33rd Annual International Conference of the IEEE EMBS
Boston, Massachusetts USA, August 30 - September 3, 2011

Development of a BCI Master Switch Based on Single-trial Detection of Contingent Negative Variation Related Potentials

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***Abstract*—To control the startup/shutdown of a conventional brain-computer interface (BCI) that is always running for daily use, we proposed and developed a new BCI system called a BCI master switch. We designed it with on/off switching functions by detecting the contingent negative variation (CNV) -related potentials. We chose CNV to improve the single-trial discrimination of user intentions to switch because CNV had a high signal-to-noise ratio and needed high concentration for its elicitation. We also applied a support vector machine (SVM) to improve the single-trial detection of CNV-related potentials. As the best parameters of SVM were estimated and applied, the offline evaluation's best performance achieved a CNV detection rate of 99.3% for the intention to switch and 2.1% for the intention not to switch. Remarkably, this performance was achieved from single-trial detection, imaginary response of user's intention without physical reaction, and the data from only one recording electrode. These results suggest that our proposed BCI system might work as a master switch by single-trial detection.**

I. Introduction

THe goal of our ongoing project is to develop a brain-computer interface (BCI) for our day-to-day lives. Over the past couple of decades, a wide variety of BCIs have been developed to control external devices for. However, most conventional BCIs do not consider situations when users are not using them (i.e., an idling state) and during startup/shutdown. If these BCIs are applied to daily use when the BCI system is always running, their usage becomes unsafe because the BCI might unintentionally react to brain activities even when users do not intend to use it [1-4]. In such a situation, users may need help to setup the BCI system for startup and shutdown.

To overcome this problem, we proposed a new BCI system called the BCI master switch that integrated the on/off switching functions to a BCI system like a television's master remote control switch. This controls the startup/shutdown of conventional BCIs (Fig. 2(a)) without any help, depending on user desire. Fig. 1 illustrates this concept. The BCI master switch was designed to be activated by detection of the contingent negative variation (CNV) -related potentials. CNV is the event-related potentials when people are only concentrating on the interval between warning (S1) and imperative (S2) stimuli [4, 5]. The following are its advantages for the BCI master switch: (1) it minimizes system glitches because CNV elicitation needs a highly attentive process, and we can evaluate three features of CNV-related potentials: S1-related evoked potential, CNV, and S2- related evoked potential, as shown in Fig. 2(b); (2) it shortens the processing time from the detection of brain signals to their output because the CNV-related potentials have a higher signal-to-noise ratio than other ERPs, which decreases the number of averages for detection that may realize single-trail detection; (3) it improves user comfort for long-term continuous use because it only requires one

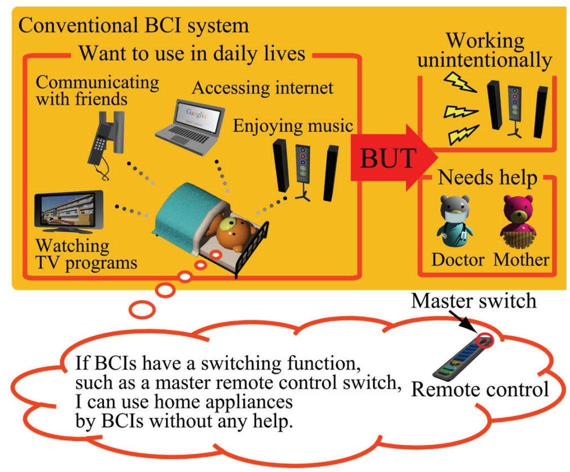

Fig. 1. Illustration of the issue and its solution to use a conventional BCI system for daily lives.

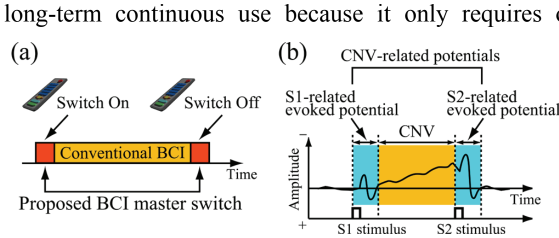

Fig 2. Concept of proposed BCI master switch and illustration of CNV-related potentials. (a) Usage example of our proposed BCI master switch to control on/off switching for a conventional BCI system. (b) EEG response of CNV-related potentials and three representative features: S1-related evoked potential, CNV, and S2-related evoked potential.

Manuscript received April 8, 2011. This work was partly supported by a Grant-in-Aid for Scientific Research (A) 22240008 from the Ministry of Education, Culture, Sports, Science and Technology of Japan. *Asterisk indicates corresponding author.*

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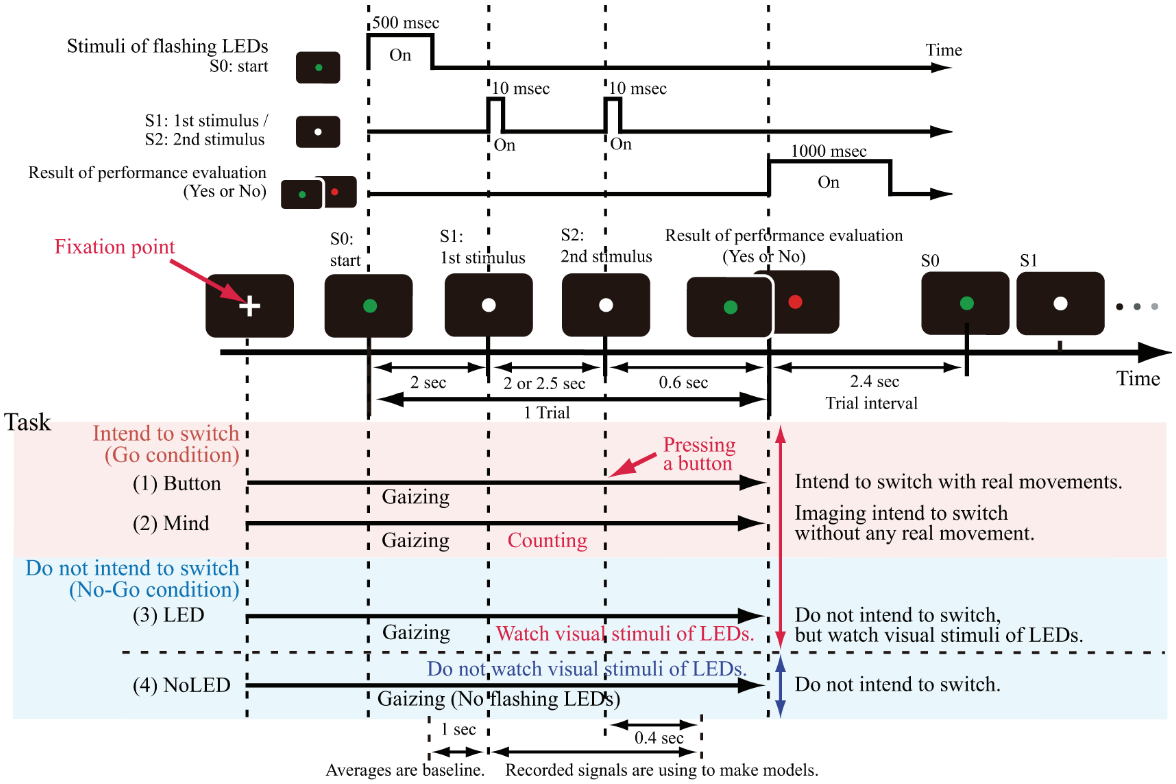

Fig. 3. Experimental procedures to evaluate an efficacy of proposed BCI master switch.

recording electrode for detection. We also applied a support vector machine (SVM), particularly LIBSVM [6], to improve the single-trial detection of the CNV-related potentials. Thus, we assume that our proposed BCI master switch works based on just single-trial detection by using CNV-related responses with SVM.

In this study, we evaluated the following three conditions to observe the efficacy of our proposed BCI system by the online and offline analysis: (1) whether our system could detect CNV-related potentials from a single-trial data using SVM (i.e., Button vs. NoLED, see the methods section of II. A); (2) whether our system could detect CNV-related potentials by the imaginary response of intention to switch without physical responses (i.e., Mind vs. NoLED); (3) whether our system could distinguish between the response of unintentional switches (i.e., user watches LED, but does not intend to switch) and intentional switches (i.e., Mind vs. LED).

II. METHODS

A. Experimental Protocols

We employed a female and six male participants who ranged from 21 to 31 years of age. As shown in Fig. 3, they were instructed in the following four tasks to test the feasibility of our proposed BCI master switch: (1) "Button," responding by pressing a button as fast as possible when the LED visual stimulus of S2 flashed (i.e., physically intend to switch); (2) "Mind," mentally counting as fast as possible between the LED visual stimuli of S1 and S2 for focusing attention (i.e., imaging intend to switch); (3) "LED," gazing at a fixation point without intending to switch (i.e., watching the LED without intending to switch) and also serving as a control condition to observe an effect of visual evoked potentials; (4) "NoLED," only gazing at a fixation point without flashing LEDs and without intending to switch (i.e., without intending to switch). As the classical conditioning of a Go/No-Go task, the conditions in Button and Mind are the Go condition and the conditions in LED and NoLED are the No-Go condition. The durations between the LED visual stimuli of S1 and S2 (stimulus onset asynchrony: SOA) were 2.0 or 2.5 s and selected as uniform random numbers. These durations were chosen because a SOA duration less than 1.5 s would be strongly affected by the visual evoked potentials, such as P300, which would complicate CNV detection, and because a SOA duration longer than 5 s would increase eye blinks and strain, making it difficult for participants to fixate on a

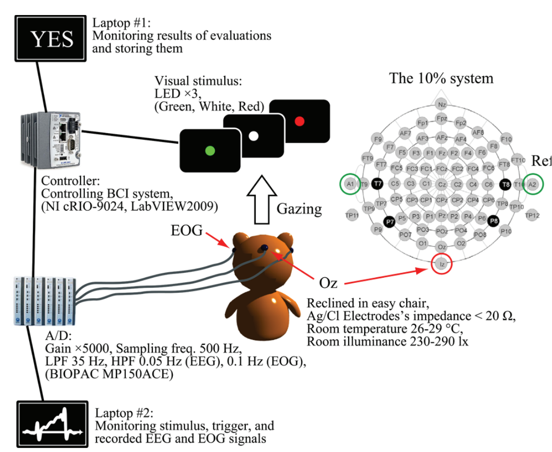

Fig. 4. Overview of experimental setup for our proposed BCI master switch.

target (a flashing LED) for an appropriate period. The task order was counterbalanced across participants, all of whom gave written informed consent for the experiment that was approved by the local Ethics Committees of Osaka University.

B. Data Acquisition

Fig. 4 shows an overview of the experimental setup. The recordings were performed using a controller (cRIO-9024, LabVIEW2009, National Instruments) with three LED visual stimuli. The LED colors were green, white, and red. The Ag/AgCl electrode was placed at the midline occipital area (Oz) and referenced to the earlobes. Oz was chosen because the occipital area on a headrest of a wheelchair or a pillow of the bed is a suitable position to easily place a recording electrode if disabled people use. An EEG electrode paste (GEL102, BIOPAC) was used to stick the electrode to the scalp for a long period and to reduce its impedance. The participants were comfortably seated in reclined chair with a headrest for head stabilization. The distance between the eyes and the LEDs was fixed to 100 cm. To detect such eye-movement artifacts as blinks, an electrooculogram (EOG) was also recorded using an Ag/AgCl electrode placed on the orbicularis oculi muscle above the left eye. The impedances of the electrodes were maintained below 20 kΩ. The recorded signals were amplified with a gain of 5000 and sampled by an AD converter (MP150ACE, BIOPAC) at a sampling frequency of 500 Hz. The filters were a low-pass filter of 35 Hz and a high-pass filter of 0.05 Hz for recording EEG and 0.1 Hz for recording EOG. All experiments were conducted under ambient room illumination of 209 ± 24.1 lx (mean ± SD) at chair's headrest.

C. Classification

SVM was applied to distinguish between "intend to switch (with CNV-related potentials)" and "do not intend to switch (without CNV-related potentials)" from the recorded data. 40 trials, which included 20 for "intend to switch" and 20 for "do not intend to switch," were used for creating a model in the Button vs. NoLED condition (Training 1 in BN model) and in the Mind vs. NoLED condition (Training 2 in MN model). The discrimination accuracy of CNV detection between them from a single-trial detection of the recorded data was also evaluated. The data sets for making the SVM models and evaluating the BCI system in the online and offline analysis are shown in Fig. 5.

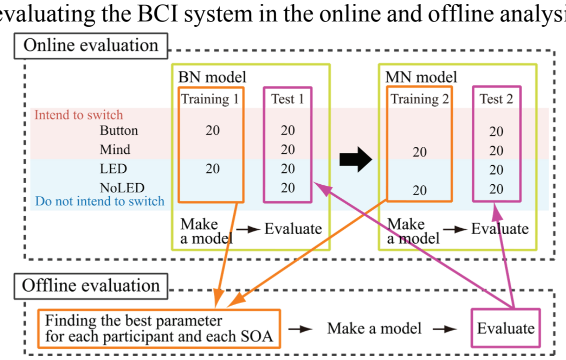

Fig. 5. Data set for making SVM models and evaluating proposed BCI master switch in online and offline analysis. 20 indicates total number of trials in each section.

In the offline analysis, the pairs of values (C and gamma) in SVM of LIBSVM parameters were varied to find the best accuracy of CNV detection, depending on participants and SOAs. C is the penalty parameter of the error term and gamma is the kernel parameter [6]. The data of Tests 1 and 2 were evaluated from two models after the best parameters of SVM were estimated and applied. These test data were different from training data. One model was the data from the Button for "intend to switch" and NoLED for "do not intend to switch" (BN model). The other model was the data from Mind for "intend to switch" and NoLED for "do not intend to switch" (MN model). We also observed a model's temporal stability with the best SVM parameters.

III. RESULTS AND DISCUSSIONS

We proposed and developed a BCI master switch using SVM by single-trial detection of CNV-related potentials. As shown in Fig. 6, the results of the online performances for "intend to switch" were between 41.4 ± 7.8% (mean ± SD) as the worst case in Button with the MN model and 65.7 ± 6.8% as the best case in Button with the BN model and for "do not intend to switch" between 60.0 ± 6.5% as the worst case in NoLED with the BN model and 43.6 ± 7.2% in LED and 43.6 ± 3.7% in NoLED as the best case with the MN model. This indicates that our online system did not distinguish between "intend to switch" and "do not intend to switch," probably because we used the default parameters of SVM in LIBSVM for the discrimination of the CNV-related potentials. Thus, in the offline analysis,

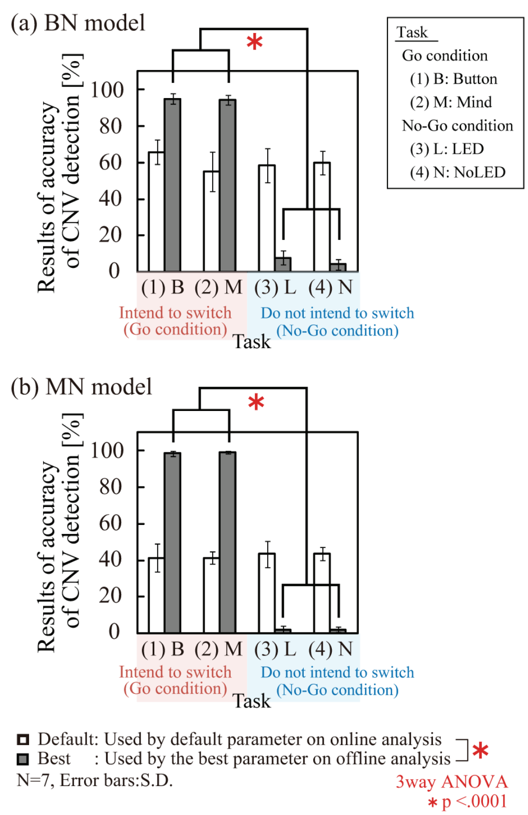

Fig. 6. Results of accuracy of CNV detection in online and offline analysis. Offline analysis was used after the best parameters in SVM were estimated and applied.

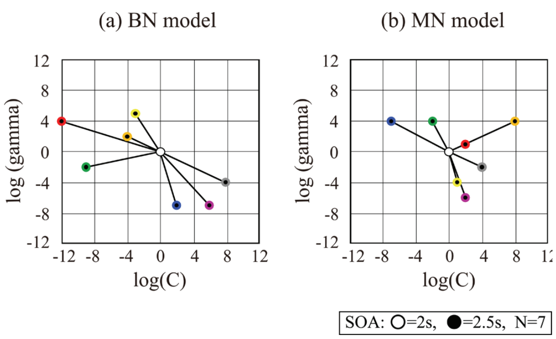

Fig. 7. Best parameters of pairs of C and gamma in LIBSVM normalized by 2 s of SOAs. Colors of circles represent individual best parameters in (a) and (b).

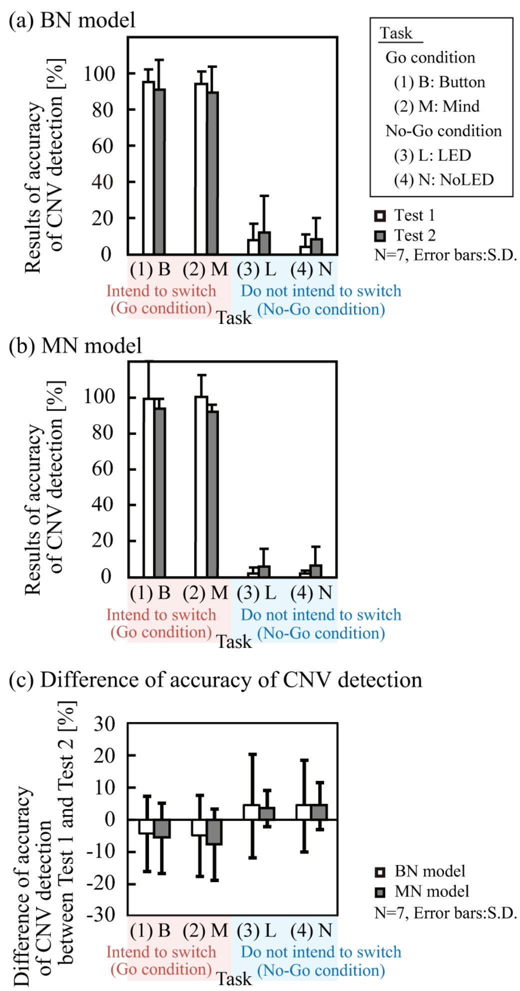

Fig. 8.Temporal effect of SVM's parameters for accuracy of CNV detection normalized by 2s of SOAs. (a) Accuracy of CNV detection in Tests 1 and 2 for BN model. (b) Accuracy of CNV detection in Tests 1 and 2 for MN model. (c) Difference of accuracy of CNV detection between Tests 1 and 2.

we estimated the best parameters of C and gamma to make an optimal model before the performance evaluation.

In the offline evaluation results, the accuracy of CNV detection was significantly improved. The best performance was the MN model whose detection ratio for "intend to switch" were 98.6 ± 1.4% in Button and 99.3 ± 0.7% in Mind and 2.1 ± 2.1% in LED and 2.1 ± 1.5% in NoLED for "do not intend to switch." The CNV detection ratio in the BN model were also notably improved: 95.0 ± 2.9% in Button and 94.3 ± 2.8% in Mind for "intend to switch" and 7.9 ± 3.8 % in LED and 4.3 ± 2.8 % in NoLED for "do not intend to switch". These best parameters of SVM were not constant, but were dependent on participants and SOAs (Fig. 7).

The average test time between the beginning and end was three hours and the longest time was twelve hours. Figs. 8(a) and (b) show the accuracy of CNV detection in Tests 1 and 2, where no significant difference was found in each condition. Fig. 8(c) shows the differences between the rate of the accuracy of CNV detection in Tests 1 and 2. The largest difference was -5.0 ± 12.6% in Mind for the BN model and -7.9 ± 11.1% in Mind for the MN model. Although the CNV detection ratio in Test 2 was decreased by several percentages, these differences were no significant and high CNV detection ratio over 90% remained. Thus, after the models were created by the best parameters, the accuracy of CNV detection were stable for at most twelve hours, indicating that frequently updating the best SVM parameters was not required.

In summary, we achieved the following high accuracy of CNV detection of our proposed system in offline evaluation with the best parameters of SVM: (1) it detected CNV-related potentials from single-trial data using SVM with high accuracy of CNV detection; (2) it detected its potentials by the imaginary response of the intention to switch without physical responses; (3) it distinguished responses between unintentional and intentional switches. Thus, the integration of our system with a conventional BCI for daily use would improve the quality of life not only for the physically disabled, but also for their caregivers.

IV. Conclusion

We proposed and developed a BCI master switch whose offline evaluation showed remarkable performance to distinguish between intentions to switch and not to switch. These results suggest a high possibility that the BCI master switch would work as a master switch by single-trial detection without physical action. We are currently applying a real-time estimation of the best SVM parameter to our system.

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