Abstract: Early diagnosis is important in the treatment of dementia; however, many dementia patients are resist seeking medical attention. In our laboratory, we are developing a dementia screening tool using the P300-based Spelling-Brain-Computer Interface (Spelling-BCI) to facilitate early dementia diagnosis. By estimating the results of neuropsychological examinations that must be performed by a specialist with BCI, we consider that an easy cognitive function test with Spelling-BCI can be realized. Multiple regression analysis was performed using the features obtained from the Spelling-BCI and the age of the subjects, and Mini-Mental State Examination (MMSE), Japanese Version of Montreal Cognitive Assessment (MoCA-J), and Frontal Assessment Battery (FAB) scores were estimated. In the multiple regression analysis, variable selection was performed using the forward-backward stepwise selection method, and data exceeding the 95% confidence interval of the estimation error were excluded. As a result, the adjusted R-squared exceeded 0.95 in the estimation model of each neuropsychological examination. Therefore, the experimental results suggest that neuropsychological examinations can be estimated using the Spelling-BCI.

Keywords: Dementia, BCI, MMSE, MoCA-J, FAB

1. INTRODUCTION

The number of dementia patients in Japan is projected to increase to approximately 6.5-7 million in 2025 and approximately 8.5-11.5 million in 2060 [1]. Early detection is important in the treatment of dementia; however, according to Black et al., the mean time from initial symptoms to the first consultation is 7.4±6.9 months [2]. In addition, the mean time from the first consultation to formal diagnosis is 2.9±11.0 months [2]. Thus, early diagnosis of dementia is difficult. Therefore, a testing device that can easily measure dementia patients at home or in public facilities without going to the hospital is required to recommend seeing a specialist depending on the results.

In our laboratory, we are developing a cost effective and simple dementia screening device that uses the P300-based Spelling-Brain-Computer Interface (Spelling-BCI). Previously, Kurihara et al. demonstrated the relationship between the erroneous input distance value Spelling-Error Distance Value (SEDV) and cognitive decline, and they identified that it is possible to realize a simple screening device [3].

According to Black et al., 81.2% of dementia patients are examined by specialists that perform various tests, e.g., neuropsychological examinations [2]. Miwa et al. estimated the score of the neuropsychological examination Mini-Mental State Examination (MMSE) by measuring P300, and its adjusted R-squared was 0.73 [4].

Therefore, in this study, we attempt to estimate the results of neuropsychological examinations at high accuracy by measuring cognitive functions using the Spelling-BCI in order to realize tests that are similar to those of specialists.

2. EXPERIMENT

2.1 Experimental method

This study was conducted on a total of 78 patients in their 60s to 90s (average age: 79.3±5.43 years) who visited the outpatient department of the Department of Elderly Care, Tokyo Medical University. This experiment was conducted based on the research ethics examination "New cognitive function test method for early diagnosis of dementia 2019-B-18" for humans at Kogakuin University. all subjects provided written consent prior to
A 6 x 10 letter matrix was presented to each subject, and each subject was given a specific character and asked to gaze at it. Figure 1 shows the display of the Spelling-BCI, and Figure 2 shows the experimental environment. While the subject gazed at the character, the rows or columns of the matrix blinked in a random sequence as stimulus. The P300 component of the subject was averaged in each row and column, and the character at the intersection of the row and column where the P300 component was detected the most was estimated as the character being gazed at. Characters that prompted the subject were defined as task characters, and characters estimated by the Spelling-BCI were defined as estimated characters. After the subjects were given instructions, five or six characters were input alternately for 60 or 120 s, and a total of four inputs were made. The first input was treated as learning data for linear discriminant analysis (LDA), and the remaining three inputs are used as analysis target data.

2.2 BCI system

A diagram of the Spelling-BCI system used in this study is shown in Figure 3. Electroencephalograms were measured using an active electrode (LADY bird electrode manufactured by g.tec), collected using an electrode box (g.SAHARAbox manufactured by g.tec), and the signal was amplified using a bio-amplifier (g.USBamp manufactured by g.tec). In addition, MATLAB 2012a was used for EEG recording, stimulus presentation, and analysis processing. The electrodes were placed at eight locations: Fz, Cz, P3, P4, Pz, O1, O2 and Oz (as defined by the International 10–20 system).

2.3 Measurement items

The SEDV [char] is the relative distance between the task character and the estimated character; the SEDV is calculated in consideration of the characteristics of the Spelling-BCI. The minimum SEDV is 0[char], and the maximum value is 10.3[char]. For healthy subjects, the SEDV is approximately 1[char]. The higher the SEDV, the lower the input accuracy, and the lower the attention concentration.

The P300 discrimination rate [%] is the detection accuracy of the P300 component obtained from the training data. The higher the P300 discrimination rate, the higher the subject’s level of concentration.

P300 latency [ms] is the time from presentation of the stimulus to the apex of the P300 component. In normal subjects, P300 latency is approximately 300 [ms] after presentation of a stimulus. It has been reported previously that longer P300 latency results in a smaller MMSE score [5].

The P300 amplitude ΔFz-Oz [μV], which is the difference in P300 amplitude between the Oz electrode located in the occipital region and the Fz electrode farthest from the Oz electrode, was calculated. A reduction in occipital cerebral blood flow can be quantified by P300 amplitude ΔFz-Oz.

3. NEUROPSYCHOLOGICAL EXAMINATION

The MMSE is the most widely used clinical and research test for dementia screening. The MMSE has a maximum score of 30 points, where a score of 23 or less is generally considered to indicate dementia.

Japanese Version of Montreal Cognitive Assessment (MoCA-J) is an effective screening test to detect Mild Cognitive Impairment (MCI), which is difficult with
MMSE. With the MoCA-J screening test, a score of 25 or less is diagnosed to indicate MCI.

Frontal Assessment Battery (FAB) is a screening test for the frontal lobe. With this screening test, if the score is less than 18, MCI is suspected.

4. ANALYSIS

4.1 Estimation of neuropsychological examination

Multiple regression analysis was performed on the BCI measurement data and subject age to create an estimated model for neuropsychological examinations.

4.2 Forward-backward stepwise selection method

The forward-backward stepwise selection method searches for the optimum combination of explanatory variables by repeatedly taking in variables that are valid for prediction and deleting variables that are not valid. A two-step threshold (for example, 0.05 and 0.1) is set, variables with p-values below 0.05 are adopted, variables above 0.1 are rejected, and variables with 0.05 < p < 0.1 are put on hold.

4.3 Confidence interval for estimation error

The error between the estimated value of the neuropsychological examination and the score of the subject's neuropsychological examination was used as the estimation error. Here, the 95% confidence interval was calculated based on the standard deviation of the estimation error. In addition, data whose with error exceeding the 95% confidence interval were excluded to avoid loss of estimation accuracy.

5. RESULTS

5.1 MMSE estimation model

Equation (1) is the MMSE estimation model. SEDV and P300 latency were selected as explanatory variables. Here, the adjusted R-squared, which indicates the accuracy of the estimation, is 0.96. Table 1 shows the change in the amount of data and adjusted R-squared by outlier removal. Figure 4 shows the relationship between the estimated MMSE score and the subject's MMSE score.

Estimated MMSE = \(-0.99 \times \text{SEDV} + 0.07 \times \text{P300 latency}\) \hspace{1cm} (1)

| Data | Adjusted R-squared |
|------|--------------------|
| Before removal | 211 | 0.26 |
| After removal | 30 | 0.96 |

Figure 4: Estimated MMSE score (N=30)

5.2 MoCA-J estimation model

Equation (2) is the MoCA-J estimation model. SEDV and P300 amplitude ΔFz-Oz were selected as explanatory variables. Here, the adjusted R-squared is 0.98. Table 2 shows the change in the amount of data and adjusted R-squared by outlier removal. Figure 5 shows the relationship between the estimated MoCA-J score and the subject's MoCA-J score.

Estimated MoCA-J = \(-1.1 \times \text{SEDV} - 0.23 \times \left(\text{P300 amplitude } \Delta Fz - Oz\right)\) \hspace{1cm} (2)

| Data | Adjusted R-squared |
|------|--------------------|
| Before removal | 211 | 0.26 |
| After removal | 26 | 0.98 |

Table 2: Data and adjusted R-squared about MoCA-J

Figure 5: Estimated MoCA-J score (N=26)

5.3 FAB estimation model

Equation (3) is the FAB estimation model. SEDV, age, P300 latency and P300 discrimination rate were selected
as explanatory variables. Here, the adjusted R-squared is 0.97. Table 3 shows the change in the amount of data and adjusted R-squared by outlier removal. Figure 6 shows the relationship between the estimated FAB score and the subject's FAB score.

\[
\text{Estimated FAB} = -0.95 \times (\text{SEDV}) - 0.56 \times (\text{age}) + 0.38 \times (\text{P300 latency}) - 0.06 \times (\text{P300 discrimination rate})
\]

(3)

| Data | Adjusted R-squared |
|------|--------------------|
| Before removal | 209 | 0.25 |
| After removal | 30 | 0.97 |

Table 3: Data and adjusted R-squared about FAB

![Estimated FAB score by BCI (N=30)](image)

6. DISCUSSION

In the estimation model of each neuropsychological examination, the standard partial regression coefficient of SEDV was the largest compared to the standard partial regression coefficient of other explanatory variables. Therefore, it can be considered that SEDV is the most effective relative to estimating the neuropsychological test score among the features obtained from the measurement by the Spelling-BCI.

In the MMSE and FAB estimation models, the standard partial regression coefficient at P300 latency became positive value (Equations (1) and (3)). In other words, according to the results, longer P300 latency is related to higher MMSE and FAB results. However, as mentioned in Section 2.3, the longer the P300 latency, the smaller the MMSE score. Equation (1) shows that the standardized partial regression coefficient of P300 latency is 0.07, which is less than that of SEDV; thus, the influence of P300 latency in the estimation model of MMSE is low.

7. CONCLUSION

In this study, multiple regression analysis was performed using features obtained from the Spelling-BCI and the age of the subjects, and the MMSE, MoCA-J, and FAB scores were estimated. As a result of removing outliers, the adjusted R-squared value exceeded 0.95 in the estimation model of each neuropsychological examination, and a highly accurate estimation model was created compared to a previous study [4]. In future, it will be necessary to clarify the estimation error when outlier data are included and verify the estimation model.

ACKNOWLEDGMENTS

We would like to thank all collaborators who participated in our experiment. We also thank everyone at the Department of Elderly Care, Tokyo Medical University for their cooperation. This research was supported in part by a research fund for the development of minimally invasive treatment and diagnostic equipment, which is a joint research project of Tokyo Medical University and Kogakuin University. In addition, this research was supported in part by research funding from JSPS KAKENHI (Grant Number JP19K12880).

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