilitation Hospital affiliated to the National Rehabilitation Assistive Devices Research Center under Application No. S20220210, and performed in line with the Declaration of Helsinki.

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I. Introduction

MOTOR dysfunction is a common consequence of stroke, which can manifest as muscle weakness, abnormal muscle tone and abnormal postural reflexes. These symptoms can trigger joint response, co-movement, and tonic spasm, reducing limb movement stability, motor precision, and coordination ability [1]. Therefore, it is significant to research on effective methods of motor function assessment, which can provide a basis for later rehabilitation treatment after stroke.

At present, the clinical assessment of stroke motor function is based on the motor assessment scale (MAS), Fugl-Meyer scale (FMA) or Brunnstrom scale. These scales are based on the performance of stroke and used to assess the level of impairment and daily motor function after stroke. Gil-Agudo et al. constructed a system using nine-axis inertial-based sensors to assess upper limb function rehabilitation after central nervous system injury [2]. Rodrigo and his team created a monitoring system that utilizes inertial sensors to collect data on joint angles and establish a kinematic model. This model helps clinical rehabilitation practitioners accurately assess the current status of their patients' upper limb motion in 3D, improving motor assessment [3]. Anne et al. investigated how the arm length, weight of the object, target height, and other factors affect the movements of the trunk, elbow, wrist, and fingers during motion. They also studied how these movements relate to clinically measured impairments in motor function status by analyzing inertial signals [4]. Most studies on stroke focus on analyzing limb movement using either EEG or inertial signals, extracting physiological indexes, and exploring changes in motor function. However, motor dysfunction in stroke can manifest in different ways such as nerve and limb movement. To comprehensively and effectively assess motor function status, it is important to construct neuromotor-based assessment indexes that consider various aspects of neuromotor function.

Corticokinematic coherence (CKC) is the coupling intensity of the EEG and ACC data, which presents the information flow between the brain and the limbs. It can reflect the international connection between the nerves and the motion. CKC is used to investigate cortical processing and the effects of training, rehabilitation, and plasticity at the cortical level. CKC reflects coupling between primary sensorimotor cortex EEG and kinematic signals, e.g. acceleration and velocity; kinetic signals, e.g. [5] and [6]. The analysis of CKC contributes to the understanding of neuro-motor control mechanisms and provides new quantitative indicators for motor function assessment. It has been shown that CKC has the potential to be used as a tool to detect and follow proprioceptive impairments throughout the lifespan (from newborns to ageing effects), effectivity of rehabilitation and recovery of sensorimotor impairments (stroke, early detection of CP, neuropathy) [7], [8], [9]. CKC provides a non-invasive way to map the functional connectivity between the brain and limb kinematics during movement. This can help researchers understand how the brain processes information related to movement and how it can be affected by training or rehabilitation. Additionally, CKC can be used to plan brain surgery by identifying the areas of the brain that are responsible for specific movements. Research has shown that EEG and ACC signals can represent the connection between brain and limb movements [10], [11], [12], [13], and EEG signals can be used to decode limb movements. However, there has been limited research on the correlation between EEG and inertial signals for assessing motor function. We can better understand how the motor system controls limb movement by exploring this correlation.

Coordinated limb movements result from the multifaceted process of neural, motor, and sensory functions in motor control. There is a strong link between the brain and limbs. The brain controls limb movements and affects brain signals during movement. Analyzing the correlation between EEG and ACC signals through corticokinematic coherence is useful in comprehending the mechanism and pathology behind motor control in stroke. Moreover, local frequency bands in EEG signals can exhibit distinct changes based on the motor state. In order to investigate the correlation between EEG and ACC signals in local frequency bands, we examined healthy individuals and stroke patients performing bilateral upper limb movements. We analyzed the correlated coupling characteristics of these signals during both movement execution and maintenance, providing valuable insights into motor function. It is helpful to understand the neurodynamic coupling mechanism of the motor control system and establish effective motor physiological indexes for quantitative assessment of motor function status.

II. Material And Methods

A. Subjects

The experimental group consisted of 10 stroke patients, as shown in Table I. Each participant was accompanied by a physician and voluntarily took part in the study while remaining awake. The control group, on the other hand, consisted of 10 elderly individuals who were both physically and mentally healthy. This group was made up of 6 men and 4 women aged between 40 to 75 years. All participants had no prior history of brain-related diseases, were right-handed, had normal or corrected normal vision, and willingly participated in the experiment.

TABLE I
Physical Status Statistics of Stroke

Patients	Gender	Age (years)	Movement disorder site
1	Men	66	Right-sided hemiplegia
2	Men	42	Bilateral hemiparesis, right side is severe
3	Men	75	Left-sided hemiplegia
4	Men	52	Right-sided hemiplegia
5	Women	62	Left-sided hemiplegia
6	Men	38	Left-sided hemiplegia
7	Men	46	Left-sided hemiplegia
8	Men	43	Bilateral hemiparesis, right side is severe
9	Men	42	Left-sided hemiplegia
10	Women	63	Right-sided hemiplegia

Before the whole experiment, the subjects were asked the corresponding basic information and explained the purpose of the experiment and the content of the experiment. The experiment was in accordance with the declaration of Helsinki and gained consent and approval of the ethical review board of the ethical committee of the rehabilitation hospital affiliated to the National Rehabilitation Assistive Devices Research Center.

B. Data Recording and Experimental Paradigm

1) Experimental Paradigm: In this study, participants were comfortably seated 60 cm from a computer screen, as depicted in Figure 1(a). The experiment was divided into two parts: resting and task states. Each task state involved using either the right or left upper limb for a task, followed by 60s of relaxation, as shown in Figure 1(c). The resting state experiment was conducted first, consisting of a 3s preparation time and a 10-minute rest time, during which participants kept both arms naturally relaxed. Following the 10-minute rest, the right upper limb task experiment began. This involved a 3s preparation time, 20s of rest, and 34s of task execution. The task execution process involved touching the ipsilateral ear with the back of the hand for 3s (dynamic force), maintaining the action for 4 seconds (static force), touching the contralateral knee with the heart of the hand for 3s (dynamic force), maintaining the action for 4s (static force), and resting for 20s. This task was performed sequentially in five sets of experiments, with participants instructed to keep other body parts as still as possible while performing the dorsal hand touching the ear action. After 60s of relaxation, the left upper limb task was performed, with the same requirements and procedures as the right upper limb task.

2) Data Recording and Preprocessing: The experimental equipment for EEG signal acquisition was the NeuSen W

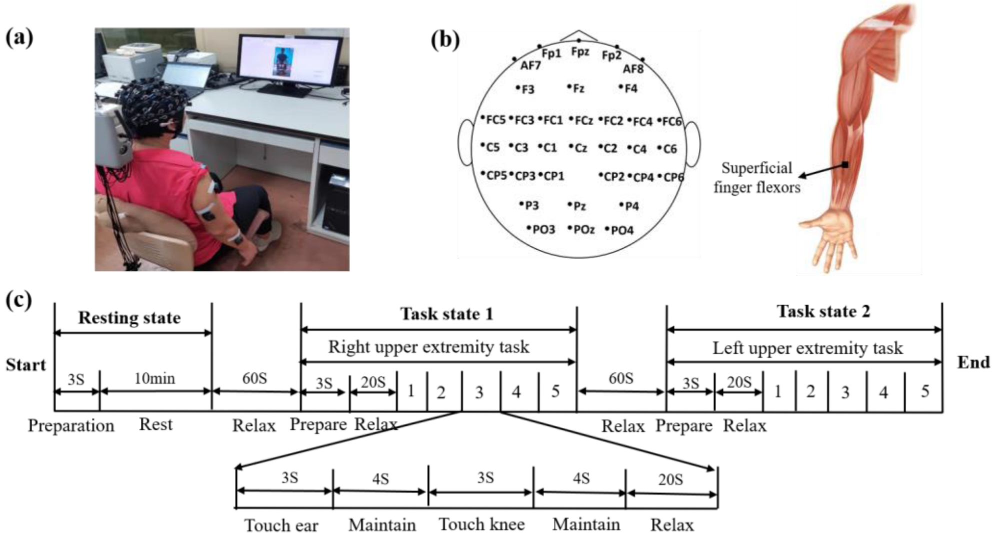

Fig. 1. Experimental procedure and data acquisition.

series wireless EEG acquisition system from Borealis. The positions of the EEG cap electrodes followed the international 10-20 system. We collected EEG data using 34 motion-related signal channels with a sampling frequency of 1000 Hz. The electrode positions for the EEG signals are displayed in Figure 1(b). Studies have demonstrated that the brain is symmetrical between hemispheres and that brain-limb control follows a contralateral principle [14]. In this study, we analyzed EEG signals from six channels located in the motor area of the brain: FC3, FC4, C3, C4, CP3, and CP4. These channels were further divided into two regions. Left sensorimotor (LSM) contains FC3, C3, and CP3; right sensorimotor (RSM) contains FC4, C4, and CP4. As shown in Figure 1, we used the Trigno Avanti EMG system with 14 modules, each with seven sites, for an inertial acquisition experiment. The ACC system has a sampling frequency of 150 Hz and we selected the tri-axial acceleration signal from the finger flexor position for concurrent analysis with the EEG signal.

To enhance the precision and relevance of EEG signal analysis, a series of steps were taken in preprocessing. These included implementing least squares, applying a low-pass filter set to 100Hz, utilizing an adaptive 50 Hz filter to eliminate baseline drift, high frequency noise, and industrial frequency interference from the data [15], [16], employing an independent component analysis algorithm to eliminate external interference from sources like EOG and ECG, and lastly, performing Laplace re-referencing of the selected channels to accentuate the local features of the data [17]. In the preprocessing process of ACC data, we used the smoothing filtering to remove outliers from the data. To ensure accurate data collection, a 20Hz low-pass filter was used to eliminate redundant information within the frequency range of 0-20 Hz, as human activity falls within this range [18]. Additionally, the effects of gravitational acceleration were eliminated by subtracting the data after applying a 0.3Hz low-pass filter [19]. Finally, the three-axis ACC signals were combined using Euclidean parametric calculations to generate a single axis of data and remove any orientation-related effects on the data [20].

C. Analysis Method

To investigate the cross-kingdom correlation (CKC) properties between electroencephalogram (EEG) and acceleration (ACC) signals, a coherence analysis was conducted in the frequency domain, utilizing the amplitude squared coherence function [15]. This analytical technique enabled a quantitative description of the correlation strength between the EEG and acceleration signals, as observed in the frequency domain. To analyze two signals simultaneously, the self-spectrum and mutual spectrum were calculated separately. The coupling strength of the two signals in the frequency domain was determined by dividing the value of the mutual spectrum by the upper self-spectrum, which provides a measure of the coherence strength. Let the EEG signal be denoted as x and the ACC signal be denoted as y. The expressions are as follows:

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

where $C_{\mathrm{xy}}(f)$ is the value of the frequency domain coherence function of the two signals. $P_{xy}(f)$ is the mutual spectral density function of the two signals. $P_{xx}(f)$ and $P_{yy}(f)$ are the self-spectral density functions of the two signals, respectively. These expressions are as follows:

$$P_{xy}(f) = X(f)(Y(f))^* \tag{2}$$

$$P_{xx}(f) = X(f)(X(f))^* \tag{3}$$

$$P_{yy}(f) = Y(f)(Y(f))^* \tag{4}$$

where $*$ denotes the conjugate. $X(f)$ and $Y(f)$ denote the information contained in the frequency domain of the EEG signal and the ACC signal.

The correlation strength $C_{\mathrm{xy}}(f)$ can be evaluated on a scale ranging from 0 to 1. A coherence value of 1 signifies the strongest correlation, whereas a value of 0 indicates no correlation. The assorted values indicate different degrees of

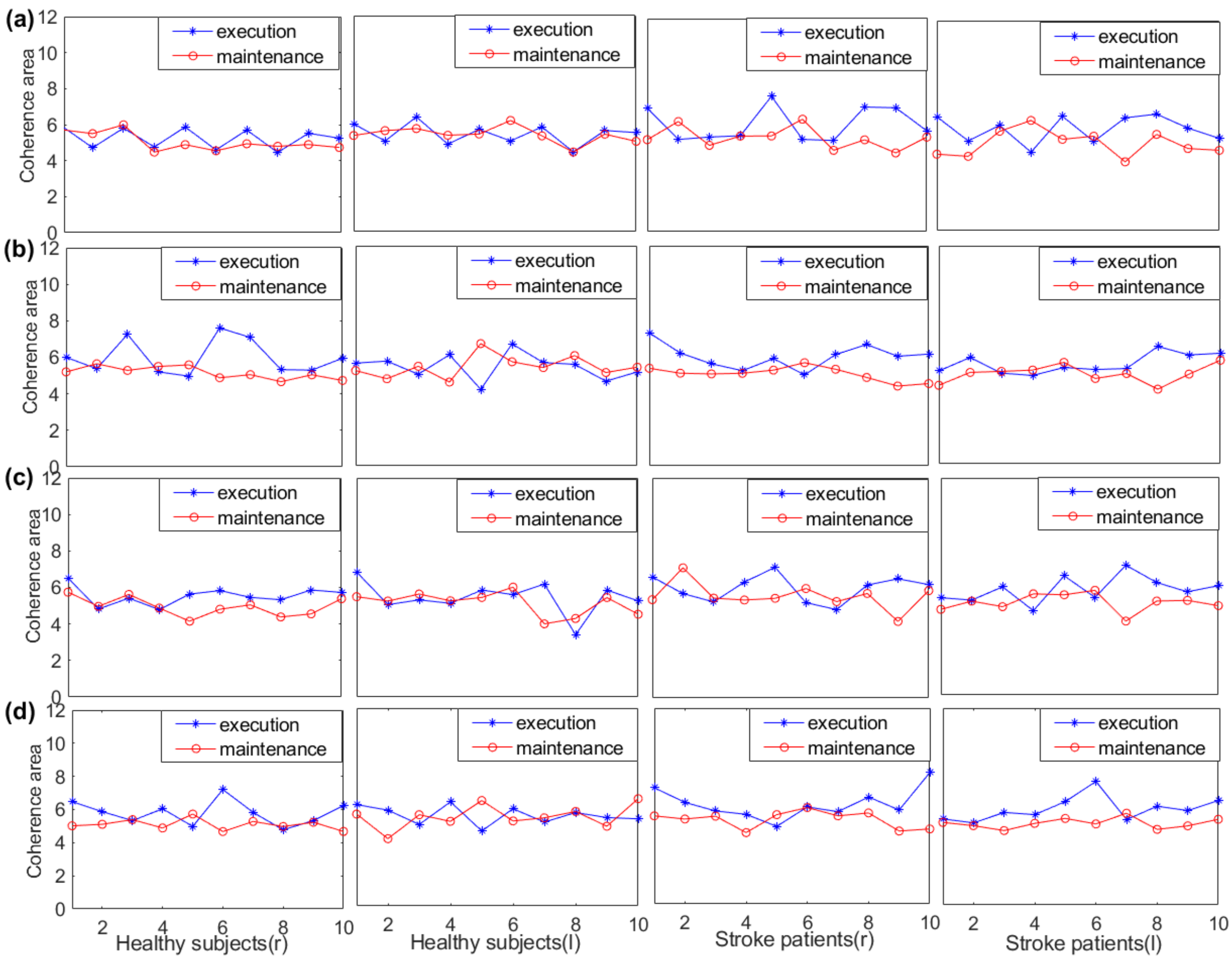

Fig. 2. Comparison plots of CKC results of EEG and ACC signals under different motion states. (a) Right palpable ear motion coupling characteristic graph. (b) Right palpable knee motion coupling characteristic graph, (c) left palpable ear motion coupling characteristics, (d) left palpable knee motion coupling characteristic analysis.

synchronous coupling strength. To accurately evaluate the coupling strength of synchronous analysis, the coherence strength of the signals is determined by the threshold value of significant coherence. Its expression is as follows:

$$CL(\alpha) = 1 - \alpha^{\frac{1}{N-1}} \tag{5}$$

where N denotes the total number of the sliding window, and α generally takes the value of 0.05, indicating that the confidence level is 0.95. When the coherence value exceeds the threshold indicator, the coherence intensity of the two signals is considered to be significantly coherent. By utilizing the threshold indicator provided above, we were able to accurately calculate the notable area that was enclosed by both the coherence curve and the threshold indicator.

D. Statistical Method

To quantitatively analyze the significant coherence between the EEG and EMG signals in a local band ($f_1 \sim f_2$) and avoid the differences from the bandwidth, the normalized significant area, defined as $A_{C(f_1 \sim f_2)}$, was calculated as

$$A_{C(f_1 \sim f_2)} = \frac{1}{f_2 - f_1} \sum_{f_1 \sim f_2} \Delta f \cdot \left(C_{xy}(f) - CL \right) \tag{6}$$

where Δf denotes frequency resolution; We defined $A_{C(f_1 \sim f_2)}$ as the normalized significant area over whole frequency bands.

To ensure the validity of our findings, we proceeded to test the obtained results for significance. Considered the distribution and characteristics of the data, we used the different statistical method to test the significance of CKC results. The statistical method was chosen by the principle of data character. Two-sample t-test could better analyze the data with normal distribution, while Wilcoxon rank sum is more suitable for the data with nonnormal distribution. Therefore, we used two-sample t-test in the analysis of full-frequency EEG. In the local band analysis, we used Wilcoxon rank sum for its nonnormal distribution. In the later study, $p < 0.05$ was considered significant. SPSS 19.0 for windows (SPSS Inc., Chicago, IL, USA) was used for all statistical computations.

III. Results

A. CKC Analysis of Full-Frequency EEG and ACC Signal

To analyze the relationship between full-frequency EEG and ACC signals during four phases of touching the ear and knee actions, we averaged the signals for six channel EEG signals within the motor sensory brain area. We then used equation (1) to compare the squared ratio of the mutual power

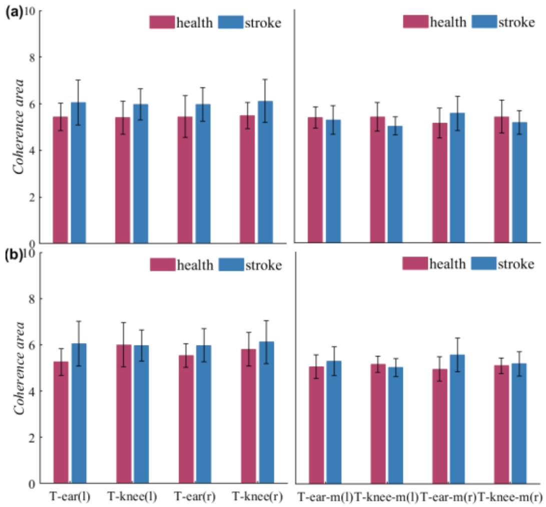

Fig. 3. Comparison of CKC analysis results between healthy subjects and stroke patients is shown. (a) indicates the comparison of CKC analysis results in the right movement execution and maintenance phases. (b) indicates the comparison of CKC analysis results in the left movement execution and maintenance phases. “l” means left side, and “r” means right side. “T” represents touch movement. “m” represents maintenance phases.

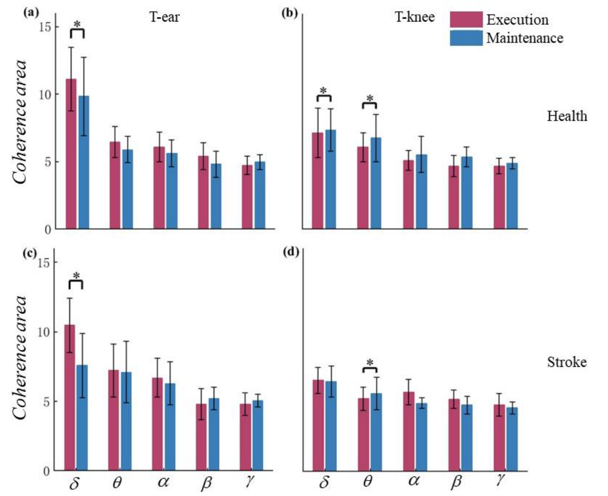

Fig. 4. Comparison analysis for movement execution and maintenance in different EEG bands. “$*$” denotes p<0.05. (a) CKC value of healthy subjects under touching ear. (b) the CKC value of healthy subjects under touching knee. (c) CKC value of stroke under touching ear. (d) the CKC value of stroke under touching knee.

spectrum of the EEG and ACC signals on the self-power spectrum to determine the coherent coupling characteristics. Additionally, we calculated the significant coherence area of the full-frequency EEG and ACC signals using equation (5) to quantify the strength of the frequency domain association between the two signals.

The coherence analysis of EEG and ACC signals for healthy subjects and stroke patients with different lateral upper limb movements is presented in Figure 2. The right-sided motor-encephalic tapping and left-sided motor-encephalic tapping were executed and maintained during the experiments. The mean values of the results of the five experimental groups were calculated for each subject to represent the frequency domain characteristics of their current motor state. In the Figure 2, it is evident that both healthy subjects and stroke patients showed higher significant coherence during movement execution compared to movement maintenance, for both ear and knee touch movements. Two-sample t-tests for both movement execution and maintenance showed significant differences ($p < 0.05$). A comparative analysis of the associative coupling properties between the left-right and right-right motor brain areas in all subjects demonstrated no significant differences in either the movement execution or maintenance phase, regardless of whether they were healthy or stroke. The results were not significant ($p > 0.05$).

To compare healthy individuals with stroke patients, two phases of movement were analyzed: execution and maintenance. The comparison of stroke patients and healthy subjects in different movements and sided was shown in Figure 3. It can be concluded that during the movement execution, stroke patients had a higher significant coherence area than healthy subjects for most movements. However, there was no significant difference during the movement maintenance phase ($p > 0.05$). The correlation between neurodynamic knee touch movements and coupling properties based on full-frequency EEG and ACC signals could not reflect the differences between healthy subjects and stroke patients. Therefore, it is crucial to investigate the correlated coupling properties of local EEG band and ACC in the later section.

B. CKC Analysis of Local EEG Band and ACC Signal

To analyze the correlation between EEG and ACC data, the sampling rate of the data was changed to 256 Hz after lifting and sampling. This facilitated the analysis of frequency band specific EEG data and ACC data coupling characteristics. The wavelet packet decomposition algorithm [21] was used to extract five frequency bands of δ (1)-3 Hz), θ (3)-8 Hz), α (8-13 Hz), β (13-30 Hz), and γ (30-80 Hz) signals from the EEG signal. The five bands were then analyzed with the ACC signal for correlated coupling characteristics.

We analyzed the CKC values of healthy subjects for left and right sides using ACC data. The results were tested with the Wilcoxon rank sum test, which revealed no significant difference between both sides of healthy subjects. Since all subjects were right-handed, the study used the right side of healthy subjects as a base in the subsequent analysis for efficiency and accuracy. Equation (1) was used to compare the EEG and ACC data during four phases of touching the ear, touching the knee, and maintaining each action. Coupling analysis was performed on each frequency band of EEG and ACC data during movement execution and action maintenance phases. Using the significant coherence area threshold in Equation (5), we calculated the significant coherence area of the full-frequency EEG and ACC signals, which are shown in Figure 4. The main differences were in the low-frequency segment, which was consistent with the coherence results of the full-frequency EEG and ACC signals. The coherence intensity was significantly higher during the motor execution phase than during the movement maintenance phase. In healthy subjects, the CKC value of δ band during touching ear and touching knee were both with significant difference ($p < 0.05$). However, the CKC value of θ band had a more significant difference in touching knee movement. While in stroke, the significant difference mainly focused on the δ band in touching ear movement and θ band in touching knee movement ($p < 0.05$).

From the comparison of the results of movement execution and maintenance, it can be concluded that the CKC value varied in different frequency bands during different motor states. It is particularly evident in the δ band. Therefore, we further compared the changes in CKC results of EEG and ACC signals between healthy individuals and stroke patients. Figure 5 illustrated the CKC analysis results in different frequency bands. It can be concluded that healthy individuals showed higher CKC value in δ band, and the difference was significant ($p < 0.05$). Conversely, during the knee-touch movement execution phase of stroke, the CKC results of δ band was not significantly different with all other bands ($p > 0.05$). The results remained consistent during the phase of maintaining movement.

Through the results of the comparison for CKC values in local EEG bands and ACC signals, it was concluded that the motor dysfunction produced by stroke has an effect on the EEG and ACC signals. To gain a deeper understanding of how motor dysfunction impacts CKC results in EEG bands and ACC signals, we further compared the CKC values in δ band from healthy individuals performing right-sided movements and stroke performing the same movements on their affected side. The statistical analysis of the comparison was shown in Figure 6. It was clear that the CKC intensity of the δ band in the healthy subject was significantly higher than that those of the patient when performing the knee touch movement ($p = 0.037$, $p = 0.022$). It was evident in the data from both the left and right side of the brain area. which was reflected in the signals of the left and right side of the brain area. However, there were no significant differences in the CKC results for other EEG bands and movements.

IV. Discussion

This manuscript explored the changes of EEG and ACC data during different motor performance to find the effective indicators for motor function evaluation. Additionally, the relationship and coupling characteristics of EEG and ACC signals during movement execution and maintenance were analyzed. The results showed no significant differences between the movement execution and maintenance at full-frequency band. The CKC results in local bands were further analyzed to investigate the mechanism of stroke disease. Therefore, we compared the CKC values in local frequency bands between healthy subjects and stroke patients. It was concluded that the CKC results in δ band during the knee touch execution phase can provide a new physiological indicator for assessing motor function in stroke.

A. Mechanism of Motor Performance Effect on CKC

This study explored the differences between difference motor performances in stroke and healthy. The results showed that the difference was more significant in movement maintenance, especially in the knee touch maintenance stage. It is due to the fact that the ACC is a type of inertial signal, which relies on inertial to convert to ACC signals [22]. The signal shows significant fluctuations in the movement execution stage. In the experiment stage, the EEG signal also changes accordingly, as reflected in the change of the local frequency band signal, which also presented a significant difference in the CKC results. Moreover, researches have proved that the movement rate does not affect coherence levels and CKC source location during movements. The similar result also occurred in our study. Example for the comparison of healthy and stroke in Figure 3, stroke had higher CKC in movement execution. This is quite the opposite in our cognitive. One possible reason may be due to the degree of force using in the movement execution. It is easy for health controls to complete the experiment and hard for stroke patients. They must use more efforts in the process, and their sensorimotor could be more activated [23].

B. Absent Corticokinematic Coherence at δ-Band in Stroke

Results showed that δ-band band presented significant difference from other band, which is consistent with previous study. The ACC and coherence spectra showed peaks around 3-5 Hz and 6-10 Hz, corresponding to the movement frequencies [5]. Apart from the delta oscillations that occur during sleep, literature suggested that the δ band is also associated with cognitive function in the awake state [22], [24]. Increase of δ power has been documented in a wide array of developmental disorders and pathological conditions. Motor dysfunction in stroke is primarily caused by cerebral hemorrhage or brain injury, which leads to damage to neural pathways. Severe patients may also experience cognitive function problems. Therefore, the significant difference in the δ band observed in this study could be attributed to the cognitive and motor function problems in stroke participants.

In the comparative analysis of healthy subjects and stroke patients, the CKC results of full-frequency EEG had presented differences, but the results were not significant. This may due to the effect of disease in brain, causing changes in EEG signals in local frequency bands [25], [26]. The CKC analysis of EEG and ACC signals in δ band showed that the CKC results were higher in healthy subjects than stroke patients during the knee touch phase. The results were not significant in other movement states. Most of the motor dysfunctions in stroke were basically or partially completed by inward bending movements, but it was more difficult to complete the extension movements. The results were more variable in the knee movement.

C. Limitations and Future Work

In this manuscript, we focused on the corticokinematic coherence analysis to investigate the changes in the neurokinetic coupling analysis caused by stroke disease and to construct physiological indicators that can be used for motor function assessment. Therefore, in the subsequent study, we will increase the sample size of the data and refine

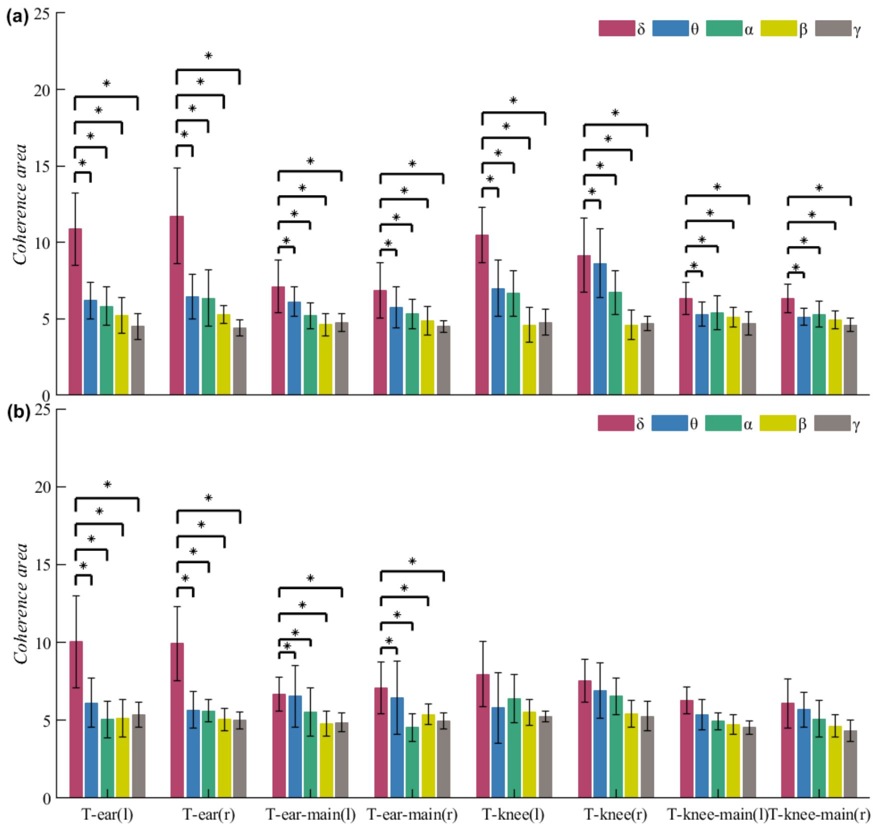

Fig. 5. Comparison analysis of CKC results for each EEG band in both healthy subjects and stroke patients. (a) represents the comparison under right side in healthy subjects. (b) represents the comparison under affected side in stroke. "∗" denotes $p < 0.05$. "l" means left side, and "r" means right side. "T" represents touch movement. "m" represents maintenance phases.

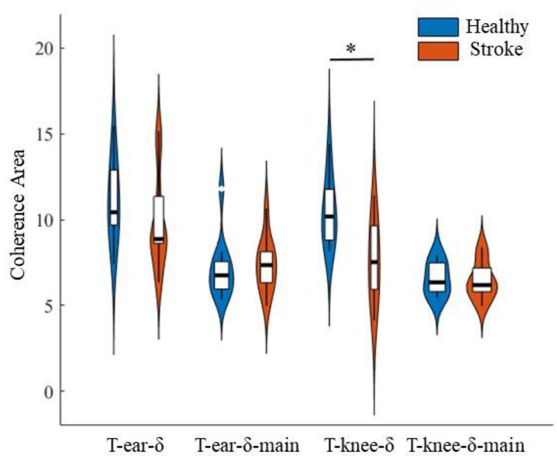

Fig. 6. Comparison analysis for healthy subjects and stroke in movement execution and maintenance. "∗" denotes p<0.05. The results were based on the δ band of EEG. "l" means left side, and "r" means right side. "T" represents touch movement. "main" represents maintenance state.

the analysis for the different conditions of left and right hemiplegia. We also plan to analyze patients in different rehabilitation stages simultaneously to investigate the neuromotor coupling between different rehabilitation sites and different rehabilitation stages. In the subsequent study, we will increase the sample size of subjects, further refine the analysis for the different conditions of left and right hemiplegia, and analyze the patients in different rehabilitation stages simultaneously to investigate the differences in neuromotor coupling analysis in different rehabilitation sites and stages. Our objective is to construct physiological indicators and motor function assessment for CKC analysis to analyze the accuracy and validity of physiological indicators. After this supplementary research finished, we will validate the effectiveness of CKC as an evaluation index. At that time, CKC may provide a new quantitative index for the subsequent assessment of motor function status in stroke. It can provide a theoretical basis for motor function evaluation of patients with stroke. Rehabilitation after stroke is a long-term and variable process, the CKC value might be changed during this time. Therefore, the regularity of CKC should be explored in the later study. These researches could add to the understanding of neuro-motor control mechanisms and provide new quantitative indicators on the motor function assessment.

V. Conclusion

This study investigated the differences in the correlated coupling properties of EEG and ACC data between healthy subjects and stroke patients. The experiment was performed during the movement execution and maintenance phases. We analyzed the neuromotor coupling analysis of EEG and ACC signals. In the full-frequency EEG-ACC coupling analysis, it was found that the intensity of the motor execution phase was significantly higher than that of the movement maintenance phase. This difference was more pronounced in low-frequency EEG signals than in full-frequency, particularly in δ band. The coherence results of the δ band in the knee touch movement, which reflected the higher intensity in healthy subjects than in stroke patients. The corticokinematic coherence analysis can reflect the difference between healthy subjects and stroke patients, which could provide a new quantitative index for the subsequent assessment of motor function status in stroke.

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