2021 43rd Annual International Conference of the
IEEE Engineering in Medicine & Biology Society (EMBC)
Oct 31 - Nov 4, 2021. Virtual Conference

A method for detecting the EFRP P300 component by using ICA to reduce the number of required experimental trials

Nodoka Yamada, Kazutaka Ueda, Shinya Takada, and Masayuki Nakao

Abstract— **By using independent component analysis, signal separation, and machine learning, we succeeded in detecting P300, one of the major eye fixation-related potentials (EFRP).**

Clinical Relevance— **We determined P300 latency using only a third as many trials as usually required by the conventional averaging method.**

I. INTRODUCTION

The P300 latency of the eye fixation-related potential (EFRP) is used to evaluate the information processing load during observations of visual stimuli. The averaging method conventionally used to calculate the P300 latency requires presentation of many stimulus trials, which prolongs the experiment time and causes participant's fatigue. In this study, we developed a new method to calculate the P300 latency of the EFRP using EEG signal separation by the independent component analysis (ICA) and machine learning.

II. METHODS

Training data: To determine whether each signal separated by the ICA from the raw EEG data during the presentation of visual stimuli contains the P300 component of EFRP by machine learning, we set up an experimental "pre-task" for collecting teacher data for each participant. The EEG was recorded by 26 electrodes, using the average of both earlobes as reference. Pre-task comprised i) task-P, using the P300 speller in which the participants gazed at the letters taught in advance; ii) task-B, in which the participants blinked according to the timing of the display on the screen; and iii) task-S, in which the participants moved their gaze horizontally according to the timing of the display on the screen. In task-P, we extracted the target EEG data up to 700 ms after the taught letter was presented, and EEG data from the other letter were considered as non-target. The EEG data of tasks B and S were annotated as blink and saccade, respectively, down-sampled to 20 Hz [1], and classified into four classes. Then, the data of 10 electrodes (F7, F8, Fz, Cz, Pz, P7, P8, O1, O2, Oz) were used as features to train a linear discriminant analysis model.

Test experiment: We created an experimental task in which the amount of information had four levels [2]. During the experiment, participants gazed at the cross in the center of the LCD monitor screen, and when the target image (arrow) was presented on the left side of the screen, they turned their eyes and responded to the task with a button click. The target image was presented for 36 trials in each level.

N. Yamada, K. Ueda and M. Nakao are with the Department of Mechanical Engineering, Graduate School of Engineering, University of Tokyo, Tokyo, Japan. Correspondence: ueda@hnl.t.u-tokyo.ac.jp.

Determination of EEG components: Ten of the trials in which the target image was presented were randomly selected. The end time of eye movement E was calculated from the electrooculogram, and the reference time S was selected from E_{-200} ms to E_{+700} ms at 10 ms intervals. The extracted EEG data were separated into components by ICA for each information level and each reference time S, and the average EEG of the 10 trials for each component was calculated. Features were created for the calculated EEG data in the same way as for the teacher data. The cleaned EEG consisting of only the target components was recalculated by applying the classifiers already created for the participants.

Identification of P300: For the recalculated EEG at each reference time S and the average waveform of the target class teacher data, the correlation coefficient score of the time series data of the electrodes [Cz, CP1, CP2, P3, P4, Pz] was calculated by the Pearson's method. Two peaks of the score for S were selected in the descending order, and the EEG containing all ICA target components was recalculated with these two data points to derive the P300 waveform at each information level.

III. RESULTS & DISCUSSION

The P300 latencies were calculated at each level by the averaging method, which excluded the badly contaminated trials from 36 trials, and the proposed method. A two-factor analysis of variance of the P300 latency found that the amount of information had a significant effect ($p < .05$), but not the method (Figure 1). Thus, our proposed method had similar performance to that of the conventional averaging method, but required only a third as many experimental trials.

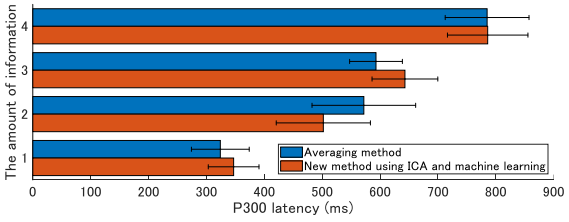

Figure 1: P300 latency values calculated by the two methods (data are presented as the mean ± standard error of the mean, n = 10).

REFERENCES

[1] D. J. Krusienski, et al. (2008). Toward enhanced P300 speller performance. *Journal of Neuroscience Methods*, 167(1), 15–21.

[2] S. Takada, et al. (2019). Evaluation of driver's cognitive load when presented information on the windshield using p300 latency in eye-fixation related potentials. In *2019 IEEE Intelligent Transportation Systems Conference (ITSC)*, pp. 4006–4011.