Development of a Brain-Computer Interface-Based Symbol Digit Modalities Test and Validation in Healthy Elderly Volunteers and Stroke Patients

Xiaogang Chen, *Member, IEEE*, Nan Hu, and Xiaorong Gao, *Member, IEEE*

***Abstract*— Standard cognitive assessment tools often involve motor or verbal responses, making them impossible for severely motor-disabled individuals. Brain-computer interfaces (BCIs) are expected to help severely motor-impaired individuals to perform cognitive assessment because BCIs can circumvent motor and verbal requirements. Currently, the field of research to develop cognitive tasks based on BCI is still in its nascent stage and needs further development. This study explored the possibility of developing a BCI version of symbol digit modalities test (BCI-SDMT). Steady-state visual evoked potential (SSVEP) was adopted to build the BCI and a 9-target SSVEP-BCI was realized to send examinees' responses. A training-free algorithm (i.e., filter bank canonical correlation analysis) was used for SSVEP identification. Thus, examinees are able to start the proposed BCI-SDMT immediately. Eighty-nine healthy elderly volunteers and 9 stroke patients were enrolled to validate the technical feasibility of the developed BCI-SDMT. For all participants, the average recognition accuracies of the developed BCI and BCI-SDMT were 93.89 ± 8.48% and 92.58 ± 10.52%, respectively, were considerably above the chance level (i.e., 11.11%). These results indicated that both healthy elderly volunteers and stroke patients could elicit sufficient SSVEPs to control the BCI. Furthermore, patient use of the developed BCI-SDMT was unaffected by the presence of motor impairment. They could understand instructions, pair numbers with specific symbols, and send commands using the BCI. The proposed BCI-SDMT can be used as a complement to the existing versions of the SDMT and has the potential to evaluate cognitive abilities in individuals with severe motor disabilities.**

***Index Terms*— BCI, SDMT, SSVEP, EEG.**

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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 Institutional Review Board of The Second Affiliated Hospital of Guangzhou Medical University.

Xiaogang Chen is with the Institute of Biomedical Engineering, Chinese Academy of Medical Sciences and Peking Union Medical College, Tianjin 300192, China (e-mail: chenxg@bme.cams.cn).

Nan Hu is with the Rehabilitation Department, The Second Affiliated Hospital of Guangzhou Medical University, Guangzhou 510260, China (e-mail: nanhuajm@163.com).

Xiaorong Gao is with the Department of Biomedical Engineering, School of Medicine, Tsinghua University, Beijing 100084, China (e-mail: gxr-dea@tsinghua.edu.cn).

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I. Introduction

STROKE is an acute cerebrovascular disease, which has become the second leading cause of death and the third leading cause of combined death and disability globally [1]. More than 80 million stroke survivors are disabled worldwide [2]. The number of stroke survivors is foreseen to grow due to an aging population and improvements in treatment and stroke care [3]. Stroke survivors are usually accompanied by multiple impairments, including motor impairments, speech dyfunctions, cognitive deficits, and emotional problems [4]. Thus, it is necessary to seek better and more effective rehabilitation interventions.

Cognition deficit is common in stroke patients and has become one of the top ten research priorities for stroke survivors [5]. Cognitive impairment post stroke will significantly reduce patients' participation in daily activities, thereby placing a heavy burden on families and society. Processing speed and attention are critical cognitive functions for individuals [6]. Stroke survivors often have deficit in processing speed and attention [7]–[8]. Early detection facilitates early intervention, which will generate better results in reduction of brain damage and other complications. Therefore, assessing processing speed and attention is crucial for stroke rehabilitation. Symbol digit modalities test (SDMT) is a symbol substitution test and is widely utilized to assess executive function, processing speed, and attention in both healthy examinees and peoples with a variety of neurological diseases [9]–[10], including stroke [6], [8], multiple sclerosis [11], and Alzheimer's disease [12]. Examinees are given a series of symbols and a key consisting of nine symbol-number pairs. They then need to pair as many specific numbers as possible with given geometric symbols based on the reference key within a 90-s period. This test involves multiple cognitive processes, including attention, visual scanning, and motor speed [13]. The SDMT can be implemented in various versions. In the written version of the SDMT, examinees need to write matching numbers on the paper as quickly and accurately as possible. In the oral version, examinees say the matching numbers and examiners record the

TABLE I
DEMOGRAPHIC AND CLINICAL CHARACTERISTICS OF THE STROKE PATIENTS

Patients	Age (years)	Gender	Stroke type	Time since stroke onset (months)	Side of hemiplegia	Dysfunction	Barthel Index
P1	33	Male	Cerebral haemorrage	10.5	Right	Motor	85
P2	47	Male	Cerebral infarction	7.5	Left	Motor, speech	65
P3	42	Male	Cerebral infarction	4	Left	Motor, sensation	85
P4	34	Male	Cerebral haemorrage	3	Left	Motor, speech, sensation	65
P5	64	Male	Cerebral infarction	0.5	Right	Motor, speech	60
P6	66	Male	Cerebral infarction	0.5	Right	Motor, speech, sensation	60
P7	74	Female	Cerebral infarction	2.5	Bilateral	Motor	70
P8	58	Male	Cerebral haemorrage	12	Right	Motor, speech	60
P9	85	Male	Cerebral infarction	1	Right	Motor, speech, deglutition	55
Mean±SD	55.89±18.11	-	-	4.61±4.36	-	-	67.22±10.93

examinees' responses. The computerized SDMT presents nine symbol-number pairs and nine probe symbols on a computer screen, and then requires a verbal response from the examinees [14]. Recently, Tablet-based SDMT [15] and smartphone-based SDMT [16] have been proposed successively. However, these aforementioned versions require examinees to have a certain level of motor ability. Thus, these versions may be challenging for severely motor-impaired individuals. Over the past decade, brain-computer interfaces (BCIs) have emerged as one of the most promising techniques for severely motor-impaired individuals. BCIs allow individuals to interact with the outside world using brain signals [17]. This feature enables BCIs to provide individuals with motor disabilities an alternative way to communicate with the external environment and control their daily behaviors.

The present study attempted to develop a novel BCI-based SDMT (BCI-SDMT). The nine symbols with clearly distinct shapes were adopted in the BCI-SDMT to better distinguish the symbols and thus reduce SDMT's random measurement error. Furthermore, the symbol-number pairs and the symbol probe are different for all trials to avoid a possible practice effect. Examinees were required to pair specific number with the symbol probe according to the symbol-number pairs. Steady-state visual evoked potential (SSVEP) was adopted to build a BCI, which was built consisting of nine targets arranged in a 3-by-3 grid design to send examinees' commands. Examinees focused their attention on the corresponding target to input their responses. Thus, the proposed BCI-SDMT was also suitable for severely motor-impaired individuals. The online experimental results obtained from healthy elderly individuals and stroke patients verified the proposed BCI-SDMT's feasibility.

II. METHODS

A. Participants

A total of 98 participants (89 healthy elderly volunteers and 9 stroke patients) were recruited for this study. There were eighty-nine healthy elderly volunteers (27 males and 62 females, age range 51-81 years, mean age 63.18 years) and nine in-hospital stroke patients (8 males and 1 female, age range 33-85 years, mean age 55.89 years) (see Table I). Both healthy elderly volunteers and stroke patients were naïve BCI users. Each participant signed an informed consent form and received appropriate monetary compensation after the experiments. The present study was approved by the Institutional Review Board of The Second Affiliated Hospital of Guangzhou Medical University.

B. Behavioral Task

The written format of the SDMT was adopted in the present study. Examinees are presented a 9 symbol-number pairs key, where each geometric symbol is paired with a specific number. In accordance with the coded key, examinees were required to match specific numbers with given symbols. After completing a practice session of 15 items with guidance, examinees begin to perform the formal test. In this study, we obtained the number of correct written responses per subject within a 90-s period. Since SDMT only involves numbers and geometric symbols, SDMT is relatively culture-free and can be used by both children (eight years and older) and adults.

i-SDMT is also a substitute task in which numbers are paired with geometric symbols and the correct written number needs to be determined for a sequence of geometric symbols [18]. i-SDMT is similar to SDMT except that the geometric symbol is different. To reduce SDMT's random measurement error, the nine symbols with clearly distinct shapes were adopted in the i-SDMT for better symbol differentiation [15], [18]. The procedure of i-SDMT is the same as that of SDMT.

C. BCI-SDMT

The present study developed a novel BCI-SDMT. The nine symbols in BCI-SDMT remain the same as the nine symbols in i-SDMT. Fig. 1(a) shows the schematic representation of the BCI-SDMT user interface. As illustrated in Fig. 1, a coded key pairing each geometric symbol with a different number is displayed at the top of the user interface. According to the coded key, examinees were required to seek the number to pair with the symbol in the middle of the user interface. Subsequently, examinees were asked to gaze at the corresponding number on the 3-by-3 grid at the bottom of the user interface. A nine-target SSVEP-BCI was developed to encode visual stimuli for numbers on the 3-by-3 grid. Figure 1(b) shows the encoded phase and frequency values for each target. The stimulation frequencies used to induce SSVEPs ranged from 8.0 Hz to 12.0 Hz. The frequency interval and phase interval between adjacent stimulation frequencies were 0.5 Hz and 0.5π, respectively. In this study, the sampled sinusoidal stimulation approach [19] was adopted to realize

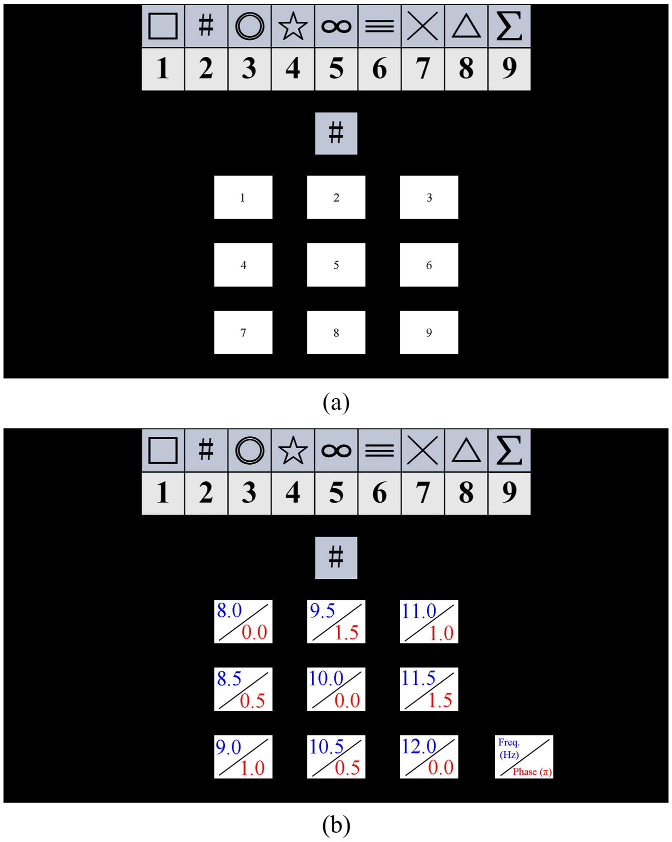

Fig. 1. System design of the developed BCI-SDMT. (a) The schematic representation of the BCI-SDMT user interface. (b) The encoded phase and frequency values for each target.

visual stimuli. Visual stimuli were presented on a 27-inch computer monitor (1920 × 1080 pixels, 60 Hz refresh rate). The size of each target was 168 × 125 pixels. The horizontal and vertical distances of adjacent targets were 100 pixels and 70 pixels, respectively.

D. Experimental Procedure

The i-SDMT and SDMT were performed in all participants in a random order. We could obtain the number of correct written responses in 90 seconds.

An online BCI experiment was carried out to test the BCI performance of the BCI-SDMT. The nine symbol-number pairs at the top of the user interface and the symbol probe in the middle of the user interface remained unchanged throughout this experiment. Seven blocks were recorded in this experiment. Nine trials were included in each block, and each trial corresponded to each target. Therefore, each target obtained 7 trials in the online BCI experiment. A 4-s visual cue (a green rectangle at the target location) was first presented on the screen. Subsequently, all nine visual stimuli flashed simultaneously for 5 seconds, and participants were required to gaze at the target stimulus. After the flicker offset, participants received visual feedback, which was presented for 1 second. Namely, the identified target stimulus would turn red. Thus, each trial lasted 10 seconds (see Fig. 2).

An online BCI-SDMT experiment was performed to verify the proposed BCI-SDMT's feasibility. The online BCI-SDMT consisted of 7 blocks. Each block included one trial for each target. Thus, each block included 9 trials. A user interface of the BCI-SDMT was first presented on the screen and was presented for 4 seconds. During this period, participants were asked to first look at the symbol probe in the middle of the user interface, then seek the corresponding number to pair with the symbol probe according to the nine symbol-number pairs at the top of the user interface, and finally gaze at the corresponding number on the 3-by-3 grid at the bottom of the user interface. Subsequently, all nine visual stimuli at the bottom of the user interface flashed simultaneously for 5 seconds, and participants were required to continuously focus their attention on the target stimulus. After the flicker offset, the identified target stimulus would turn red and present for 1 second (see Fig. 3). The length of one trial was 10 seconds. The symbol-number pairs are different for all trials to avoid a possible practice effect. Moreover, the proposed system can automatically record examinees' responses, which can reduce labor costs.

E. EEG Acquisition

A Neuroscan SynAmps2 amplifier (sampling rate 1000 Hz, band pass 0.15-200 Hz) was adopted to acquire EEG data. An online notch filter was set to eliminate 50 Hz line frequency interface. The reference and ground electrodes were mounted on vertex and between FPz and Fz, respectively. The stimulus onset was marked in the EEG data through parallel port.

F. EEG Analysis

According to the event markers, the EEG data were segmented into event-related epochs. The visual system's latency delay [20] was taken into account in the epoch analysis, and then the epochs were extracted 0.14-s after the stimulation onset. To facilitate efficient data processing, all epochs were downsampled to 250 Hz.

The filter bank canonical correlation analysis (FBCCA) was used for SSVEP identification [21]. FBCCA first decomposes an epoch into multiple sub-bands through filter bank analysis, and then performs CCA on each sub-band separately. In the present study, the n-th sub-band frequency range was from $n \times 8$ Hz to 88 Hz. Subsequently, CCA is performed on each sub-band to obtain the correlation values between sine-cosine reference signals and each sub-band and then form the correlation vector $\rho_f = \left[\rho_f^1, \ldots, \rho_f^N\right]^T$, where N is the number of sub-bands. A weighted sum of the square of the correlation values corresponding to all sub-bands is acted as the feature for target identification:

$$\tilde{\rho}_f = \sum_{n=1}^{N} w(n) \cdot \left(\rho_f^n\right)^2 \tag{1}$$

where weight $w(n)$ was set to $n^{-a} + b$. In this study, a, b, and the number of sub-bands were set to 1.25, 0.25, and 5, respectively. $\tilde{\rho}_f$ corresponding to all stimulation frequencies are calculated, and the frequency of the reference signals with the maximum correlation is determined as the target stimulus.

III. Results

All participants performed the SDMT, i-SDMT, and BCI-SDMT tasks. The number of correct responses on the SDMT in the healthy elderly volunteers ranged from 22 to 65

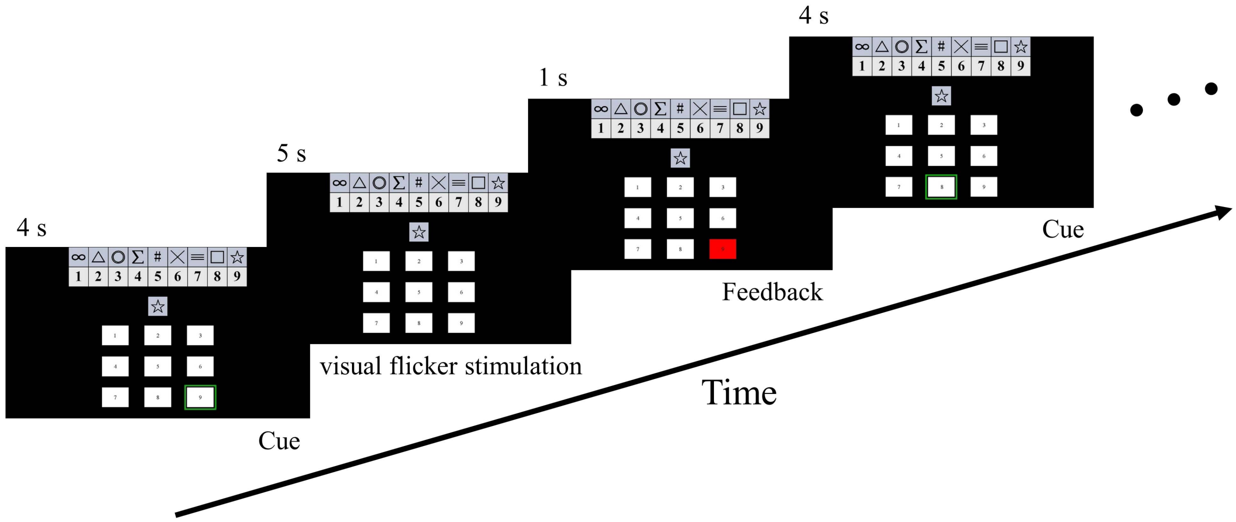

Fig. 2. Schematic illustration of a trial sequence for the online BCI experiment.

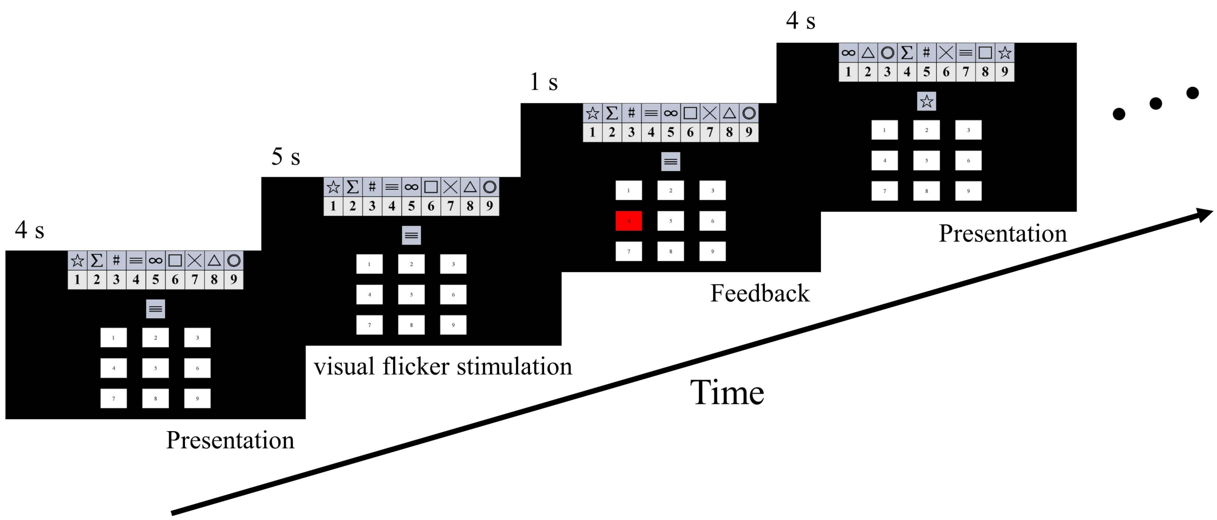

Fig. 3. Schematic illustration of a trial sequence for the online BCI-SDMT experiment.

TABLE II
EXPERIMENTAL RESULTS OF THE STROKE PATIENTS

Patients	SDMT	i-SDMT	BCI (%)	BCI-SDMT (%)
P1	23	25	100.00	100.00
P2	26	45	77.78	77.78
P3	62	69	100.00	93.65
P4	31	26	92.06	92.06
P5	23	24	79.37	73.02
P6	27	22	92.06	93.65
P7	17	19	68.25	74.60
P8	14	18	95.24	100.00
P9	11	11	63.49	82.54
Mean	26.00	28.78	85.36	87.48
SD	14.96	17.68	13.60	10.63

(mean $= 34.78 \pm 8.19$) (see Fig. 4(a)). The SDMT results obtained from the healthy elderly volunteers were within the normal range. Table II shows the results obtained from the stroke patients. As listed in Table II, the number of correct responses performed by the stroke patients on the SDMT ranged from 11 to 62 (mean $= 26.00 \pm 14.96$). Wilcoxon rank sum test revealed a significant difference in SDMT results between healthy elderly volunteers and stroke patients ($p < 0.01$). The number of correct answers performed by the healthy elderly volunteers on the i-SDMT ranged from 25 to 76 (mean $= 42.72 \pm 9.33$). And the average number of correct responses for the i-SDMT in the stroke patient was 28.78 ± 17.68. Wilcoxon rank sum test showed that a significant difference was found in the i-SDMT performance between healthy elderly volunteers and stroke patients ($p < 0.01$). These results suggested that healthy elderly volunteers performed better on the SDMT and i-SDMT compared to stroke patients. Motor responses were required for the SDMT and the i-SDMT in this study. These results indicated that impaired motor function could affect the responses of the SDMT and the i-SDMT. To investigate assessment of consistency between the SDMT and the i-SDMT, this study regressed the results of the SDMT and the i-SDMT (see Fig. 4(b)). This analysis included results from healthy elderly volunteers and stroke patients. As shown in Fig. 4 (b), the i-SDMT shows strong association with the SDMT ($R^2 = 0.65$,

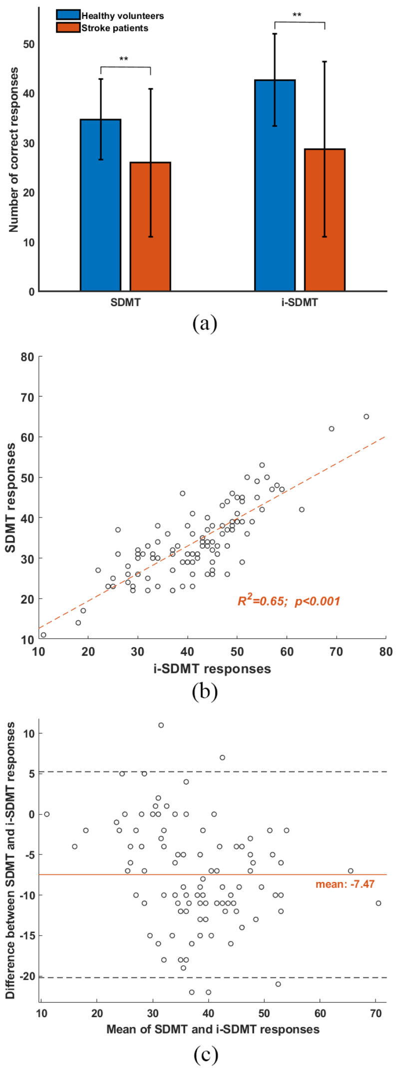

Fig. 4. Behavioral results from the SDMT and i-SDMT. (a) Average number (±SD) of correct responses by healthy elderly volunteers and stroke patients in the SDMT and i-SDMT. The error bar indicates the standard deviation. (b) Association of the SDMT and the i-SDMT. (c) Bland-Altman comparison of the i-SDMT with the SDMT.

$p < 0.001$). Fig. 4 (c) illustrates Bland-Altman comparison of the SDMT and i-SDMT results. As show in Fig. 4 (c), the limits of agreement are −20.19 and 5.25. The difference between SDMT and i-SDMT responses is −7.47. Namely, participants obtained a mean of 7.47 responses higher for the i-SDMT compared with the SDMT. This may be due to the use of symbols with clearly different shapes, which facilitates user testing. Thus, the symbols with clearly different shapes were adopted in the subsequent experiments.

Fig. 5 shows the mean identification accuracy of the proposed BCI for each command. It can be seen that the mean identification accuracy of each command is above 90%. Furthermore, the accuracy of each command is comparable. One-way repeated measures ANOVA showed a statistical significance ($F(8,776) = 2.88$, $p = 0.02$), but no statistically significant differences were not found in the post-hoc tests. The average accuracies of the proposed BCI were 93.89 ± 8.48 %. All participants were naïve BCI users. The high accuracy of the proposed BCI revealed that all participants

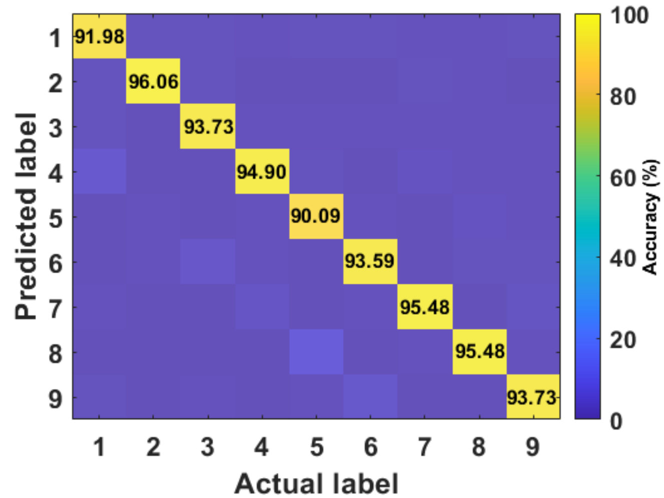

Fig. 5. The mean identification accuracy of the proposed BCI for each command.

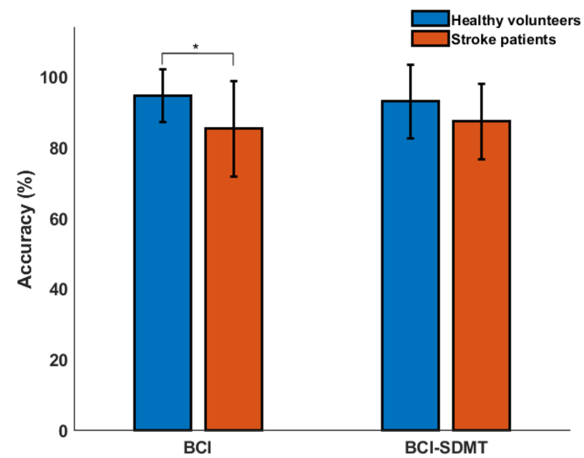

Fig. 6. The online results obtained from the BCI experiment and BCI-SDMT experiment. The error bar represents the standard deviation.

were able to generate SSVEPs and were sufficient to control the nine-command BCI.

Fig. 6 shows the online results obtained from the BCI experiment and BCI-SDMT experiment. As can be seen from Fig. 6, the healthy elderly volunteers obtained an average recognition accuracy of 94.76 ± 7.36% in the BCI experiment. While the average recognition accuracy for the stroke patients is 85.36 ± 13.60%. Healthy elderly volunteers' performance was better than stroke patients' performance. Wilcoxon rank sum test revealed a significant difference in BCI accuracy between healthy elderly volunteers and stroke patients ($p < 0.05$). In the BCI-SDMT experiment, the mean recognition accuracies for the healthy elderly volunteers and stroke patients are 93.10 ± 10.43% and 87.48 ± 10.74%, respectively. Although healthy elderly volunteers' performance was slightly better than stroke patients' performance, Wilcoxon rank sum test showed no obvious difference in BCI-SDMT performance between healthy elderly volunteers and stroke patients ($p > 0.05$). These results suggested that impaired motor function did not seem to affect the performance of the proposed BCI-SDMT. In this study, all participants performed the BCI

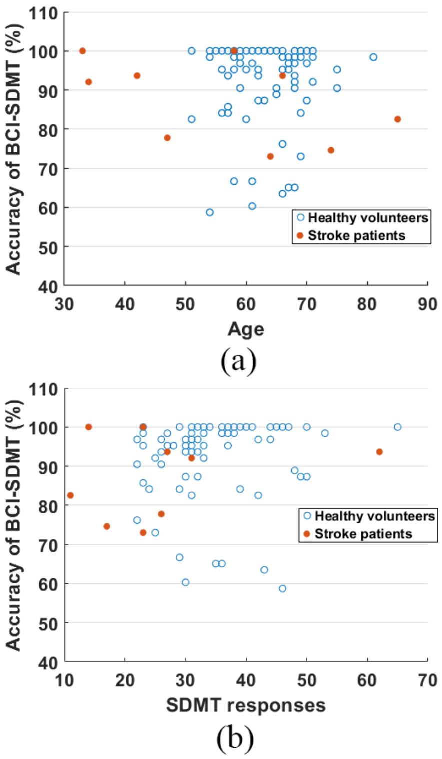

Fig. 7. The relationship between the BCI-SDMT accuracy and the age of all participants (a), and the BCI-SDMT accuracy and the SDMT responses (b).

task first, followed by the BCI-SDMT task. After performing the BCI task, some patients might be familiar with the SSVEP paradigm and be better able to perform the BCI-SDMT task. In addition, the sample size of stroke patients was relatively small. The results of some patients might have a greater impact on the overall results. Paired t-test showed that the BCI performance of healthy elderly volunteers outperformed their BCI-SDMT performance ($p < 0.05$). While the BCI performance of stroke patients was not significantly different from their BCI-SDMT performance ($p > 0.05$). For all participants (including 89 healthy elderly volunteers and 9 stroke patients), the average accuracies of the BCI and the BCI-SDMT were $93.89 \pm 8.48\%$ and $92.58 \pm 10.52\%$, respectively. The high performance indicated that all participants were able to use the proposed BCI to select command. Thus, these results suggested that both healthy elderly volunteers and stroke patients had intact visual discrimination since they were able to choose the correct visual target according to the instruction. Paired t-test showed that BCI-SDMT performance was significantly lower than the BCI performance ($p < 0.05$), which verified that the BCI-SDMT task was harder than the BCI task.

Fig. 7(a) shows the relationship between the recognition accuracy of the BCI-SDMT and the age of all participants. The chance level for the nine-choice task is 11.11%. As shown in Fig. 7(a), the recognition accuracies of the BCI-SDMT for all participants are above the chance level (i.e., 11.11 %). Moreover, the BCI-SDMT performance measured as recognition accuracy is independent of age in all participants ($R^2 = 0.0008$, $p = 0.78$). Besides, no significant correlation was observed between the SDMT responses and the BCI-SDMT accuracy ($R^2 = 0.033$, $p = 0.074$).

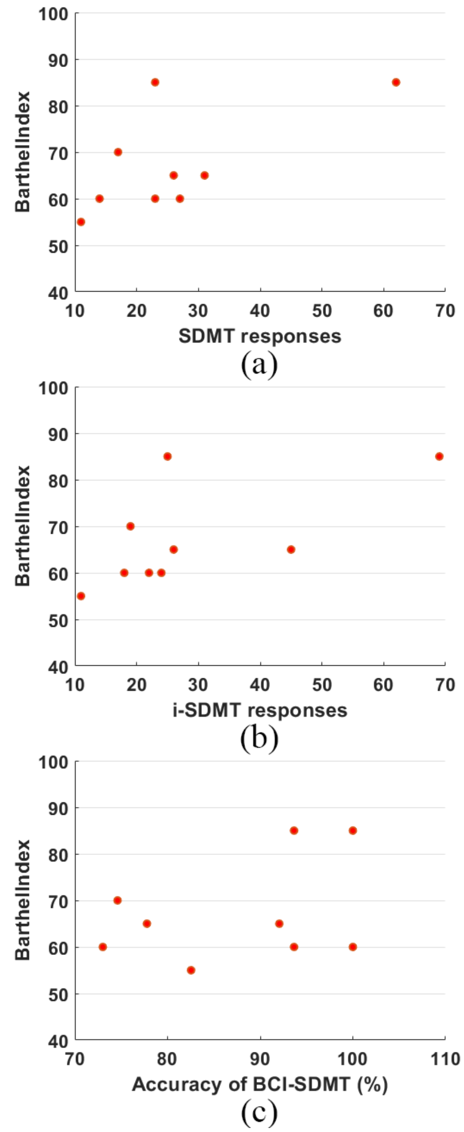

Fig. 8. The relationship between the Barthel Index and the SDMT response (a), the Barthel Index and the i-SDMT response (b), and the Barthel Index and the recognition accuracy of the BCI-SDMT (c).

Based on the data obtained from the stroke patients, we further investigated the relationship between the Barthel Index and the SDMT response, the Barthel Index and the i-SDMT response, and the Barthel Index and the recognition accuracy of the BCI-SDMT (see Fig. 8). No significant correlation was observed between the Barthel Index and the SDMT response ($R^2 = 0.41$, $p = 0.06$), nor the Barthel Index and the i-SDMT response ($R^2 = 0.39$, $p = 0.07$). Although there was also no significant correlation between the Barthel Index and the recognition accuracy of the BCI-SDMT ($R^2 = 0.13$, $p = 0.34$), its R-square value was obviously lower than that of the Barthel Index and the SDMT response, and the R-square value of the Barthel Index and the i-SDMT response. This trend suggested that the developed BCI-SDMT was less susceptible to patient dysfunction than the SDMT and the i-SDMT.

IV. Discussion

Besides motor deficits, stroke patients have also been reported to show deficits in terms of executive function, processing speed, attention, and memory [4], [22]. Among them, attention impairment is the most common post-stroke neuropsychological change [23]. In most stroke rehabilitation therapies, patients need to maintain sustained attention to rehabilitation tasks [4], which is very important for their functional prognosis [23]. Therefore, it is very necessary for stroke patients to perform cognitive assessment, especially the attention assessment. The SDMT is a commonly used tool for evaluating attention, processing speed and executive function in several neurological disorders [9]–[10]. Since the SDMT involves multiple cognitive processes, it is associated with brain activity in several brain regions, including regions of the frontoparietal attentional network and occipital cortex, cuneus, precuneus, cerebellum [10]. Although various versions of SDMT have been developed in recent years, examinees need to have a certain level of motor ability to use them. According to Table I, motor impairment is one of the most common dysfunctions after stroke. Impaired motor function will directly affect the outcome of the SDMT. The stroke patients performed poorly compared to healthy elderly volunteers in the SDMT and i-SDMT (see Fig. 4). This suggested possible relational motor deficits in stroke patients. Furthermore, individuals with severe motor disabilities are difficult to use traditional cognitive assessment methods because of motor impairment. The assessment and training of cognitive function are of great help in the recovery of other functions. Thus, cognitive assessment in individuals with severe motor disabilities is a challenging issue. In addition, speech dysfunctions can also affect the assessment of attention disorders. For example, the oral version of the SDMT can be used for patients with movement disorder, but it cannot be used for patients with both speech and movement disorders. BCIs allow individuals to use brain signal to directly communicate or control external devices, which provides individuals the possibility of performing cognitive assessment without verbal or motor response requirements. Several BCI-based neuropsychological assessment methods have been developed in recent years [18], [24]–[27]. For example, BCI-based Raven's Coloured Progressive Matrices (RCPM) [24]–[25], BCI-based peabody picture vocabulary test (PPVT-IV) [27], and BCI-based Digit Symbol Substitution Test (DSST) [18]. These abovementioned studies demonstrate the potential of BCI for cognitive assessment. To the best of our knowledge, no BCI-based SDMT related studies have been reported to date.

Since SSVEP-based BCI has the advantages of high communication rate and no or less training [28]–[30], this study adopted SSVEP-based BCI to send examinees' commands. A 9-target SSVEP-BCI was realized in this study. Examinees shifted their attention to the selected flickering digit stimulus to convey their intention without verbal or motor response requirements. Moreover, SSVEP has been widely used as a sensitive index of selective attention, which increases SSVEP strength [31]–[33]. Therefore, the proposed BCI-SDMT circumvented motor and verbal requirements, thereby providing a more robust assessment of attention components. Target identification algorithm is a critical part in a BCI system. The present study adopted the FBCCA method to detect SSVEPs. The FBCCA method is a training-free method, which does not need to collect any training data. Thus, users are able to start the proposed BCI-SDMT immediately. In addition, this study adopted nine symbols with clearly distinct shapes to build the proposed BCI-SDMT. These symbols were the same as those in Tung *et al.*'s (2016) [15] and Tang *et al.*'s (2018) [34] and had been verified to reduce the SDMT's random measurement error. The symbol-number pairs and the symbol probe are different from trial to trial to avoid a possible practice effect. Moreover, the proposed BCI-SDMT could automatically record examinees' responses, which could reduce the burden on examiners. For all participants, the average accuracies of the BCI and the BCI-SDMT were $93.89 \pm 8.48\%$ and $92.58 \pm 10.52\%$, respectively, were considerably above the chance level (i.e., 11.11%). High accuracy of the developed BCI-SDMT verified that both healthy elderly volunteers and stroke patients understood the experimental instructions and were able to use the developed BCI to choose the correct visual target. In this study, the number of correct responses in the written SDMT for three stroke patients (i.e., P7, P8, and P9) is less than 21, which was not in the normal range. However, the BCI-SDMT accuracy for these three patients was higher than 70%, which were considerably above the chance level (i.e., 11.11%). The results obtained from the proposed BCI-SDMT indicated that the three patients could control the proposed BCI system with a nine-choice task and had a proper cognitive skill to choose correct answers. Moreover, no significantly difference was found in BCI-SDMT accuracy between healthy elderly volunteers and stroke patients (see Fig. 6). The written SDMT requires motor responses, and impairment of motor function can affect its outcome. While patient use of the developed BCI-SDMT was unaffected by the presence of motor impairment. The proposed BCI-SDMT can be used as a complement to the existing versions of the SDMT. These results suggested that the proposed BCI-SDMT had great potential for use in testing populations for whom standardized testing was not available.

Subsequent studies will employ different strategies to facilitate flexible use of the proposed BCI-SDMT in patients with cognitive impairment, such as increasing stimulation duration or its size, while using high-frequency stimulation to improve system comfort. New hydrogel-based flexible electrode technology [35] will be used to develop BCI system for reducing setup time. Further work will try to develop asynchronous control mode, which allows examinees to self-control the pace of the assessment. Execution time may be served as an optional metric for BCI-based cognitive assessment [36]. In this study, only 9 stroke patients participated these experiments. Compared with 89 healthy elderly subjects, the sample size of stroke patients was relatively small. In the present study, all participants (including 89 healthy elderly volunteers and 9 stroke patients) had normal cognitive function. The results from these participants verified the feasibility of the proposed BCI-SDMT. Further work will try to recruit patients with cognitive impairment to further verify the feasibility of the proposed BCI-SDMT. Meanwhile, we will focus on increasing the sample size and expanding the target population. For example, an attempt will be made to verify the developed system's feasibility on peoples with Parkinson's and Alzheimer's patients.

V. Conclusion

The present study developed a novel BCI-based SDMT for cognitive assessment. Nine stroke patients and 89 healthy elderly subjects were used to evaluate the feasibility of the proposed BCI-SDMT. All participants successfully completed the proposed BCI-SDMT task and obtained an average accuracy of 92.58 ± 10.52%, which was considerably above the chance level. The accuracy of stroke patients was comparable to that of the healthy elderly subjects. Although three patients obtained lower SDMT and i-SDMT results due to the patients' motor impairment, they still obtained a high BCI-SDMT accuracy. These results suggested that patient use of the developed BCI-SDMT was unaffected by the presence of motor impairment. The proposed BCI-SDMT was a motor-verbal free test that could provide related information for clinical practice. Individuals with severe motor impairments are expected to benefit from the proposed system.

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