Effect of BCI-Controlled Pedaling Training System With Multiple Modalities of Feedback on Motor and Cognitive Function Rehabilitation of Early Subacute Stroke Patients

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***Abstract*— Brain-computer interfaces (BCIs) are currently integrated into traditional rehabilitation interventions after stroke. Although BCIs bring many benefits to the rehabilitation process, their effects are limited since many patients cannot concentrate during training. Despite this outcome post-stroke motor-attention dual-task training using BCIs has remained mostly unexplored. This study was a randomized placebo-controlled blinded-endpoint clinical trial to investigate the effects of a BCI-controlled pedaling training system (BCI-PT) on the motor and cognitive function of stroke patients during rehabilitation. A total of 30 early subacute ischemic stroke patients with hemiplegia and cognitive impairment were randomly assigned to the BCI-PT or traditional pedaling training. We used single-channel Fp1 to collect electroencephalography data and analyze the attention index. The BCI-PT system timely provided visual, auditory, and somatosensory feedback to enhance the patient's participation to pedaling based on the real-time attention index. After 24 training sessions, the attention index of the experimental group was significantly higher than that of the control group. The lower limbs motor function (FMA-L) increased by an average of 4.5 points in the BCI-PT group and 2.1 points in the control group (P = 0.022) after treatments. The difference was still significant after adjusting for the baseline indicators ($\beta = 2.41$, 95%CI: 0.48-4.34, P = 0.024). We found that BCI-PT significantly improved the patient's lower limb motor function by increasing the patient's participation. (clinicaltrials.gov: NCT04612426)**

***Index Terms*— Ischemic stroke, brain-computer interfaces, EEG, attention, neurorehabilitation.**

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I. Introduction

ABOUT 50% of stroke patients are unable to live independently because of their disabilities, which has brought a heavy burden to families, medical institutions, and society [1]. The evaluation and improvement of post-stroke motor dysfunction has always been a research hotspot [2]. Pedaling training is a training method often used in sports rehabilitation after stroke and has shown effectiveness in lower-limb rehabilitation [3]. To further promote functional rehabilitation after stroke, brain-computer interfaces (BCIs) are currently integrated into traditional rehabilitation. BCIs are communication systems that measure central nervous system (CNS) activity and translate it into control signals of external devices that may replace, restore, enhance, supplement or improve the natural CNS output [4]. By bridging the stroke-induced gap between motor intention and sensory feedback (in forms like actual movement, haptic feedback, visual feedback, etc.) of motor movement, BCI-based interventions may further improve the limb motor function [5].

Following the success in upper-limb rehabilitation, a few studies have found promising improvements in the lower limb functions after BCI-based rehabilitation. Chung *et al.* have reported further clinical improvements in the balance and gait function of chronic stroke patients following a BCI-based functional electrical stimulation (FES) intervention when compared to FES alone [6]. Another study found it could effectively improve the gait of subacute stroke patients using electroencephalography(EEG)-based neurofeedback training in the form of visual feedback, and observed improved sensorimotor rhythm [7]. Tang *et al.* [8] indicated that motor imagery-BCI rehabilitation with visual feedback could improve lower-limb mobility in chronic stroke patients. Recently, Delisle-Rodriguez *et al.* [9] proposed a recognition system of pedaling motor imagery for lower limber rehabilitation. However, no study has integrated BCIs into actual pedaling training.

In recent years, attention toward cognitive dysfunction after stroke has gradually increased. About 25%-80% of stroke survivors suffer from cognitive impairments [10], [11]. Many patients, especially those with cognitive impairment, cannot concentrate during pedaling, which weakens the training effect. A few studies have investigated BCI-based cognitive training in stroke patients and shown promising preliminary results by activating the upper alpha band [12]–[14]. Furthermore, research has shown a mutually reinforcing relationship between motor and cognitive functions in stroke rehabilitation [15]. Chung *et al.* [6], [16] found that one of the reasons why FES controlled by BCI could improve motor function more than traditional FES was that it also increased the patient's attention index of Fp1 and Fp2 domains and activated Fp1 domain during training. However, there was no research to promote motor function recovery directly by training attention. It has been found that cognitive and motor dual-task training could further improve post-stroke motor rehabilitation [17], [18]. However, dual-task training is more cognitively demanding, and stroke patients, especially with cognitive impairment, have difficulties in performing cognitive and motor tasks simultaneously [19], as the added cognitive task reduced the attention and performance on the primary motor task [20]. Still, post-stroke motor-attention dual-task training using BCIs has remained mostly unexplored.

Thus, we designed an attention-pedaling dual-task training system using BCIs with multiple modalities of feedback and aimed to investigate its effects on the motor and cognitive function rehabilitation of early subacute stroke patients (clinicaltrials.gov: NCT04612426).

II. Methods

A. Population

The study involved patients from our rehabilitation center with early ischemic stroke (confirmed by head diffusion-weighted imaging), hemiplegia, and cognitive impairment. The main inclusion criteria were as follows: 1. Aged 40-80 years old; 2. Patients with first subcortical ischemic stroke onset from 1 week to 3 months; 3. Hemiplegia and cognitive impairment (Mini-Mental State Examination (MMSE) score < 28 or Montreal Cognitive Assessment (MoCA), < 25); 4. Consciousness; 5. Sitting balance level 1 or above; 6. Can cooperate with assessment and treatment; 7. The patient or its authorized agent signed the informed consent form. Exclusion criteria: 1. Severely impaired cognition or inability to pay attention to and understand screen information; 2. Severe lower extremity pain or spasticity preventing pedaling training.

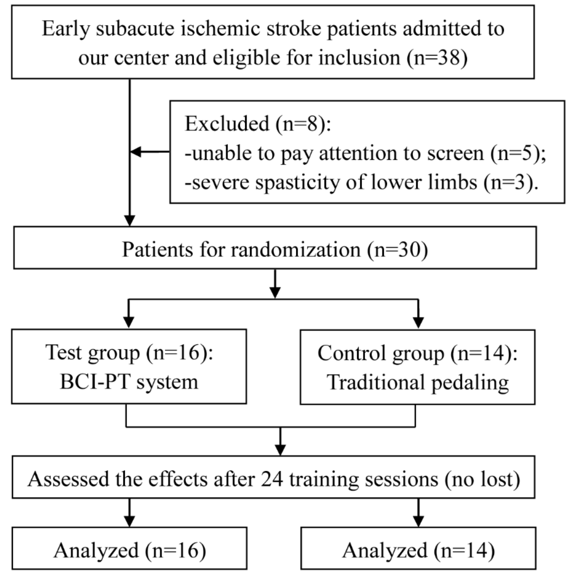

Fig. 1. CONSORT flow diagram.

The study was approved by the Ethics Committee of the First Affiliated Hospital of Xi'an Jiaotong University on August 14, 2020 (No. XJTU1AF2020LSK-149), and all patients or their authorized agents have signed informed consent.

B. Intervention

The study was a randomized placebo-controlled blinded-endpoint clinical trial. The flow diagram for the subject assignment is shown in Fig. 1. The patients who met the enrollment criteria were randomly divided into two groups according to the coated random number table generated by a technician who did not participate in the study. The odd numbers were entered into the experimental group, that is, the BCI-controlled pedaling training system (BCI-PT) group. And the even numbers were entered into the control group. This group used traditional pedaling training equipment with a monitor showing real-time speed, and the patients wore the same BCI equipment, which only collected attention index-related data but did not guide pedaling training. Both groups of patients were trained once a day for two consecutive sessions each time and were required to pedal as fast as possible. There were 6 times a week for a total of 2 weeks of exercise. Other rehabilitation training included acupuncture, physical therapy, occupational therapy, and electronic biofeedback. The four treatments of the two groups of patients were once a day, and each of them was completed by a therapist during the trial period. The differences in the improvement of sports and cognitive functions of the two groups of patients after 2 weeks of rehabilitation training were compared.

1) BCI-PT: BCI-PT was a BCI-controlled attention-pedaling dual-task training system with multiple modalities of feedback based on EEG. Its structure is presented in Fig. 2. The system consists of three components: (1) An EEG collection system (ZhenTec NT1, ZhenTec Intelligence, China) to record EEG data at the scalp. This system uses a semi-dry electrode, and the correlation between its signal and the wet electrode

Fig. 2. The structure of the rehabilitation training system.

Fig. 3. Interactive screen of BCI-controlled pedaling training system during training.

reaches 0.95 [21]. It is a gel-free electrode, which is more comfortable and convenient for clinical use. (2) A virtual reality training system to present a training game interface, motivate patients to actively participate in a training course, and convert EEG data into attention value with a processing algorithm. (3) A pedaling training robot (ZhenTec R1, ZhenTec Intelligence, China) to drive lower limbs to make a circular motion. The upper-limb motion mainly depended on the patient's active force.

The lower limb's rotational speed n of the training robot was controlled by the value of the attention index.

$$n = k \times atn \tag{1}$$

where k is a constant and atn is the attention index of the patient, which is calculated from the patients' EEG signals (see Equation 2-6). The higher the attention index, the higher the lower limb's rotational motion speed of the training robot.

During training, the patients were asked to concentrate on the avatar's lower limb on the screen and try to imagine and operate their limbs to complete pedaling task. The system would timely provide visual, auditory, and somatosensory feedback to enhance the patient's participation in pedaling based on the real-time attention index (Fig. 3). Firstly, the pedaling motion of the avatar displayed on the screen in front of the patient was synchronized with the actual pedaling motion of the patient and the patient's attention index was displayed in real-time on the screen using a bar and number. Secondly, when the patient's attention index was high, the lower limb's rotational speed of the training robot would be high. It would display accelerated visual effects to reward patients. When the patient's attention index was reduced, there would be virtual opponents to overtake the patient's avatar, visual effects reminders on the screen, a beep would be emitted, and the system would reduce the assistance of the pedaling so that the patient's body could perceive this change. These measures encouraged patients to take the initiative to increase participation.

C. Outcomes

1) Primary Outcome: The primary outcome was the change of Fugl-Meyer assessment of lower limbs motor function (FMA-L) between the post training and enrollment portions (cFMA-L). The score range was 0-36 points. The higher the score, the better the lower limb motor function. A doctor who was not involved in the treatment and who was blind to the group, was responsible for the evaluation of FMA-L and the cognitive function scales used as part of the secondary outcomes.

2) Secondary Outcomes: The attention index was calculated by EEG signals. In this study, three electrodes (signal (Fp1), reference (CPz), and ground (AFz)) were placed on the scalp according to the standard "10-20 system". Single-channel Fp1 was used as a reliable and convenient way to collect EEG data and analyze attention [22], [23]. The electrodes were connected to a high signal-to-noise EEG amplifier for EEG signal collection and pre-processing. The EEG amplifier converted the analog EEG signals into digital EEG data with 24 bits of precision.

The EEG recordings mainly contained the delta band (0.5-4 Hz), theta band (4-7 Hz), alpha band (7-13 Hz), beta band (14-30 Hz), and gamma band (>30 Hz) signals [24]. It has been demonstrated that alpha band and beta band signals were most related to human attention states [25], [26]. The attention was estimated using the energy distribution of different EEG rhythms. In this study, the attention intensity features were calculated by the energy ratio of the beta band and alpha band signals. The EEG signals were sampled in real-time at 500 Hz. To simplify the data processing method, the EEG signals were processed by a 7-30Hz band-pass filter to keep only the signals of interest [27], [28]. A time duration-based sliding window of length 4 seconds and sliding interval of 1 second was evaluated every 1 second. The longer the sliding window, the less artifact interference the result received, but the response speed was slower. After testing, a window length of 4 seconds was chosen to balance response speed and artifact interference.

The window was transformed to the frequency domain by fast Fourier transform (FFT). Assuming

$F(n)(n = 1, 2, 3, \ldots, N)$ is the FFT result of a window, the Power Spectral Density (PSD) [29] is as follows:

$$P(n) = \frac{F(n)F^{*}(n)}{N} \tag{2}$$

where $P(n)$ is the PSD, $F^{*}(n)$ is the conjugate function of $F(n)$ and N is the number of sampling points in the window, here is 2000.

Assuming that P_f is the PSD at the frequency f, the energy ratio of beta and alpha R can be calculated as follows:

$$E_\alpha = \sum\nolimits_{f=7}^{13} P_f \tag{3}$$

$$E_\beta = \sum\nolimits_{f=14}^{30} P_f \tag{4}$$

$$R = \frac{E\beta}{E\alpha} \tag{5}$$

The energy ratio is normalized to an integer value between 0 and 100. The attention index *atn* can be defined as follows:

$$atn = MIN + \frac{(MAX - MIN)(R - min)}{max - min} \tag{6}$$

where $MAX = 100$, $MIN = 0$. They are the normalized upper and lower limits. *max* and *min* are empirical constants that were decided by calculating a large amount of EEG data. This data set contained the EEG data of 20 trials for each of 50 people. The process of each trial was as follows: preparation(4s) + concentration(8s) + rest(8s). Among them, "concentration" allowed the subject to concentrate and stare at the white dot in the middle of the black screen; "rest" allowed the subject to relax and not stare at the object. For a total of 1000 trials, the maximum value of R in the concentration state was calculated as *max*, and the minimum value of R in the rest state was *min*. In this article, $max = 3.50$, $min = 0.35$.

The *atn* was updated every second. Once new data was added, the oldest data would be deleted and the *atn* would be recomputed. The higher the *atn*, the higher the participation. The arithmetic average of all the values during two consecutive sessions was used as the attention index of this training.

Other outcomes included the scores of commonly used scales for assessing cognitive function and attention after 2 weeks of treatment, and their changes from the time of enrollment: MMSE (Chinese version), MoCA (Chinese version), Digital Span Test (DST, both of DST-forward and DST-backward) reflecting the breadth of attention, and Symbol Digit Modalities Test (SDMT) reflecting attention and executive function.

D. Sample Size

Based on previous literature and clinical experience, we estimated that the change of FMA-L was 5 and 2 points in the BCI-PT and control group respectively, and the standard deviation was 2.7 points. We had 80% power to detect a significant difference between groups using a two-sided alpha of 0.05. According to the sample size calculation formula for comparing the means of two independent samples, each group required 13 patients. Considering the loss to follow-up, at least 30 patients needed to be recruited.

E. Statistical Analysis

Measurement data were expressed by median (IQR), and count data were expressed by rate or composition ratio. The mean comparison between the two groups was performed by t-test or Kruskal-Wallis rank-sum test; rate comparison was performed by chi-square test or Fisher's exact test. The scale scores after 2 weeks between the two groups were compared by covariance analysis, adjusting FMA-L, MMSE, MoCA, DST, and SDMT at admission. In addition, we calculated the false discovery rate (FDR)-corrected p values using BH procedure that compared the differences of the four attention-related scales. Multivariate regression analysis was used to compare the effects of the two treatments after adjusting covariates. Covariates included age, gender, time from onset to admission, education, hemisensory disorder (the somatosensory decreased or disappeared found by physical examination), and the National Institutes of Health Stroke Scale (NIHSS) at admission. The interaction of the above covariates was tested. The subjects were divided into the following subgroups for further analysis: sex, age $\geq 65/ < 65$ years, time of stroke onset $\geq 8/< 8$ weeks, FMA-L $\geq 13/ < 13$, and whether with hemisensory disorder. Take $\alpha = 0.05$ (two sides). Empower (R) (www.empowerstats.com; X&Y solutions, Inc., Boston MA), R software, version 3.1.2 (http://www.r-project.org) and SPSS version 25.0 (IBM Corp., USA) was used for all statistical analyses.

III. Results

A. Patients and Baseline Characteristics

A total of 30 stroke patients with subcortical infarction and mild to moderately impaired cognition were enrolled in our center from November 2020 to February 2021. The BCI-PT group finally involved 16 patients and the remaining 14 patients were regarded as the control group. No patient was lost to follow-up after randomization (Fig. 1). All patients were right-handed, of which 25 (83.3%) were right hemiplegia and 8 (26.7%) with hemisensory disorder. The median age of patients was 64.5 (IQR: 58.2-67.5) years, and there were 13 female patients (43.3%). 70% of patients were of high school education. Among the patients, the most common comorbidities were hypertension (86.7%) and diabetes 43.3%). The median time from onset to admission was 6.5 (IQR: 2.8-10.2) weeks in the intervention group, and that was 7.5 (IQR: 4.2-11.5) weeks in the control group ($P = 0.451$). No significant difference was observed in NIHSS (7 vs. 8 points, $P = 0.369$) and other baseline characteristics between the two groups (Table I). At the time of enrollment, the lower limb motor function and cognition and attention scores of the two groups were similar, and there was no significant difference (Table I).

B. Attention Index

The EEG attention index analysis results of the BCI therapy and the control method are shown in Fig. 4. It could be seen that the attention index of the BCI group and the control group were close at the first time, and both showed a gradual upward trend after training. After 12 training times, the attention index of the BCI-PT group was significantly higher than that of the control group ($P = 0.002$).

TABLE I
BASELINE CHARACTERISTICS OF STROKE PATIENTS[a]

Group	All	BCI-PT	Control	*P*-value
N	30	16	14	
Age	64.5 (58.2-67.5)	62.0 (56.8-65.2)	65.5 (62.5-69.8)	0.173[b]
Female	13 (43.3%)	5 (31.2%)	8 (57.1%)	0.153[c]
Education				0.830[d]
primary or lower	2 (6.7%)	1 (6.2%)	1 (7.1%)	
junior high	7 (23.3%)	3 (18.8%)	4 (28.6%)	
high or above	21 (70.0%)	12 (75.0%)	9 (64.3%)	
Time of onset	7.0 (4.0-10.8)	6.5 (2.8-10.2)	7.5 (4.2-11.5)	0.522[b]
NIHSS	7.5 (5.0-9.8)	7.0 (4.8-9.0)	8.0 (5.2-10.8)	0.252[b]
Hypertension	26 (86.7%)	13 (81.2%)	13 (92.9%)	0.602[d]
Diabetes	13 (43.3%)	7 (43.8%)	6 (42.9%)	0.961[c]
Hemiparetic side				1.00[d]
left	5 (16.7%)	3 (18.8%)	2 (14.3%)	
Hemisensory disorder	8 (26.7%)	5 (31.2%)	3 (21.4%)	0.689[d]
Function scales				
FMA-L	12.5 (8.2-19.8)	12.5 (8.8-20.0)	13.5 (8.2-19.0)	0.835[e]
MMSE	17.5 (14.2-24.5)	18.5 (13.8-25.0)	17.5 (15.0-20.8)	0.436[b]
MOCA	12.5 (9.0-20.5)	15.0 (9.8-21.0)	11.5 (8.2-18.0)	0.424[b]
DST	12.0 (8.0-15.0)	12.0 (6.8-16.0)	13.5 (8.5-15.0)	0.857[b]
SDMT	7.0 (3.0-15.2)	7.0 (3.8-17.2)	7.0 (3.0-12.5)	0.677[e]

Abbreviations: BCI-PT, BCI-controlled pedaling training; NIHSS, National Institutes of Health Stroke Scale; FMA-L, Fugl-Meyer assessment of lower limbs motor function; MMSE, Mini-Mental State Examination; MoCA, Montreal Cognitive Assessment; DST, Digital Span Test; SDMT, Symbol Digit Modalities Test.
[a] Values are presented as median(Q1-Q3) or N(%).
[b] Evaluated using *t* test.
[c] Evaluated using chi-square test.
[d] Evaluated using Fisher's exact test.
[e] Evaluated using *Kruskal-Wallis* rank-sum test.

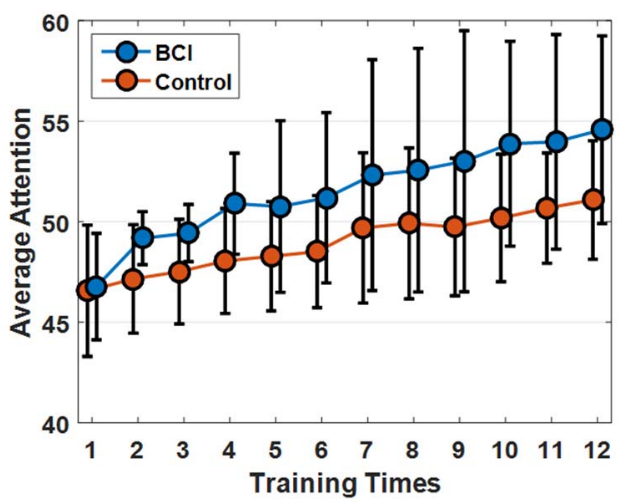

Fig. 4. Changing of attention index along 12 training sessions between groups.

C. Motor and Cognitive Function

The five clinical scales of the two groups of patients were improved compared to when they were enrolled; the improvement of the experimental group was even greater (Fig. 5). Using covariance analysis, after adjusting the scores of each scale before the intervention, the FMA-L of the experimental group after treatment was significantly higher than that of the control group ($P = 0.025$), and the DST ($P = 0.019$) and SDMT ($P = 0.032$) scores of the BCI-PT group were also significantly better than those of the control group (Fig. 6). After treatment, the MMSE and MoCA of the experimental group were slightly higher than those of the traditional pedaling group, but there was no statistical difference (Fig. 6). However, the FDR-corrected p values of the four attention-related scales were all > 0.05: $P = 0.434$ for MMSE, $P = 0.831$ for MoCA, $P = 0.064$ for DST and $P = 0.064$ for SDMT respectively (Fig. 6).

We found that the FMA-L increased by an average of 4.5 points in the experimental group and 2.1 points in the control group ($P = 0.022$) after treatments. The DST ($P = 0.017$) and SDMT ($P = 0.036$) of the experimental group were improved by 1.1 points more than the control group, and the MMSE (0.6 points, $P = 0.201$) and MoCA (0.2 points, $P = 0.672$) improved slightly when compared to the control group. After adjusting for the age, sex, time of onset, education, hemisensory disorder and NIHSS, the scales of FMA-L ($\beta = 2.34$, 95%CI: 0.35-4.33, $P = 0.032$) and DST ($\beta = 0.97$, 95%CI: 0.07-1.88, $P = 0.049$) still improved significantly; the difference in SDMT changes between the two groups was no longer significant (Table II).

Through subgroup analysis, there was no significant difference in the motor and cognition functions among patients of different ages, sex, time of onset, and severity (Table III).

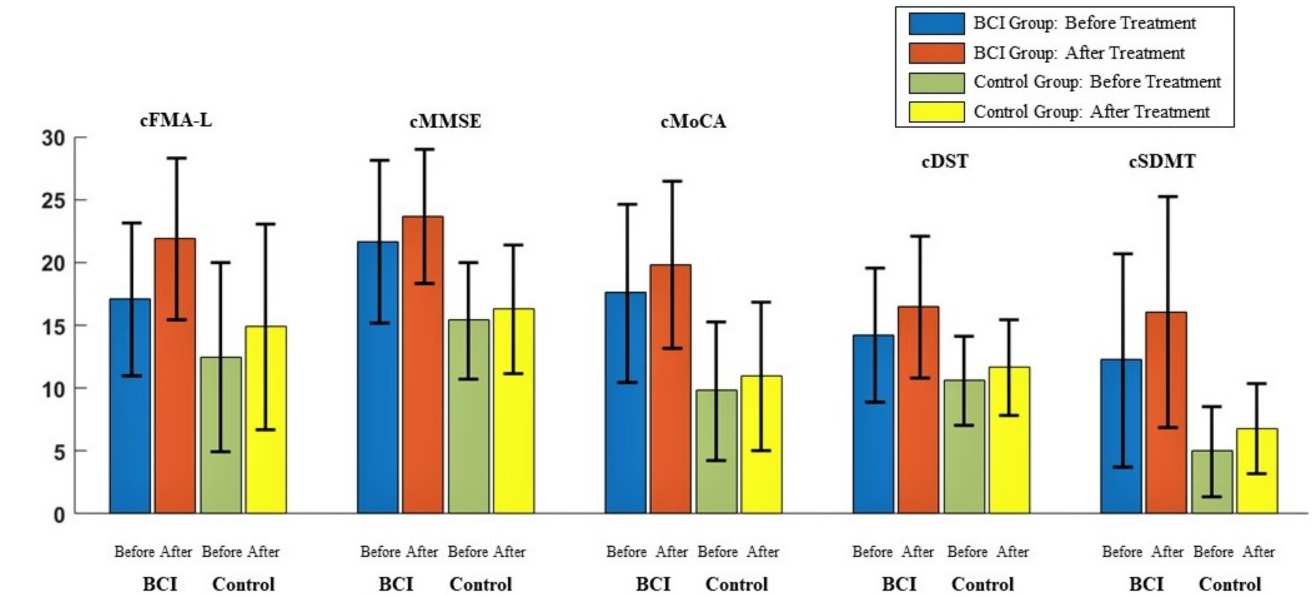

Fig. 5. Motor and cognitive function scales before and after exercises and between treatment groups.

TABLE II
MULTIVARIATE REGRESSION ANALYSIS OF MOTOR AND COGNITIVE FUNCTION SCALES BETWEEN TREATMENT GROUPS

	Group	β (95%CI) *P*-value Non-adjusted	Adjust I[a]	Adjust II[b]
	Control	0	0	0
cFMA-L	BCI-PT	2.36 (0.45, 4.26) 0.022	2.68 (0.66, 4.71) 0.015	2.34 (0.35, 4.33) 0.032
cMMSE	BCI-PT	0.65 (-0.32, 1.63) 0.201	0.62 (-0.43, 1.66) 0.260	0.32 (-0.82, 1.47) 0.585
cMoCA	BCI-PT	0.21 (-0.77, 1.20) 0.672	0.34 (-0.71, 1.39) 0.530	0.04 (-1.01, 1.08) 0.945
cDST	BCI-PT	1.15 (0.27, 2.04) 0.017	1.04 (0.16, 1.92) 0.029	0.97 (0.07, 1.88) 0.049
cSDMT	BCI-PT	1.10 (0.12, 2.07) 0.036	0.93 (-0.12, 1.98) 0.095	0.80 (-0.30, 1.90) 0.169

Abbreviations: BCI-PT, BCI-controlled pedaling training; FMA-L, Fugl-Meyer assessment of lower limbs motor function; MMSE, Mini-Mental State Examination; MoCA, Montreal Cognitive Assessment; DST, Digital Span Test; SDMT, Symbol Digit Modalities Test; the c before the scales means change.
[a] Adjusted for: age, sex;
[b] Adjusted for: age, sex, time of onset, education, hemisensory disorder, and NIHSS at admission.

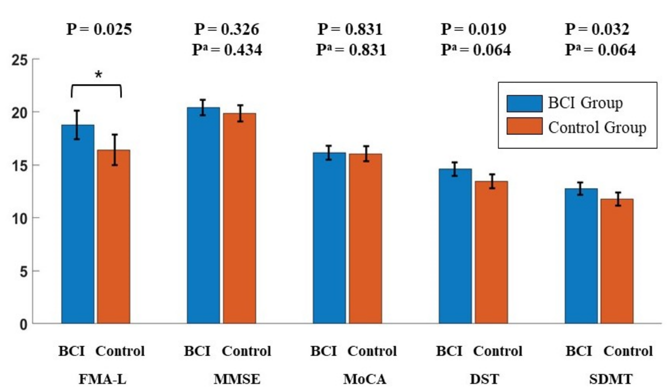

Fig. 6. Analysis of covariance of motor and cognitive function scales between treatment groups. * indicated $p < 0.05$;[a] FDR-corrected p-value.

BCI-controlled pedaling seemed to have greater benefits in terms of motor rehabilitation for more severe (FMA-L $<$ 13 vs. $\geq$ 13, $\beta = 4.09$ vs. 2.80) and older (age $\geq$ 65y vs. $<$ 65y, $\beta = 2.07$ vs. 0.91) patients. Similar trends could be observed for the four cognitive function scales in the above two subgroups. Patients with hemisensory disorder seemed to benefit more from BCI-PT. It has the equivalent effect on patients of different disease courses and gender.

IV. DISCUSSION

The study found that compared with pedaling training alone, the BCI system adopted multiple modalities of feedback to make patients more focused on pedaling training, and further improved the lower limb motor function of patients with subacute stroke. Neuroplasticity is the scientific basis of all of the post-stroke rehabilitative interventions [30], [31]. Our rehabilitation system involved four potential neuroplasticity mechanisms. The first was neurofeedback training [32]. By displaying the patient's pedaling action and attention index in real-time, the patients were provided with a continuous visualization of the motor action and brain activity from the cognitive regions and were asked to volitionally up-regulate this activity. The second mechanism was operant conditioning [33]. Rewards were given when the patient's participation was high, and multiple forms of feedback were given when

TABLE III
SUBGROUP ANALYSIS OF MOTOR AND COGNITIVE FUNCTION SCALES BETWEEN TREATMENT GROUPS

Subgroups	Adjusted β (95%CI) *P*-value[a]				
	cFMA-L	cMMSE	cMoCA	cDST	cSDMT
Age<65y	0.91 (-1.43, 3.26) 0.480	-0.96 (-1.77, -0.15) 0.068	-0.66 (-2.04, 0.73) 0.396	1.17 (0.33, 2.01) 0.042	0.01 (-2.13, 2.14) 0.994
Age≥65y	2.07 (0.79, 3.35) 0.025	1.60 (-2.49, 5.69) 0.478	0.52 (-2.78, 3.82) 0.770	1.58 (-2.00, 5.15) 0.427	0.81 (-1.42, 3.05) 0.509
Male	2.09 (-0.20, 4.38) 0.111	1.39 (-0.17, 2.95) 0.120	0.81 (-0.83, 2.45) 0.362	1.13 (0.07, 2.18) 0.070	1.55 (-0.11, 3.22) 0.105
Female	2.36 (-1.76, 6.49) 0.313	-0.96 (-1.67, -0.25) 0.046	-0.88 (-2.38, 0.62) 0.301	0.60 (-0.79, 1.99) 0.438	-0.22 (-1.68, 1.24) 0.781
Time <8w	1.26 (-0.66, 3.18) 0.235	0.47 (-1.45, 2.38) 0.645	-0.29 (-2.23, 1.66) 0.780	0.75 (-0.31, 1.82) 0.203	0.65 (-0.61, 1.92) 0.341
Time≥8w	1.64 (-3.29, 6.57) 0.561	-0.81 (-1.90, 0.27) 0.239	0.18 (-1.13, 1.48) 0.809	0.74 (-0.21, 1.68) 0.226	1.33 (-1.07, 3.73) 0.357
FMA-L<13	4.09 (0.66, 7.52) 0.067	1.57 (-0.53, 3.66) 0.202	0.85 (-0.93, 2.63) 0.393	2.16 (0.65, 3.67) 0.038	1.08 (-0.54, 2.71) 0.247
FMA-L≥13	2.80 (1.09, 4.51) 0.024	0.76 (-0.89, 2.42) 0.409	0.07 (-1.82, 1.96) 0.944	-0.35 (-1.45, 0.76) 0.563	0.28 (-1.45, 2.00) 0.765
No hemisensory disorder	1.04 (-0.58, 2.65) 0.233	-0.48 (-1.60, 0.63) 0.411	-0.82 (-1.99, 0.35) 0.195	0.90 (-0.24, 2.03) 0.147	0.09 (-1.45, 1.62) 0.915
Hemisensory disorder	1.85 (-,-) NA	3.00 (-,-) NA	3.77 (-,-) NA	3.08 (-,-) NA	3.54 (-,-) NA

Abbreviations: BCI-PT, BCI-controlled pedaling training; FMA-L, Fugl-Meyer assessment of lower limbs motor function; MMSE, Mini-Mental State Examination; MoCA, Montreal Cognitive Assessment; DST, Digital Span Test; SDMT, Symbol Digit Modalities Test; the c before the scales means change.
[a] Adjusted for: age, sex, time of onset, education, hemisensory disorder, and NIHSS at admission.

the participation was low. These two mechanisms may be the reasons that many BCI-based rehabilitation systems make the patient's attention higher during training [16], [34], [35]. But how high attention leads to better recovery of motor function is unclear [15]. It may be that only high concentration can establish effective neurofeedback. The third mechanism was the reinforcement of the motor or cognitive functional connectivity by repetitive training [15]. And the most important one was the Hebbian plasticity, that is, multiple modalities of feedback controlled by BCIs bridged the gap between CNS and peripheral limbs, and strengthened the sensory-motor loop [15].

Motor and cognitive functions promote each other in the rehabilitation process after stroke [36]–[38]. Our BCI-PT system was a dual-task training of attention and lower limb movement, and it also simultaneously trained the central nervous system and periphery limbs at the same time. Studies have confirmed that cognitive-motor dual-task training is effective in promoting the recovery of both cognitive and motor functions [39]–[41]. As in a controlled study, the authors found that dual tasks training, that is motor task accompanied with cognitive tasks including digit span, N-back, spelling words, Stroop test, and so on, significantly improved the balance and executive functions of patients with Parkinson's disease when comparing with motor task training alone [42]. However, stroke patients, especially with cognitive impairment, have difficulties in performing cognitive and motor tasks simultaneously [19], as the added cognitive task reduced the attention and performance on the primary motor task [20]. Therefore, our research chooses attention training as the cognitive training task and found that for stroke patients with mild to moderate cognitive impairment, motor-attention dual tasks training was also effective in improving the lower-limber motor function and attention index.

Many studies have observed a significant correlation between feedback accuracy and clinical functional improvements [43]–[46]. EEG has a good time and space correlation for the detection of cortical function after stroke [47], [48], thus it has the advantages in real-time monitoring [49]. Therefore, our BCI-PT system collected EEG data every 2ms and fed it back to the brain. It ensured the real-time and accuracy of feedback. However, determining the best way to select the feedback modalities and design the feedback paradigm to bring the most benefits still needs to be explored [15]. Sensory feedback using robotic or haptic devices was thought to promote neuronal repair by bridging the gap between motor intention and execution in stroke patients [46], [50]. Two studies about BCI-driven virtual reality (VR) systems confirmed the effect of visual feedback for post-stroke motor rehabilitation [51], [52]. However, another controlled study found that visual feedback alone is not sufficient to evoke functional improvements [53]. Since somatosensory abilities are essential for patients to perceive the feedback provided by the BCI system, somatosensory impairments may significantly alter the efficiency of BCI-based rehabilitation [54]. Therefore, in this study, we adopted multiple modalities of feedback such as vision, hearing, and somatosensory. As shown in the results of multivariate regression analysis, the effect was still significant after adjusting for hemisensory disorder (Table II, Adjust II model), and patients with hemisensory disorder seemed to benefit more from BCI-PT (Table III). Since EEG equipment is safe, portable, and low-cost, designing a more portable EEG head-mounted device that only collects attention index would create a system that would have the potential to be promoted as a BCI-based smart home or community rehabilitation tool.

There were a few limitations of this study. The first were issues about the signal processing of EEG. To increase portability, we used only one electrode to compute the attention index, which is less reliable than multiple electrodes. We will consider using more channels of EEG to calculate the attention index to increase its reliability in the next step. Besides, the EEG signal was transformed to the frequency domain by the FFT method to ensure higher real-time performance, but may increase variability than the other spectral power estimation methods such as the Welch method and multitaper method [55], [56]. In the future, we will use the Welch method or the multitaper method to optimize the calculation of the spectral power and attention index, thereby reducing the influence of noise on the calculation of the attention index. In addition, we will use independent component analysis, empirical mode decomposition and wavelet packet transformation to remove motion and blinking artifacts in EEG, thereby reducing the noise from these artifacts. Another limitation was that the sample size was small and the observation period was only 2 weeks. We have not observed that pedaling training under the guidance of BCI has significantly improved MMSE, MoCA, DST and SDMT. This study revealed that pedaling training based on BCI significantly improved the patient's lower extremity motor function and attention index. Yet, the mechanism through which increased attention improves motor function by affecting the brain's remodeling process was unclear. Also, due to the small number of subjects, no significant differences between groups were observed in many subgroups. Whether pedaling training under the guidance of BCI can significantly improve the attention and motor function of patients in different subgroups should be further explored.

V. Conclusion

The BCI-PT system significantly improved the patient's lower limb motor function by increasing the patient's participation. Attention-related scales have a tendency to improve, but the difference was not significant, and longer-term observations may be needed. In addition, patients with hemisensory disorder seemed to benefit more from BCI-PT system. The specific neural remodeling mechanism between attention and motor function still needs to be further explored.

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