EEG-Based Focus of Attention Tracking and Regulation During Dual-Task Training for Neural Rehabilitation of Stroke Patients

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***Abstract*— Dual-task training under variable-priority instructions (DT-VP), during which subjects are required to vary their focus of attention (FOA) between two concurrent tasks, has shown a more significant improvement in neural rehabilitation than that under fixed-priority instructions. Failed FOA switching not only diminishes the recovery benefits, but also causes anxieties, which is detrimental to rehabilitation. Developing a strategy for tracking and regulating patients' FOA to achieve a better performance in task priority-following during DT-VP is thus imperative. In this study, fifteen stroke patients participated in DT-VP that comprised two tasks: a mathematical problem-solving task and a cycling task, during which their electroencephalograms were recorded simultaneously. The significantly differentiated power spectra of four brain regions extracted from single-task training were fed into a support vector machine to build a FOA tracking algorithm for patients' attention assessment during the DT-VP. Moreover, dual-task difficulty adaptation method was designed to regulate patients' FOA when their FOA and the high-priority task were not coincident. The comparison experimental results showed that the proposed method significantly improved patients' FOA distributed on the high-priority task (analysis of variance, $p < 0.05$). Meanwhile, the absolute power spectral densities of the motor cortex and the frontal region could also be improved during DT-VP under high motor and cognitive task priority instructions, respectively. These phenomena demonstrated the feasibility of the proposed method in helping stroke patients better implement FOA switching and maintenance.**

***Index Terms*— Neural rehabilitation, brain-computer interface, attention regulation, difficulty adaptation, task priority-following.**

I. Introduction

The central nervous system (CNS) damage caused by stroke usually leads to motor and cognitive dysfunctions, which seriously affect patients' ability to take care of themselves in daily life [1]. ADLs (activities of daily living) are primarily multi-tasks, in which subjects are supposed to have the ability to perform motor tasks and higher cognitive tasks simultaneously [2], [3]. In order to make sure that stroke patients can be well integrated into ADLs, dual-task training must be addressed during rehabilitation therapy [4].

During the dual-task training, subjects have to strategically allocate their attention resources to ensure dual-task performance [5]. In terms of focus of attention (FOA) priority, dual-task training can be performed by shifting attention between two concurrent tasks (dual-task training under variable-priority instructions, DT-VP) or placing equal amounts of attention on both tasks (dual-task training under fixed-priority instructions, DT-FP) [6], [7]. Recently, DT-VP has been argued to be more effective for neural rehabilitation, based on the evidence that subjects trained with DT-VP learned tasks faster and performed better than those who received training with DT-FP [7], [8].

Compared with DT-FP, DT-VP can bring out higher rehabilitation benefits mainly because attention control is more taxing in DT-VP [9]. Specifically, subjects need to constantly pay more attention to the high-priority task and shift attention between tasks across different blocks. Therefore, shifting and maintaining their FOA depending on the continuously changing priority instructions is the key to ensure the recovery benefits of DT-VP [10]. In order to help patients better regulate their FOA, some works proposed to provide individualized feedback to inform them of their current FOA [9], [11]–[13]. Subjects are required to keep their FOA as consistent as possible with the high-priority task.

However, whether patients followed or can follow the task priority instructions during DT-VP has rarely been monitored and regulated in the previous studies. Failed FOA switching not only diminishes the benefits of recovery but also causes anxieties, which is detrimental to rehabilitation [14]–[16]. Therefore, it is imperative to develop a countermeasure to track and regulate patients' FOA to achieve a better performance of task priority-following, thus minimizing anxiety or stress effects. As for the FOA tracking system, behavioral information, such as gaze and head angles, can be used for attention assessment. For example, Chong *et al.* proposed a gaze-angle-based generalized attention estimation model in 2018 [17]. In contrast to behavioral information, physiological measurements related to attention and workload also have been studied for many years [18]. The physiological information is more sensitive to the changes in cognition [18]–[20]. For example, the relationship between increased task demands and changes in heart rate, skin conductance, and respiration rate has been verified [18], [21]–[23]. Over the recent twenty years, brain signal acquisition and analysis techniques have made significant progress, providing technical foundations for automatically tracking patients' FOA during DT-VP [24]–[26]. Due to the sufficiently high temporal resolution and relatively low cost of electroencephalography (EEG), EEG has been one important neural data source for exploring subjects' FOA variations [18], [27], [28].

Furthermore, another pressing question for DT-VP is that if the subjects' FOA is classified as that on the task with low priority, what kinds of measures can be adopted to help patients follow the task priorities better. In the previous studies, individualized feedback was provided continuously to the subjects in order to ensure that task priority instructions were followed [9], [11]–[13]. For example, feedback took the shape of two changing color bars to inform subjects of their FOA. Each bar was related to one task. Subjects were asked

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to try to maintain the bars in the green zone and prevent them from turning red.

Although continuous feedback can make subjects deliberately and coercively focus on the high-priority task, this involuntary attention will be hard to maintain. For example, if the difficulty of the high-priority task is pretty lower than that of the other, in order to ensure dual task performance, subjects had to devote more attention resources to the more difficult task, even though this task had a low priority. Under this situation, subjects can hardly put their FOA on the task with high priority, even with feedback. It has been argued that humans would pay more attention to the relatively more difficult task during dual-task situations [29], [30]. Therefore, we assume that the performance-assessment-based task difficulty adjustment method can be used to regulate subjects' FOA.

This study aimed to track and regulate stroke patients' FOA during DT-VP based on EEG data to help them better follow the changing task priorities. Firstly, cognitive-motor dual-task training, which included a mathematical problem-solving task and a speed-tracking cycling task, was designed for VP-DT. Then, FOA classifiers, which were designed based on the EEG data collected from the single-task training, were used to track subjects' FOA continuously during the DT-VP. Moreover, the dual-task difficulty adaptation method was designed and introduced to regulate subjects' FOA when their FOA and the high-priority task was not in-sync. Finally, fifteen patients with neurological deficits were recruited for the DT-VP. The comparison experiments carried out in this study verified that the proposed FOA tracking and regulation method could help patients better implement FOA switching and maintenance depending on the changing task priorities, thus further promoting the clinical application of DT-VP.

The main contributions include:

1) A new DT-VP paradigm that comprises a mathematical problem-solving task and a cycling task is proposed to induce cognitive motor interference (CMI) for stroke patients.
2) An EEG-based FOA tracking and regulation method is proposed to improve stroke patients' task-priority following ability. To the best of our knowledge, the FOA regulation method during DT-VP has rarely been researched.
3) Fifteen stroke patients were recruited in this study. The results demonstrated the feasibility of the proposed method in helping them better implement FOA switching and maintenance.

The remainder of this paper is organized as follows: the design of the proposed DT-VP paradigm and the details of FOA tracking and regulation methods are given in Section II. Section III introduces the experimental setup and the preprocessing of the acquired EEG data. Then, experimental results are presented and discussed in Section IV. Finally, Section V concludes the paper.

II. Design of the FOA Tracking and Regulation System

A. Design of the DT-VP Paradigm

Considering that cognitive-motor dual-task training can bring out more rehabilitation benefits than dual-task training that only includes cognitive or physical tasks [31], a pure mathematical problem-solving cognitive task and a pure cycling motor task are designed for the DT-VP. One of the designed VP-DT scenes can be seen in Fig. 1.

Specifically, as for the mathematical problem-solving task, different arithmetic equations are presented as red letters in the center of the screen in succession. Subjects are supposed to judge whether the equation displayed on the screen is correct or not. If the equation is correct (incorrect), the subject needs to press the left (right) mouse button as quickly as possible. Once the subject has responded to

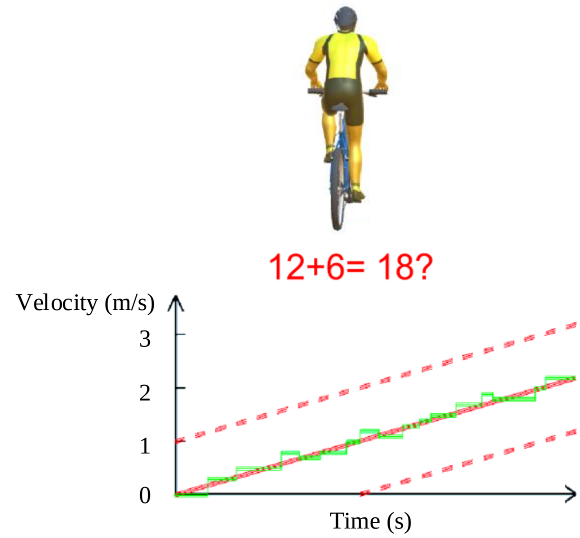

Fig. 1. The designed VP-DT paradigm, which includes one mathematical problem-solving cognitive task and one speed-tracking cycling motor task.

the displayed judgment question, the following calculation will be immediately given and displayed in the same location. The ratio of correct to incorrect equations presented is 50:50, and the difficulty is at the same level in a fixed block. The latency from the presentation of an equation to the button press responded for the corresponding equation is defined as the solution time. Subjects' average correct rate and solution time are recorded in real-time.

As for the speed-tracking riding task, the solid red curve, shown in Fig. 1, is designed as the velocity curve to be tracked. The other two dotted red curves above and below the solid red curve are designed to limit the range of variation of the patients' actual speeds. Subjects are supposed to track the reference velocity trajectory (solid red curve) as accurately as possible. During the experiment, once the actual riding speed of the subject exceeds the interval limited by the red dotted lines, the patient needs to redo the corresponding trial immediately. The average tracking error, calculated by Eq. (1), is recorded in real-time.

$$f_{\mathrm{TE}} = \frac{||\boldsymbol{V}^{\mathrm{act}} - \boldsymbol{V}^{\mathrm{ref}}||_2}{\sqrt{\mathrm{M}}} \tag{1}$$

where $||*||_2$ means the calculation of the L2-norm. $\boldsymbol{V}^{\mathrm{act}} \in \mathbb{R}^{\mathrm{M}}$ and $\boldsymbol{V}^{\mathrm{ref}} \in \mathbb{R}^{\mathrm{M}}$ are the actual and reference velocity vectors sampled at 100 Hz in the last second, respectively. M represents to the length of the vector $\boldsymbol{V}^{\mathrm{act}}$ or $\boldsymbol{V}^{\mathrm{ref}}$, which is equal to 100 in this study. The subject's actual speeds are collected using a data acquisition card and transmitted to the computer via TCP/IP protocol, which can be found in our previous work [32].

B. FOA Tracking: EEG-Based Feature Extraction and Classification

EEG signals are collected and analyzed in real-time for stroke patients' FOA assessment during DT-VP. Evidence has demonstrated that attention variation is strongly correlated with the energy changes of EEG signals in different bands. A higher attention level is often related to a decrease in the theta band and an increase in the beta band. Therefore, the theta to beta power ratio (TBR) has been widely used to indicate subjects' attention states [33]–[35]. A higher TBR value relates to a higher attention the subject is paid to the experiment. Inspired by this phenomenon, the EEG-based power spectra of the delta (1–3 Hz), theta (4–7 Hz), alpha (8–13 Hz), and beta (14–30

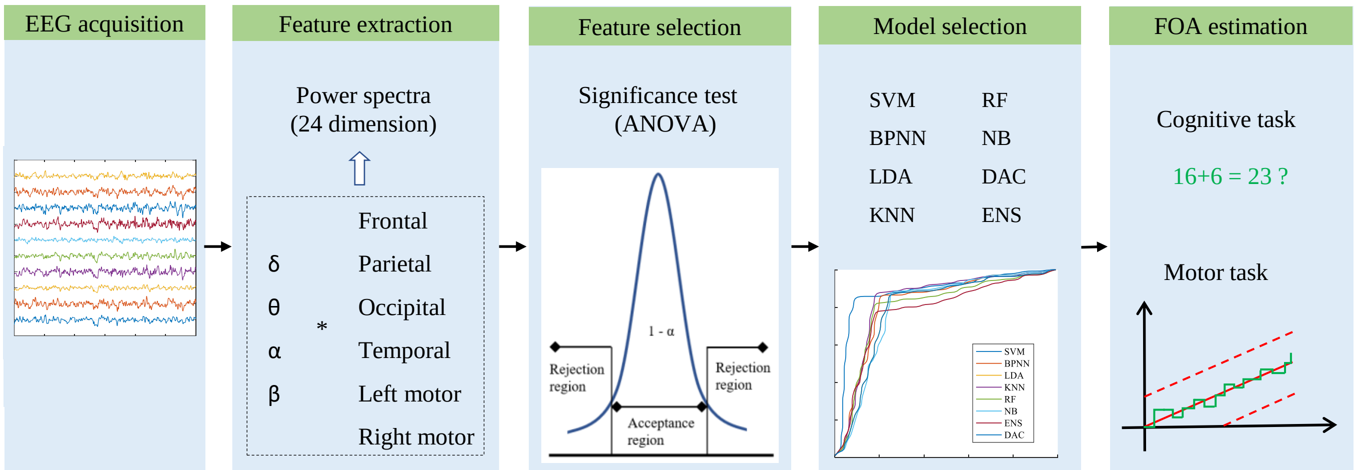

Fig. 2. EEG-based FOA tracking during DT-VP.

Hz) bands in five brain regions (frontal, central, parietal, occipital, left motor, and right motor) are calculated for the attention-related feature extraction.

Eight supervised machine learning classifiers are employed to build the candidate FOA classifiers. These classifiers include support vector machine (SVM), back-propagation neural network (BPNN), linear discriminant analysis (LDA), K-nearest neighbors (KNN with K = 5), random forest (RF), naive bayesian (NB), discriminant analysis classifier (DAC), and ensemble classifier (ENS). For implementing the SVM model, the radial basis function is used as the kernel function, and the transformation from output scores to posterior probabilities is achieved using Platt's method [36]. For the BPNN, the Tanh-function method is chosen as the activation function of the hidden layer, and the linear transfer function is chosen as the output layer. For the RF classifier, it can be considered as the ensemble learning algorithm. Thus the classification result is decided by the majority vote of decision trees. These machine learning methods are employed as candidate classifiers to compare with each other for the eventual selection of the optimal attention tracking classifier.

The recorded EEG signals in the single-task conditions are used as the training and validating data to build the FOA assessment system since subjects' FOA is clearly on the known task during the single-task training. For example, during the mathematical problem-solving task, subjects are instructed to try their best to solve the mental calculation. Thus their FOA is obviously on the cognitive task. Likewise, the subjects' FOA is on the motor task during the speed-tracking riding task. Therefore, the designed FOA assessment system is a binary classifier, indicating that subjects' current FOA is on the cognitive or motor task.

Fig. 2 shows the flow chart of the EEG-based FOA tracking system. Analysis of variance (ANOVA) is applied to select features with significant differences between single motor and single cognitive task training. In terms of classification model selection, classification accuracy, recall, F1-score, receiver operating characteristic (ROC) curves, and area under the curve (AUC) are employed to evaluate the performance of the candidate FOA classifiers [37]. Details about the feature selection and model selection are given in sections IV-A and IV-B, respectively.

C. FOA Regulation: Dual-Task Difficulty Adaptation

It has been argued that humans would pay more attention to the relatively more difficult task during the dual-task conditions [29], [30]. Therefore, if the FOA tracking system detects that the patient cannot shift or maintain their FOA successfully, a progressive dual-task difficulty adaptation method designed in this study will be triggered to help stroke patients follow the task priorities better.

The difficulty is divided into three levels (low, medium, and high) and predefined for every single-task training. For the mathematical problem-solving task, with the increase in difficulty level, patients are supposed to do adding or subtracting tasks between one digit, one and two digit, and two digits, respectively. In terms of the speeding-tracking riding task, the difficulty adjustment is realized by adjusting the distance between the two red dotted curves. The vertical distances between the two red dotted curves under low, medium, and high difficulty levels, are 3, 2, and 1, respectively.

The specific dual-task difficulty adjustment strategy is given in Fig. 3. First, the task performance definition is given as follows. Unacceptable (acceptable) cognitive task performance is defined as the average correct rate of the judgment question lower (greater) than 90% [5]. Unacceptable (acceptable) motor task performance is defined as the actual riding speed curve (does not) exceed the area formed by the two red dotted lines. At the beginning of DT-VP, the difficulty of each single task was initialized according to the neurologist's advice, which is mainly based on the assessment scores of FMA-LE (Fugl-Meyer Assessment of Lower Extremity) and MMSE (Mini-Mental State Examination). The initial difficulty level of each single task is raised with the corresponding assessment score, which can be seen from Table I.

TABLE I
TASK DIFFICULTY INITIALIZATION STRATEGIES FOR DT-VP.

FMA-LE	Initialized motor-task difficulty level	MMSE	Initialized cognitive-task difficulty level
20-24	Low	20-23	Low
25-29	Medium	24-27	Medium
30-34	High	28-30	High

It can be seen that the initial difficulty levels increase with the assessment scores. Given that the initial task difficulty level is not necessarily optimal for each patient during the DT-VP training, the proposed dual-task difficulty adaptation method will be introduced in real-time, leading to a suitable challenging task for a specific subject.

During the training, patients need to constantly shift their attention and cognitive resources distributed on each sub-task depending on the changing task priority instructions displayed on the screen, during

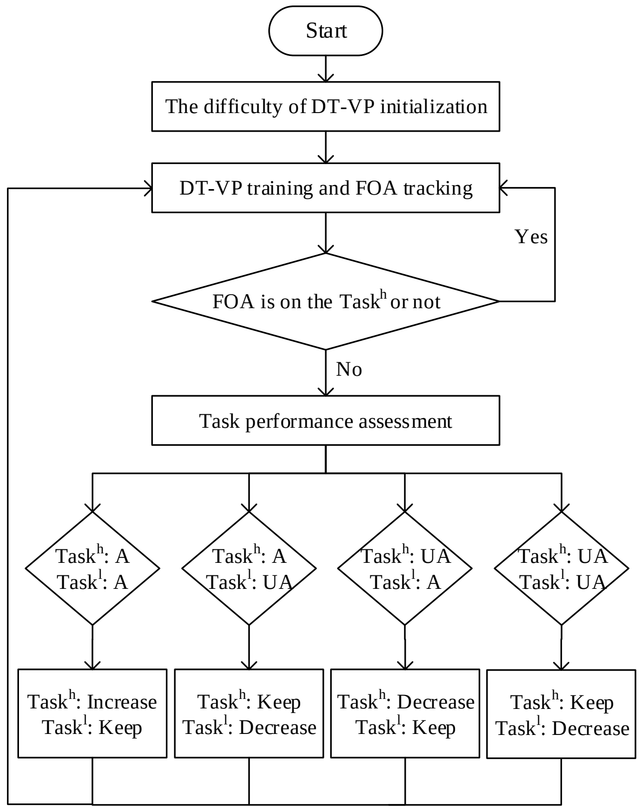

Fig. 3. The flow chart of the proposed progressive dual-task difficulty adaptation method. $\mathbf{Task^h}$ and $\mathbf{Task^l}$ denote the task with high priority and low priority, respectively. The abbreviation of "A" and "UA" represent the performance of the corresponding task are acceptable and unacceptable, respectively. The word "Keep" ("Increase" or "Decrease") indicates keep (increase or decrease) the difficulty of the corresponding task (with one level).

which patients' FOA is evaluated by the proposed FOA tracking model in real-time. If the patient can actively regulate the attention resources between tasks according to the changing task priorities, no intervention is to be taken. On the contrary, if the patient can not follow the task priority instructions actively, different task difficulty adaptation strategies will be introduced according to patients' dual-task performance to help them better regulate their FOA. Specifically, if the performance of both cognitive and motor tasks is acceptable, the task difficulty level with high priority will be raised by one level. To ensure dual-task performance, patients have to devote most of their attention to the high-priority task since the difficulty of this single task is increased. If the performance of one sub-task is acceptable and one not, the difficulty level of the poorly performed sub-task will be reduced by one. If the performance of both cognitive and motor tasks is unacceptable, the difficulty of the task with lower priority will be reduced. In conclusion, the basic principle of the proposed task difficulty adjustment method is to raise the relative difficulty of the high-priority task to the low-priority task, thus helping patients better regulate their FOA. Note that if the task difficulty cannot be updated as required by the task difficulty adjustment strategy (e.g., if the difficulty level of the cognitive task is at its highest level and still needs to be increased), the current session will be terminated.

III. Experiment Design

A. Subjects

The experiments were conducted in collaboration with Beijing Bo'ai Hospital (China Rehabilitation Research Center). Fifteen patients with neurological deficits were recruited from the hospital. Prior to the clinical experiments, the protocol of the experiment has been approved by the Ethics Committee of China Rehabilitation Research Center (approval number: 2020-138-1, date of approval: December 9, 2020). Written informed consent was signed by each patient prior to the experiment in the study. The inclusion criteria for patients selection are given as follows:

1) The patient has experienced a first-ever neurological injury caused by a stroke.
2) The patient can perform resistance exercises to ensure that he/she is able to do treadmill training autonomously without assistance.
3) The patient should not have severe cognitive impairment to ensure that patients can carry out the DT-VP compliably.
4) The patient are able to complete up to 100 additions and subtractions.
5) The patient's hearing and understanding abilities are normal.
6) Patients with a history of severe systemic diseases such as heart, lung, liver, and kidney are excluded.

The clinical characteristics of the recruited patients are presented in Table II. Considering that the designed DT-VP paradigm has high requirements on patients' cognitive functions, such as their abilities to understand, execute and communicate, most of the subjects recruited in this study were patients with motor dysfunction.

B. Experiment Setup

In order to validate the feasibility of the proposed method in helping stroke patients better implement FOA switching and maintenance during DT-VP, a contrast experiment was designed according to whether there was the FOA regulation system. For both control and experiment groups, the difficulty level of each single task was initialized according to the doctor's advice at the beginning of the experiment, and the task priorities changed randomly during the training. In addition, no interventions were taken regardless of the patients' FOA performance during DT-VP for the control group. The task difficulty would remain the same as it was when the task was initialized. However, for the experiment group, the dual-task-difficulty-adaptation based FOA regulation method would be used to regulate patients' FOA for better task priority-following performance.

The experiment was conducted in a sound-proof room. All patients had a normal or corrected-to-normal vision and participated in both control group and experiment group. The wash-out period between the two experiments was about half an hour to give patients enough time to rest, thus minimizing the influence of the previous experiment on the next experiment. Before the experiment, the patients were required to wear a 32-Ag/AgCl-electrodes EEG cap for real-time EEG signal acquisition. The electrodes were placed according to the international 10–20 system and recorded at a sampling rate of 256 Hz (NeuroScan, NeuroScan Inc., Herndon, VA, USA). Considering that patients' movement would introduce some muscle artifacts to the EEG signals inevitably, they were asked to keep their upper body motionless as much as possible to minimize artifacts caused by motion. Specifically, the DT-VP included 5 blocks, each including 3 trials. During each one-minute long trail, subjects were required to vary and maintain their FOA to ensure the dual-task performance according to the displayed task-priority instructions.

As mentioned in Section II-B, power-spectra-based features extracted from single-task training were used to train the FOA tracking system. Therefore, before the DT-VP, patients must first perform

TABLE II
DEMOGRAPHIC AND CLINICAL CHARACTERISTICS OF THE RECRUITED PATIENTS WITH NEUROLOGICAL DEFICITS.

Age/Sex	Handedness	Disease course	Etiology	Damaged parts	FMA-UE	FMA-LE	MMSE
17/M	Right	5 months	HS	Left parietal-temporal lobe	55	25	29
27/M	Right	4 months	IS	Right frontal-parietal lobe	59	24	29
34/M	Right	1 months	IS	Right frontal lobe	57	28	26
35/F	Right	3 months	HS	Left basal ganglia lobe	64	25	26
41/M	Right	2 months	IS	Right frontal-parietal region	46	27	27
47/M	Right	3 months	IS	Left basal ganglia lobe	42	24	30
50/M	Right	4 months	HS	Right frontal lobe	62	27	27
52/M	Right	4 months	IS	Left frontal lobe	52	25	25
53/F	Right	3 months	HS	Bilateral frontal lobe	41	32	22
55/M	Right	4 months	IS	Left parietal lobe	54	28	24
57/M	Right	4 months	HS	Left frontal lobe	55	28	23
59/M	Right	3 months	HS	Left frontal-parietal lobe	58	26	26
59/M	Right	6 months	IS	Bilateral frontal lobes	44	29	25
60/M	Right	4 months	IS	Left frontal-parietal lobe	62	26	29
61/M	Right	2 months	IS	Right frontal-parietal lobe	65	24	29

HS = hemorrhagic stroke, IS = ischemic stroke, FMA-UE = Fugl-Meyer Assessment of Upper Extremity, FMA-LE = Fugl-Meyer Assessment of Lower Extremity, MMSE = Mini-Mental State Examination. All standard clinical tests were carried out for the extremity of the impaired side.

single-task training for subject-specific FOA tracking system establishment, which could be seen in Fig. 4(a), (b). During the single-task training, both pure mathematical problem-solving and speed-tracking riding tasks were performed for one block. Each block included 3 trials, and each trial lasted 15 seconds around. Specifically, in each trial, patients needed to finish 10 judgments during the mathematical problem-solving task; for the speed-tracking riding task, they were required to track the reference velocity trajectory as accurately as possible. After each trial, they were allowed to rest for 10 seconds to prepare for the subsequent trial. It should be noted that the designed motor task was conducted in a sitting position rather than a standing position because patients are difficult to keep their upper body motionless during standing-based riding task. The artifacts generated by these movements would seriously pollute the collected EEG signals. Therefore, a sitting-based riding paradigm was used to minimize muscle artifacts generated by movement.

Once EEG signals under single-task conditions were obtained, the FOA tracking model can be trained spontaneously. In order to increase the number of training samples and thus improve classification performance, the sliding-window strategy was introduced to preprocess the acquired EEG signals. The sliding window length was 256 sampling points, with 128 sampling points overlapping. Hence, 15-second EEG signals were divided into 29 segments, and thus, 174 training samples were obtained for the subject-specific FOA tracking model. EEG signals in every window were regarded as a sample for feature extraction and classification. Baseline correction, a band-pass filter (0.5-50 Hz), and a 50 Hz notch filter were applied to each sample to eliminate baseline drift, noise, and power frequency interference. The implementation details of the feature extraction and classification model selection are to be given in Sections IV-A and B, respectively. The preliminary experiment showed that the FOA classification performance can be guaranteed under this sample size. Finally, the FOA tracking and regulation based DT-VP can be executed (Fig. 4(c)). Specifically, the DT-VP included 5 blocks, each including 3 trials. During each one-minute long trail, subjects were required to vary and maintain their FOA to ensure the dual-task performance according to the displayed task-priority instructions.

IV. RESULTS AND DISCUSSION

A. FOA-Related EEG Features Analysis

Different brain regions' power spectra (E_{lobe}) across subjects during single-task training were calculated to find the EEG signatures with significant differences between the implementation of pure mathematical problem-solving task and pure speed-tracking riding task. The calculated power spectra were normalized to [0, 1].

$$E_{lobe} = \sum_{c=1}^{N} |F_c(f)|^2 = \sum_{c=1}^{N} \left| \int_{-\infty}^{+\infty} \mathrm{EEG}_c(t) e^{-j2\pi f t} dt \right|^2 \quad (2)$$

$$E_{norm} = \frac{E_{lobe} - E_{min}}{E_{max} - E_{min}} \quad (3)$$

where c is channel index, N represents the total channel number used for E_{lobe} calculation.

The calculated EEG signatures distributed in the frequency of 0.5-30 Hz are given in Fig. 5. In each sub-graph, only the channels distributed in the red area of the topographic map were used for power spectra calculation. By considering that EEG signals collected from channel Fp1 and Fp2 can be easily contaminated by ocular artifacts, these two channels were not included during frontal power spectra calculation. The normalized power spectra under pure math and riding training are shown in blue and red, respectively. The solid black lines indicate the frequency bins in which the normalized power differentiated between the two pure tasks significantly based on ANOVA. The dotted black lines indicate the selected crucial bands for FOA classification.

In Fig. 5, three frequency bands in different brain regions (theta band in frontal, parietal and temporal lobes, alpha band in parietal, temporal and motor lobes, and beta band in motor lobes) showed significant spectral differences during pure riding and math training, which suggested that patients' FOA on riding or math tasks could be discriminated through the above-mentioned brain dynamics. Furthermore, the motor areas exhibited a significant difference in the alpha and beta bands between riding and math tasks. To reduce the effect of motor-related activities arising from riding versus button press, the significantly differentiated features extracted from motor regions were excluded for FOA tracking system establishment.

B. Performance of the Candidate FOA Tracking Classifiers

Accuracy, recall, and F1-score of each candidate classifier were calculated to compare with each other for the eventual selection of the optimal attention tracking classifier. It can be seen from Table III that, for the FOA classification model, SVM, BPNN, and RF showed a better performance in FOA classification than the others. Moreover, SVM achieved the highest accuracy of 87.94%, which was

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(a) Pure mathematical problem-solving task training (b) Pure speed-tracking riding task training (c) DT-VP

Fig. 4. Clinical experiment scenes. (a) Single cognitive task training: mathematical problem-solving task; (b) Single motor task training: speed-tracking riding task; (c) Cognitive-motor dual-task training: DT-VP.

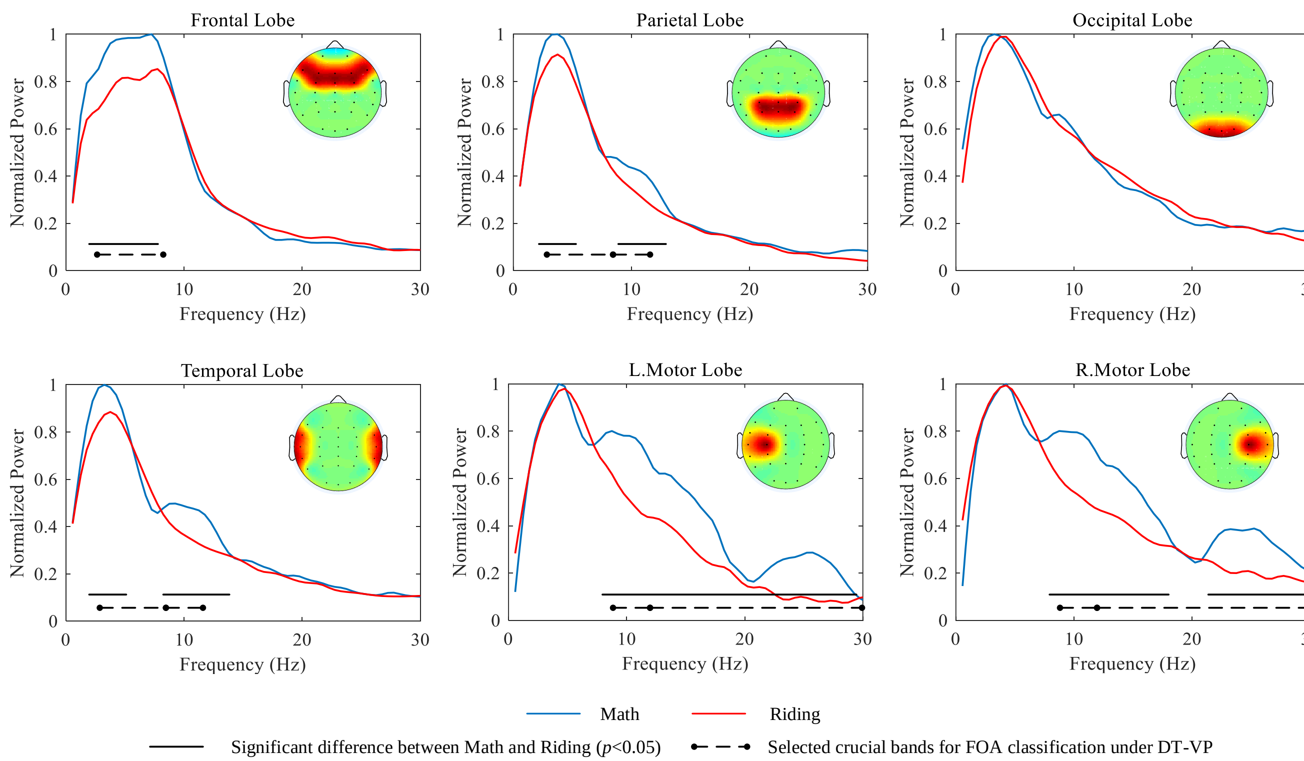

Fig. 5. Comparison of the normalized power spectra across subjects between pure mathematical problem-solving task and pure speed-tracking riding task conditions. The normalized power spectra of pure math and pure riding conditions are shown in blue and red lines, respectively. The black lines indicate the frequency bins in which the normalized power significantly differentiated between the two pure task (p <0.05). The black dot lines indicate the selected crucial bands for FOA classification under DT-VP.

higher than that of BPNN and RF by a margin of 3.19% and 5.32%, respectively.

TABLE III
THE CANDIDATE CLASSIFIER PERFORMANCE IN ACCURACY, RECALL, AND F1-SCORE.

Classifiers	Accuracy	Recall	F1-Score
SVM	**87.94**	**87.98**	**87.94**
BPNN	84.75	84.84	84.74
RF	82.62	82.70	82.61
KNN	81.91	81.96	81.91
NB	81.21	81.67	81.14
LDA	80.85	81.08	80.82
DAC	80.85	81.08	80.82
ENS	79.79	79.86	79.77

To further compare the classifiers mentioned above in FOA classification, ROC curves were plotted for all candidate classifiers, and AUC values were also calculated, which was regarded as a composite measure of classification performance among various classifiers. Fig. 6 showed that SVM had the highest AUC of 0.9 in estimating the participants' FOA on math or riding task. A larger ROC area for the SVM classifier in Fig. 6 further demonstrated the superior classification performance. Therefore, the significantly differentiated power spectra features, and SVM based FOA classifier were used to construct the FOA tracking system for DT-VP finally.

C. Behavior Performance During DT-VP

The behavioral performance is critical in revealing patients' FOA variations during the dual-task training [18]. Patients' behavioral performances under single-task and dual-task training were calculated and analyzed to validate whether the designed paradigm could induce

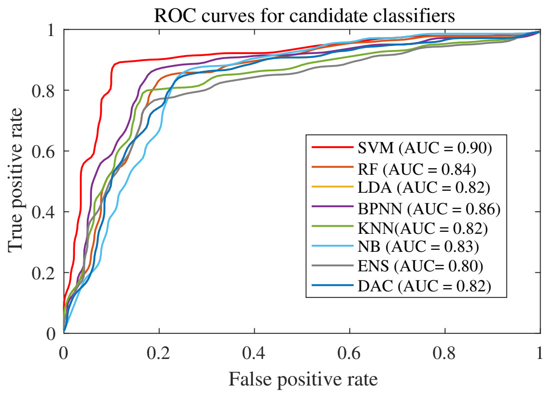

Fig. 6. ROC curves and AUC values for the candidate classifiers.

CMI first. CMI refers to the dual-task interference occurring when the simultaneous conduction of a cognitive and a motor task, leading to performance deterioration in one or both tasks. Patients' task performance under single-task training and dual-task training is given in Table IV to see whether CMI was induced in this study.

TABLE IV
MEAN CORRECT RATE, SOLUTION TIME, AND TRACKING ERROR PERFORMANCE DURING SINGLE TASK TRAINING AND DT-VP.

Settings	Priority	Performances: Correct rate	Solution time	Tracking error
Single-task training (Motor task)	/	/	/	0.35
Single-task training (Cognitive task)	/	0.93	1.49	/
DT-VP (Control group)	CT >MT	0.92	1.53*	0.47*
	MT >CT	0.94	1.64*	0.44*
DT-VP (Experiment group)	CT >MT	0.93	1.51*	0.52*
	MT >CT	0.93	1.75*	0.37*

"CT >MT" or "MT >CT" represent that the task priority of cognitive task (CT) is higher or lower than motor task (MT) during DT-VP. "*" represents for the significant difference between the dual-task training and the corresponding single-task training ($p < 0.05$).

In table IV, "CT >MT" or "MT >CT" represent that the task priority of cognitive task (CT) was higher or lower than motor task (MT) during DT-VP. "*" represents the existence of a significant difference between the task performance in dual-task training and the corresponding single-task training ($p < 0.05$). It can be seen that, as for the motor task performance, patients' tracking error in both control and experiment group under dual-task training was significantly increased than that under single motor task training; As for the cognitive task performance, patients' solution time in both control and experiment groups under dual-task training was significantly increased than that in single cognitive task training. These results showed that patients' performance under dual-task training was significantly decreased than that under single-task training, demonstrating the occurrence of CMI.

In order to validate the feasibility of the proposed method in task-priority following ability enhancement, the significance analysis of task performance between the control group and the experiment group during DT-VP was calculated and given in Table V. Patients' average correct rate performance between experiment group and control group did not show significant difference. As for the other two indicators, when the cognitive task was the high-priority task, patients' solution time in the experiment group showed a slight decrease but without a significant difference than that in the control group, and the tracking

TABLE V
SIGNIFICANCE ANALYSIS OF TASK PERFORMANCE BETWEEN CONTROL AND EXPERIMENTAL GROUPS DURING DT-VP.

Settings	Priority	Performances: Correct rate	Solution time	Tracking error
Control group	CT >MT	0.92±0.04	1.53±0.12	0.47±0.05
	MT >CT	0.94±0.04	1.64±0.16	0.44±0.03
Experiment group	CT >MT	0.93±0.03	1.51±0.14	0.52±0.06
	MT >CT	0.93±0.05	1.75±0.18	0.37±0.03
Significant test	CT >MT	$p = 0.884$	$p = 0.067$	$p = 0.001^*$
	MT >CT	$p = 0.729$	$p = 0.026^*$	$p = 0.002^*$

error showed a significant increase. When the motor task is the high-priority task, patients' motor task performance (tracking error) decreased significantly more than that in the control group. Meanwhile, the cognitive task performance (solution time) significantly increased. Smaller tracking errors and longer solution times suggested that patients put more attention into the speed-tracking task under high motor task priority instruction, which preliminarily validated the feasibility of the proposed method in helping patients better implement FOA switching and maintenance during DT-VP.

D. FOA During DT-VP

The percentage of time ($\triangle t$) when patients' FOA was put on the high-priority task during DT-VP was calculated for the control and the experiment groups, respectively. With the increase of $\triangle t$ ($0 \leq \triangle t \leq 100$), the more attention resources the subjects devoted to the high-priority task. It can be seen from Fig. 7 that patients paid more attention to the high-priority task during the training for both control and experiment groups ($\triangle t$ >50%). While patients in the

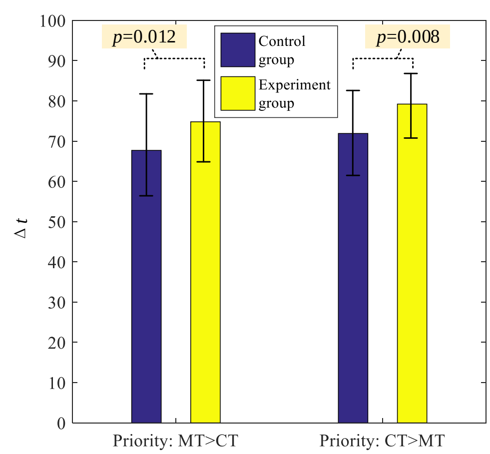

Fig. 7. The percentage of time ($\triangle t$) when patients' FOA was on the high-priority task during DT-VP.

experiment group can maintain their FOA on the high-priority task better. More concretely, when the motor task was the high-priority task, the percentage of time when patients' FOA was on the motor task in the experiment group was significantly higher than that in the control group by a margin of 7.1% ($p = 0.012$ <0.05). Likewise, when the cognitive task was the high-priority task, the percentage of time when patients' FOA was put on the cognitive task in the experiment group was significantly higher than that in the control group by a margin of 7.3% ($p = 0.0008$ <0.05).

Furthermore, to visualize the difference in neural activities under different paradigms, the PSD-based topographical maps in 3-30 Hz for both the control and experiment groups were also calculated and drawn in Fig. 8. The differences of brain activation in different

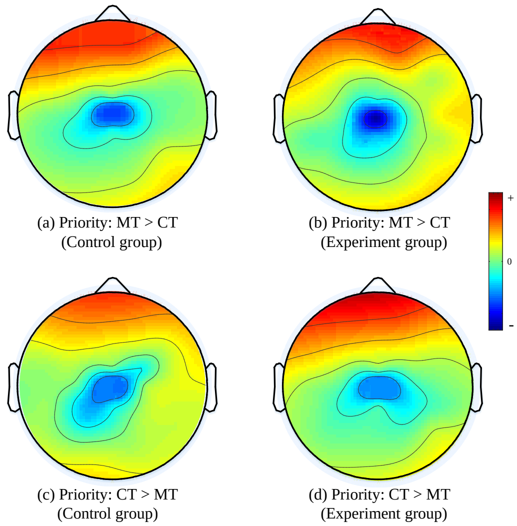

Fig. 8. The PSD based brain topographical maps for control group and experiment group.

tasks were mainly reflected in the frontal and motor cortex, which was consistent with previous studies [38]–[42]. Specifically, when the motor task was a high-priority task (Fig. 8(a) and 8(b)), the differences in brain activities was mainly reflected in the motor cortex. It has been proved that high motor task engagement was often related to an amplitude suppression of EEG signals in the motor cortex, such as the mu and central beta bands ERD (event-related desynchronization) [41], [42]. Fig. 8(a) and 8(b) showed that the ERD values (PSD) in the motor cortex was more distinct for the experiment group than that for the control group. This phenomenon demonstrated that patients could better switch and maintain their FOA on the high-priority task (motor task) using the proposed FOA regulation method.

Similarly, when the cognitive task was the high-priority task (Fig. 8(c) and 8(d)), the differences in brain activities were mainly reflected in the frontal region, and the PSD of the frontal region in the experiment group was higher than that in the control group. Since high attention level in the cognitive task was often related to an increase of theta band energy in the frontal region, Fig. 8(c) and 8(d) further revealed that patients could better switch and maintain their FOA on the high-priority task (cognitive task) in the experiment group. Based on the results mentioned above, it was verified that the proposed method could help stroke patients better implement FOA switching and maintenance by changing task priorities, and thus further promote the clinical application of DT-VP.

V. Discussion

Compared with the traditional DT-VP paradigm, the proposed FOA tracking and regulation based DT-VP training could lead to better allocation of attention, task switching, and synchronization. The results in Fig. 7 and Fig. 8 also demonstrated the feasibility of the proposed method in FOA regulation during DT-VP. Meanwhile, the activation intensity of the motor cortex and frontal region could be improved under high motor and cognitive task priority instructions, respectively.

The patient's FOA compliance is the key factor determining the rehabilitation benefits during DT-VP. In this study, the main reason for enhancing patients' task priority following ability was that the proposed dual-task difficulty adaptation strategy ensured high-priority task to attract more attention resources of patients. Specifically, during the training, if the FOA tracking system detected that patients could not shift or maintain their FOA successfully, the proposed dual-task difficulty adaptation method was triggered to increase the relative difficulty of the high-priority task with respect to the low-priority task. The corresponding high task performance constraints forced patients to pay more attention to the high-priority task, thus improving patients' task priority following ability.

In addition to the mentioned two dual-task paradigms in this paper, i.e., dual-task training under variable- or fixed-priority instructions, dual-task training with progression from variable- to fixed -priority instructions has been researched recently [43]. More concretely, in the first training session, subjects will be trained with dual-task activities exclusively under variable-priority instructions so that they can better learn and retain the motor and cognitive gains provided by this type of dual-task training. In the next training session, subjects will perform exclusively dual-task training with fixed priority to better mimic the functional activities of daily living. The validity of this paradigm needs to be studied and verified in the future.

Patients with severe cognitive impairment were excluded from this experiment. Two reasons can be given for the exclusion. First, in dual-task training, especially DT-VP, in addition to patients' computational ability, their abilities to memorize, understand, allocate attentional resources, and coordinate multi-tasks are also highly required. Patients with severe cognitive impairment generally have severe deficits in one or more of these cognitive functions. It is difficult for them to carry out the DT-VP compliably, which can easily induce their anxieties and is detrimental to rehabilitation. Secondly, in clinic, dual-task training is not recommended for patients with severe functional impairment. Studies have shown that patients with severe cognitive/motor function impairment are recommended to carry out single cognitive/motor task training and then switch to dual-task training gradually for the improvement of multitask coordination ability [44], [45].

The limitations that existed in this study can be given in three aspects. First, as for the design of the DT-VP paradigm, dual-task paradigm that constructed by a pure cognitive task and a pure motor task needs to be digged further. In this paper, the designed cognitive task was a mathematical-problem solving task. Subjects were supposed to press the left or right mouse button according to equation displayed on the screen. Therefore, motor activities caused by mouse press were inevitable, thus contaminating the collected cognitive-based EEG signals. The design of pure cognitive tasks will be studied in the future.

Second, as for the design of the FOA tracking model, the subject-independent FOA tracking model needs to be explored to reduce calibration time. EEG signals vary largely among individuals, which limits the generalization of attention tracking classifiers across subjects. Moreover, due to the non-stationary characteristic of EEG, a classifier trained early usually performs rather poorly at a later time on the same subject [46]. Therefore, the FOA classification model constructed in this study was subject-specific. Transfer learning methods, which can overcome the shortcoming that EEG patterns vary from subject to subject, can be explored to realize subject-independent FOA tracking in the future.

Finally, as for the design of the FOA regulation strategy, an optimization-based dual-task difficulty adaptation method can be introduced to achieve a better FOA regulation. The difficulty level of each single task in this study was predefined and divided into three levels. Conditions that the task difficulty level could not be updated as required by the task difficulty adjustment strategy sometimes occurred (e.g., the difficulty level of the cognitive task was at its highest level and still needed to be increased). The current session needed to be terminated under these circumstances. Therefore, optimization-based stepless task difficulty adaptation methods need to be researched in the future.

Additionally, the contrast experiment results demonstrated that patients could better shift and maintain their FOA according to the continuously changing priority instructions based on the proposed method. However, the substantial rehabilitation benefits brought out by this approach need to be confirmed in the future.

VI. Conclusion

In this study, an EEG-based FOA tracking and regulation system was designed to help stroke patients better follow the task priority instructions during DT-VP. The performance of the designed system was validated through the comparison experiments on fifteen stroke patients. The experiment results showed that patients' FOA distributed on the high-priority task was significantly improved ($p < 0.05$) using the proposed FOA regulation system. Meanwhile, the absolute PSDs of the motor cortex and the frontal region can also be improved during dual-task training under high motor and cognitive task priority instructions, respectively. These phenomena demonstrated the feasibility of the proposed method in helping stroke patients better implement FOA switching and maintenance, thus further promoting the clinical application of DT-VP.

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