Chromatic SSVEP BCI Paradigm Targeting the Higher Frequency EEG Responses

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***Abstract*—A novel approach to steady-state visual evoked potential (SSVEP) based brain-computer interface (BCI) is presented in the paper. To minimize possible side–effects of the monochromatic light SSVEP-based BCI we propose to utilize chromatic green–blue flicker stimuli in higher, comparing to the traditionally used, frequencies. The developed safer SSVEP responses are processed an classified with features drawn from EEG power spectra. Results obtained from healthy users support the research hypothesis of the chromatic and higher frequency SSVEP. The feasibility of proposed method is evaluated in a comparison of monochromatic versus chromatic SSVEP responses. We also present preliminary results with empirical mode decomposition (EMD) adaptive filtering which resulted with improved classification accuracies.**

I. Introduction

A brain computer interface (BCI) is a technology that utilizes human neurophysiological signals for the direct brain communication with an external environment, without depending on any muscle activity [1]. Particularly, in the case of patients suffering from locked-in-syndrome (LIS) [2], such technology could help them to communicate or complete various daily tasks (type messages on a virtual keyboard or control their environment using a computer, etc). This should create a very good option for amyotrophic lateral sclerosis (ALS) or coma patients to communicate with their families, friends or caretakers by using only their brainwaves.

In this paper, we report a novel BCI paradigm using the chromatic steady–state visual evoked potential (SSVEP) applied also in higher frequencies comparing to the classical monochromatic approaches [1]. SSVEP is a natural responses for visual stimulations with specific frequencies. When the retina is stimulated by a visual stimulator with one frequency, the brain generates response with same spectrum following response. This response can be used for detecting which stimulator the user is gazing at. SSVEP-based BCI is one of the type of stimulus–driven BCI which is more user friendly than imagery driven BCI in terms of training. Because the stimulus driven BCI requires that user train hard and long time to evoke specific brainwave pattern to control external devices, it could be burden to disabled patients. However, the stimulus driven BCI does not require such training because the brain response to the external stimulus is much stronger than that of imagery driven BCI.

While SSVEP have been known from many years already [1], steady–state responses–based BCI has not usually been used by disabled people due to several reasons. The barriers to use it are mainly related to its potential danger of evoking epilepsy. The conventional SSVEP can be evoked by visual stimulator flashing with below frequencies 50 Hz of human vision dynamic resolution threshold. The major reason why SSVEP BCI has not been used is because it is known that optical flashing could cause epileptic seizure called photosensitive epilepsy (PSE) for in about 10% of children suffering from epilepsy [3], [4]. This effects became famous due to *Pokémon* incident which made a number of children to suffer from the PSE related symptoms [5]. Unfortunately, 4% to 9% of all population carries the epileptic potential which often remains undetected even in adult people [6]. Because of the above reasons, the SSVEP device carries a potential danger of PSE. Moreover, the light flashing with lower frequency causes often user exhaustion when gazing at it for longer time. Based on the above limitations of the conventional SSVEP devices, we propose a safer option for BCI using green–blue color light (note that the *Pokémon* incident was caused by red-blue color flashing). The conventional SSVEP BCI uses monochromatic flashing which is relatively dangerous, on the other hand, the proposed green–blue light option is the safest choice as recently reported in [7]. To avoid a limitation imposed by a fixed refreshing rate of a general computer display (liquid crystal display - LCD or cathode ray display - CRT) which also evokes an unrelated SSVEP frequency, the light-emitting diodes (LEDs) are used to generate visual stimulus. Fortunately, the amplitude of SSVEP evoked by LEDs are stronger than that of LCD and CRT [8]. In experiments presented in this paper, we test $7, 18, 25, 39$ Hz flashing frequency SSVEP stimuli. We compare the classification accuracy of SSVEP–based BCI between response to conventional monochromatic (white–black) and the proposed chromatic (green–blue) flashing. We also report user preferences obtained from questionaries after the experiments.

II. Materials and Methods

The experiments reported in this paper were performed in the Life Science Center of TARA, University of Tsukuba,

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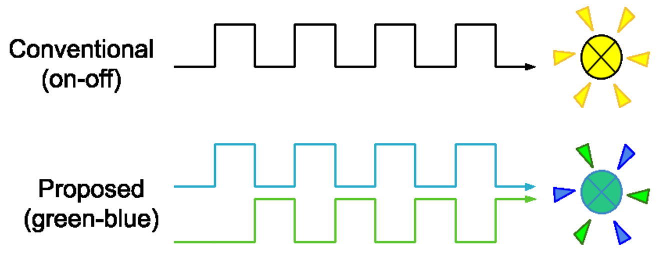

Fig. 1. The difference between conventional monochromatic (ON–OFF) and the proposed chromatic (green–blue) flashing patterns created with square waves by *ARDUINO UNO* micro–controller board.

Japan. All the details of the experimental procedure and the research targets of this approach were explained to the three human subjects, who agreed voluntarily to take a part. The psychophysical and online electroencephalogram (EEG) BCI experiments were conducted in accordance with *The World Medical Association Declaration of Helsinki - Ethical Principles for Medical Research Involving Human Subjects*. The experimental procedures were approved and designed in agreement with the ethical committee guidelines of the Faculty of Engineering, Information and Systems at University of Tsukuba, Tsukuba, Japan (experimental permission no. $2013R7$). Three volunteer subjects participated in the experiments. The average age of the subjects was 29.3 years old (standard deviation of 12.7 years old; three male participants). In the following sections we explain details of the safer SSVEP stimulus creation, together with the EEG experimental protocols.

A. Visual Stimulus Generation

The visual stimuli were flashed via white or RGB LEDs as square waves generated by *ARDUINO UNO* micro–controller board as shown in Figure 1 using software written by our project members. In this study we used $7, 18, 25, 39$ Hz flashing patterns to create four commands SSVEP-based BCI paradigm. During experiments the LEDs continued to flash simultaneously with the above different frequencies. The two monochromatic and chromatic LED SSVEP setups used in the experiments are presented in Figures 2 and 3.

The LEDs were arranged in a rectangular 7.4×5.8 cm pattern. Such short distances arrangement was decided to allow the target ALS/LIS patients in the future to use the interface with minimal eye movements necessary to switch among the patterns. In the training phase, to let subjects gaze at specific LEDs, the experiment instructions were delivered acoustically by means of the OpenViBE [9] environment and a Python program designed by our team as depicted in form of an user interface display in Figure 4.

B. BCI EEG Experiment Protocol

During the BCI EEG experiments the subjects were seated on comfortable chair in front of LED displays (see Figures 2 and 3). The distance between subject eyes and LEDs was about $30 \sim 50$ cm (chosen by the subjects for comfortable

Fig. 2. Conventional monochromatic (ON–OFF) LEDs arrangement. In the experiments presented in this paper the following flashing frequencies were used: top–left 7 Hz; bottom–left 18 Hz; bottom–right 25 Hz; and top–right 39 Hz. The LEDs were arranged in the 7.4×5.8 cm rectangular pattern. All LEDs are connected to *ARDUINO UNO* micro–controller board which generated four square waves with different frequencies.

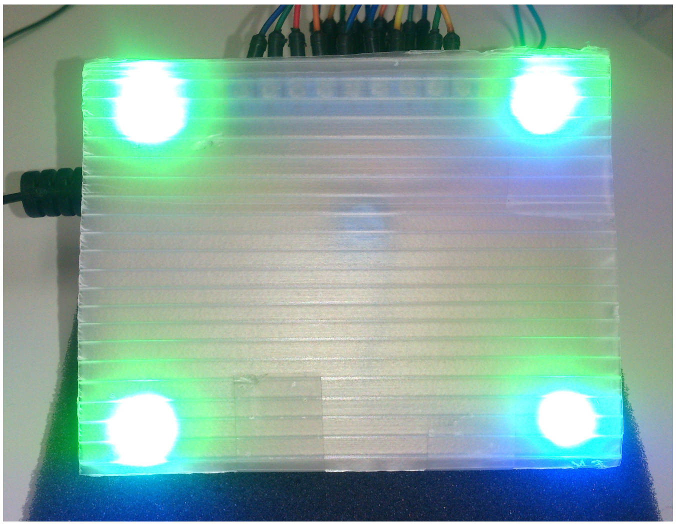

Fig. 3. Proposed chromatic (green–blue) LED interface. (where left up: 7 Hz, left down: 18 Hz, right down: 25 Hz and right up: 39 Hz). In the experiments presented in this paper the following flashing frequencies were used: top–left 7 Hz; bottom–left 18 Hz; bottom–right 25 Hz; and top–right 39 Hz. The LEDs were arranged in the 7.4×5.8 cm rectangular pattern. All LEDs are connected to *ARDUINO UNO* micro–controller board which generated four paris of phase shifted square waves with different frequencies (see Figure 1 for details).

view of all LEDs). The ambient light was moderate as in a typical office. The EEG signals were captured with a portable EEG amplifier system g.USBamp by g.tec Medical Engineering, Austria. The 8 active wet EEG electrodes were connected to the head locations O1, O2, Po3, Po4, P1, P2, Oz, and Poz as in an extended $10/10$ international system [10]. These positions were decided due to the visual cortex responses targeting experiment type [1] [11]. The ground electrode was attached to head location FPz and the reference electrode

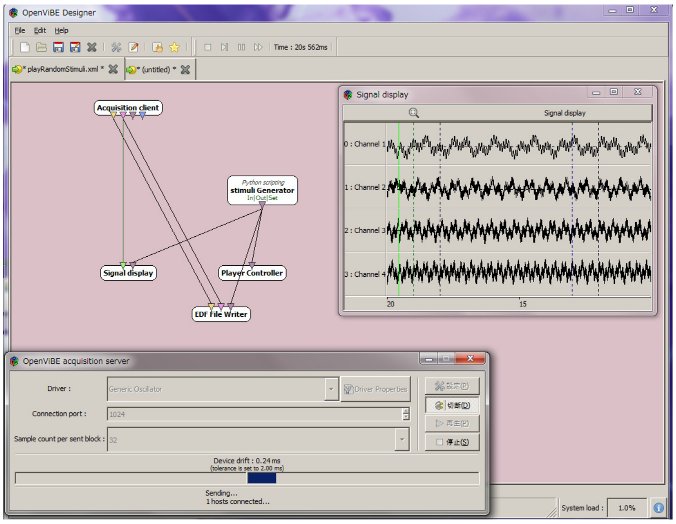

Fig. 4. OpenViBE interface used in experiments reported in this paper. The bottom window called *acquisition server* acquired the EEG signals from g.USBamp amplifier and it sent them to the main window process. The main window was called an *OpenViBE designer* which could be used for the visual programing of the whole experiment process flow. The EEG data obtained from the *acquisition server* was received by an *acquisition client* box and next recorded by connecting to an *EDF file writer* box. The window located in middle–right of the captured display showed raw EEG signals obtained from *acquisition server* during the experiment.

was attached to a left earlobe. Details of EEG experiment set up are summarized in Table I. The sampling frequency was set to 512 Hz and a notch 4^{th} order Butterworth IIR filter at rejection band of $48 \sim 52$ Hz was applied to remove power line interference of 50 Hz. The recorded EEG signals were captured and preprocessed by the OpenViBE based application [9]. The 8 channels EEG signals were next filtered with 8^{th} order Butterworth IIR high-pass filter set at 5 Hz cutoff frequency. Each experimental run took about 245 seconds, subjects gazed at each LED for six seconds after acoustic instruction generated and the EEG data were recorded five seconds after one second of the instruction time. The instruction let the subject to execute a saccade and to focus at a target LED. The auditory instruction were delivered as recorded author's voice (for Japanese speaking subjects) or in form of synthesized MacOS X system voice (Serena's voice for English speaking subjects) via OpenViBE. In a single BCI EEG experimental run experiment there were forty trials to gaze at each LED (ten trials for each target frequency stimulus). Each experimental session consisted of four repeated runs for the conventional monochromatic (white–black) and the proposed (green–blue) patterns respectively.

C. SSVEP Responses Classification

For SSVEP responses classification a soft margin support vector machine (C-SVM) [12], [13] was chosen. The C-SVM classification output was calculated as follows,

$$f(\mathbf{x}) = \mathbf{w}^{\mathrm{T}}\mathbf{x} + \mathbf{b}, \tag{1}$$

TABLE I
EEG EXPERIMENT CONDITION DETAILS

Number of subjects	3
Recording length	5000 ms for each trial
Stimulus frequencies	$7, 18, 25, 39$ Hz
EEG recording system	g.USBamp with active wet EEG electrodes system
Number of EEG channels	8
Electrode locations	O1, O2, Po3, Po4, P1, P2, Oz and Poz
Reference electrode	Left earlobe
Ground electrode	FPz
Notch filter	Butterworth 4^{th} order with rejection band of $48 \sim 52$ Hz
High–pass filter	Butterworth 8^{th} order at 5 Hz
Stimulus output devices	White or RGB LEDs
LEDs positions	Edges of a rectangle 5.8×7.4 cm
Number of runs	4 for each LED display colors

while the classifiers weights are trained as,

$$\begin{aligned} &minimize && \frac{1}{2}\mathbf{w}^2 + C\sum_i \xi_i \\ &subject\ to && f(x_i)(wx_i + b) \geq 1 - \xi_i \quad \xi_i \geq 0, \end{aligned} \tag{2}$$

where $f(x)$ was evaluation function based on trained $\mathbf{w}$ and $\mathbf{b}$; $\mathbf{x}$ stood for input feature vector extracted as power spectral density; C was a constant for soft–margin and it was set as 1 in this experiment; ξ represented non–negative slack variable which measured the degree of misclassification of the data $\mathbf{x}$. To train classifier, the w and b should be optimized by calculating equation (2) with training feature vector $\mathbf{x}$. After the $f(\mathbf{x})$ was designed by optimization, it could predict the class for input vector $\mathbf{x}$.

For linear C-SVM training, the features were calculated as power spectral densities (PSD) based on Welch's method [14]. The Welch's method PSD was calculated as follows.

$$\hat{P}(f_n) = \frac{1}{K}\sum_{k=1}^{K} I_k(f_n), \tag{3}$$

where

$$I_k(f_n) = \frac{L}{U}|A_k(n)|^2 \tag{4}$$

$$U = \frac{1}{L}\sum_{j=0}^{L-1} W^2(j) \tag{5}$$

and

$$A_k(n) = \frac{1}{L}\sum_{j=0}^{L-1} X_k(j)W(j)e^{-2kijn/L} \tag{6}$$

$$X_k(j) = X(j + (K-1)D) \quad j = 0, \cdots, L-1. \tag{7}$$

$\hat{P}(f_n)$ stood for result of spectral estimation; K was the number of segments applied for one sequential data $X(j)$ to be split. In this case, K was set to 8; L was a number of samples included in each segment. Each segment had 50% of overlapping samples; $W(j)$ was a shape of a window applied by Fourier transform (the *Hamming* window was used in the presented approach). The exemplary mean power spectral densities have been shown in Figure 5 for different stimulus frequencies.

To avoid the so called "curse of dimension", we chose the value of Welch's PSD as features only frequency bins at ± 1 of LEDs flashing pattern. Thus, the feature vector used for linear C-SVM training was constructed by 10×96 matrix for each target frequency. A test data used for classification was constructed as 1×96 feature vector in each single trial.

D. EMD–based Filtering of SSVEP Responses

In order to further enhance SSVEP response features as proposed in [15], an univariate empirical mode decomposition (EMD) approach was applied to decompose the EEG channels into intrinsic mode functions (IMF). Only the IMFs fitting frequencies of the used SSVEP frequencies were reconstructed creating an adaptive and data–driven filtering approach.

III. RESULTS

This section presents and discusses results that were obtained from offline BCI EEG experiments based on classification accuracies from a soft margin support vector machine (C-SVM) [12], [13]. We also included results from questionnaires given to the subjects after experiments.

A. EEG Experiment Results

The results of the SSVEP EEG experiment are summarized in Table II and Figure 6 with results calculated by a multi–class linear C-SVM classifier using libsvm [13] library in MATLAB. The boxplots in Figure 6 show mean results of classification accuracies when one out of four sessions was used as training data (a single boxplot was calculated from the 12 C-SVM classification results).

The results of subject #1 showed significant difference between conventional and proposed LED types. The significance test was conducted in form of pairwise t–test ($p < 0.0001$). The remaining two subjects did not resulted with significant differences ($p \approx 0.0806$ and $p \approx 0.3806$ respectively), although all means were above the chance levels.

Next, to confirm how we could possibly shorten the training and test recording datasets, we applied the same classification to EEG signals recorded as in $1, 2, 3, 4$, or 5 seconds long intervals. The results are shown in Figure 7 in form of boxplots of median accuracies. These results have shown that the longer the recording time, the more accurate results could appear except for subject #2 who did not improve at all. Also, the $p-$values of each set results were calculated by pairwise t-tests and they are shown in Table III.

The results of subjects #1 and #3 formed monotonic increase for each stimulus color type. Moreover the proposed method scored with higher accuracy results. Moreover, results of subject #1 showed significant difference (conventional versus proposed) in a range from 2 to 5 seconds. On the other hand, results of subject #3 did not contain significant differences except for the result of 1 s intervals. The above mentioned results allowed us to draw a conclusion of the proposed method superiority.

B. Subject Questionnaire Results

Results of questionnaires given for every subject have been summarized in Table IV. There were two questions asked to

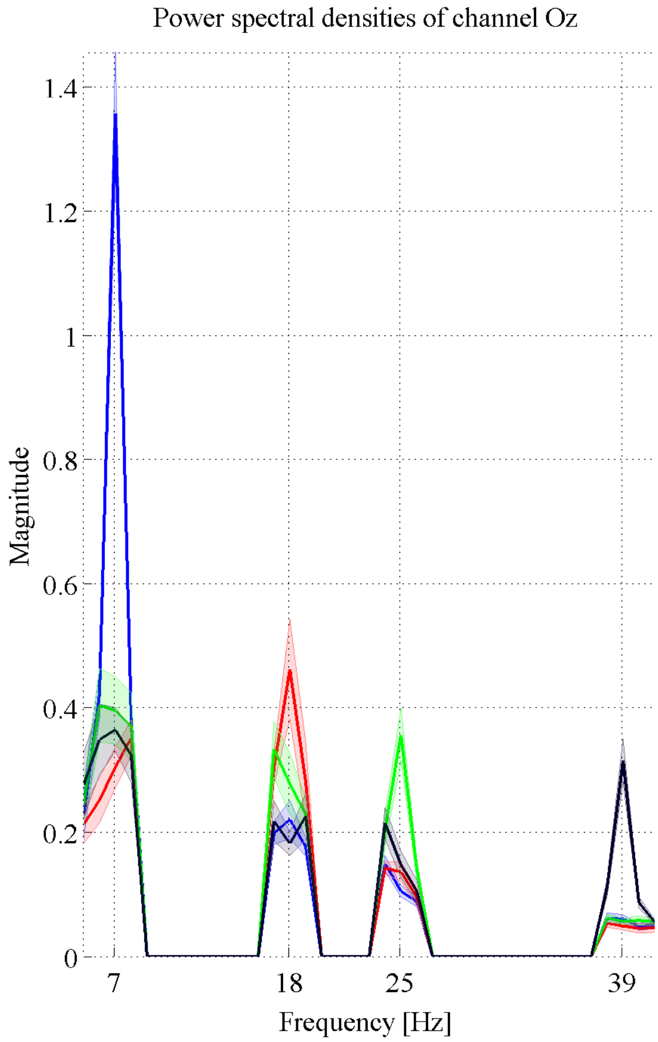

Fig. 5. Mean power spectral densities with standard error bars calculated by Welch's method. The blue line depicts PSD of 7 Hz SSVEP. The red, green, black are 18, 25, and 39 Hz respectively. These magnitude values of peaks and their neighboring ± 1 Hz bins were used as feature vectors for classification.

TABLE II
SINGLE TRIAL BASED BCI ACCURACY (NOTE, THEORETICAL CHANCE LEVEL WAS OF 25%) USING THE C-SVM CLASSIFIER.

Subject number	The averaged classification accuracy	
	chromatic	monochromatic
#1	71.0%	54.0%
#2	35.8%	31.7%
#3	53.3%	50.2%
Average	**53.4%**	**45.3%**

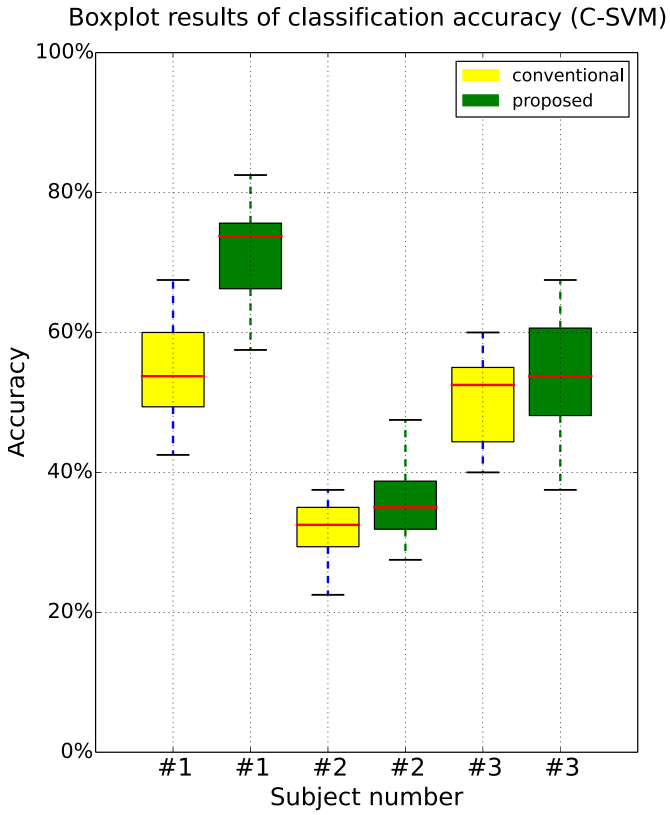

Fig. 6. SSVEP EEG experiment C-SVM classification accuracy distributions of all trials for each subject in form of the boxplots depicting medians, interquartile ranges and outliers (blue plus marks). Yellow boxes show classification accuracy of SSVEP response to conventional monochromatic flashing method. The green color depicts response to proposed chromatic (green–blue) flashing. Each number at the horizontal axis indicates subject's number. The vertical axis reports classification accuracy results. There was a significant difference observed for subject #1 between. The numerical accuracy results are summarized in Table II.

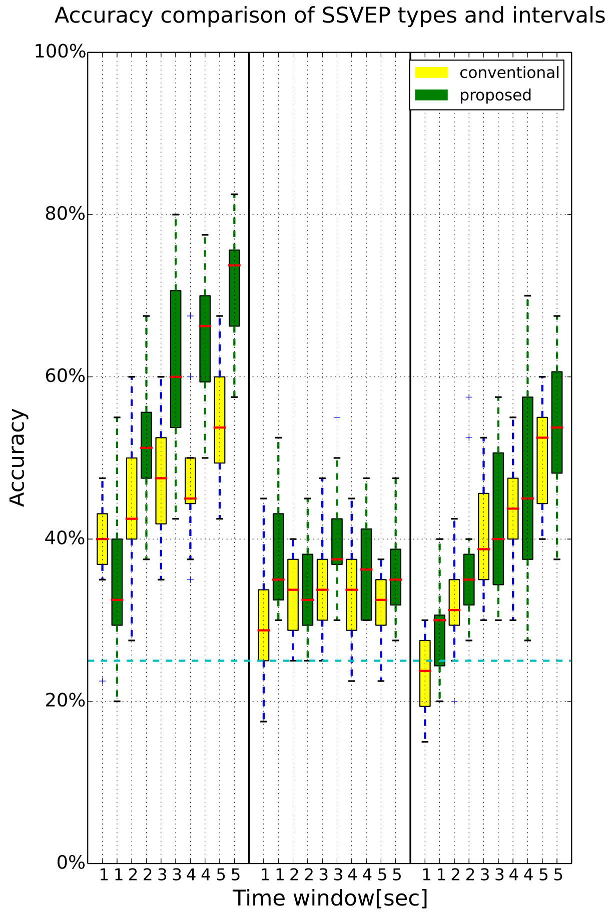

Fig. 7. SSVEP EEG classification results of every subject based on different signal analysis time windows ($1, 2, 3, 4$, and 5 seconds long) used for feature extraction and classification. The horizontal axis shows each time window length. The cyan color doted horizontal line represents theoretical chance level of 25%. These results conferment that the majority of accuracies were above a chance level and they formed monotonic increases except for subject #2. Fortunately, accuracy results of the proposed method were higher than that of conventional one. The $p-$values of pairwise t-test are summarized in Table III.

TABLE III
CHROMATIC VERSUS MONOCHROMATIC PAIRWISE T-TEST RESULTING $p-$VALUES OF THE CLASSIFICATION ACCURACY RESULTS

Subject number	training intervals [s]				
	1	2	3	4	5
#1	0.146	0.032∗	0.003∗	0.000∗	0.000∗
#2	0.012∗	0.866	0.077	0.203	0.081
#3	0.027∗	0.066	0.627	0.381	0.381

TABLE IV
QUESTIONNAIRE RESULTS FROM POINT OF VIEW OF PREFERENCE AND TIREDNESS

Subject number	Preference	Tiredness
#1	3	1
#2	5	3
#3	-1	4
Average	**2.33**	**2.67**

the subjects as follows:

- Which stimulus did your prefer monochromatic versus chromatic (response range $-5 \sim 5$)?
- Please evaluate experiment tiredness from tiring to relaxing (response range $-5 \sim 5$).

When the preference response was positive, the subject preferred chromatic (green–blue) flashing comparing to the monochromatic (white–black). Similarly, the tiredness positive scores reflected the subjects' lower tiredness with the chromatic (green–blue) LEDs. Except for preference of subject #3, the preference and tiredness scores were positive. In other words, the subjects felt that the proposed method has been better from the point of view of the mental preference and tiredness.

C. Results of EMD–based SSVEP Preprocessing

Classification accuracy improvement of EMD preprocessing of SSVEP responses has been summarized in Figure 8. The very encouraging results have been obtained in frequency

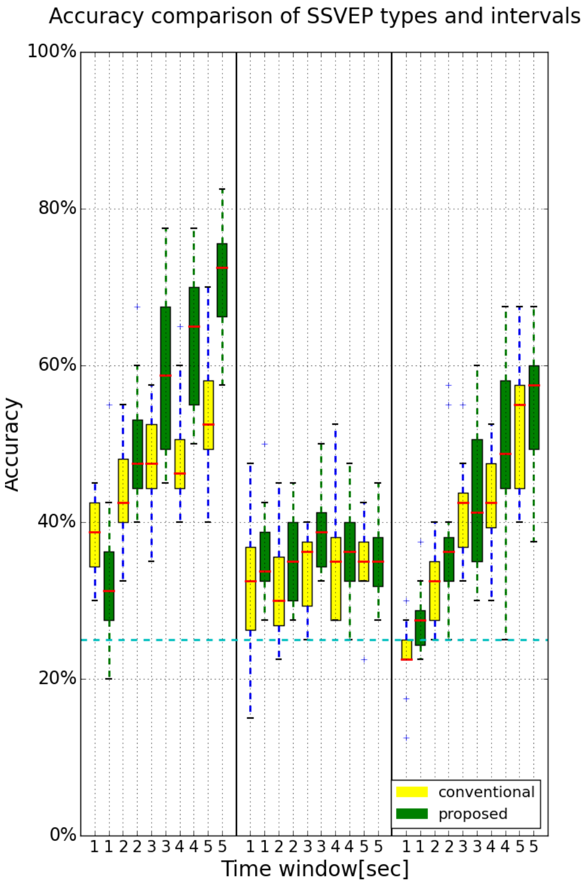

Fig. 8. Classification improvement obtained with EMD–based SSVEP responses preprocessing. Compare results with classification accuracies reported in Figure 7.

matched training and test sets offline classification settings. This would require for online application a cascade of classifiers trained in one–versus–others configuration with a second level final judgment decision making unit.

IV. Conclusions

The safer SSVEP–based BCI method with chromatic stimuli has been discussed in this paper. In order to realize the purpose, we aimed to test the chromatic (green–blue) flashing LEDs in comparison with classical SSVEP stimuli. This paper reported a successful implementation of the four command–based SSVEP BCI in offline signal analysis scenario. We conducted experiments to verify the feasibility and user experience of the proposed method. According to the results obtained from three subjects, classification accuracy of SSVEP evoked by proposed stimuli were as good or even better as of the conventional monochromatic stimuli. Moreover, majority of the BCI accuracies scored above chance levels for the proposed method even if the time window of features drawn for the classification was only one second long. In addition to these results, the subjects preferred the proposed green–blue LED flashing.

For future research, we aim to validate the prototype chromatic SSVEP–based BCI with more users to further proof the results. We will also aim at reduction of the time window for even better usability of the proposed chromatic SSVEP–based BCI paradigm.

Acknowledgments

We would like to thank Dr. Andrzej Cichocki from RIKEN BSI, Japan, and Dr. Koich Mori from Research Institute of National Rehabilitation Center for Persons with Disabilities, Japan, for very stimulating discussions about chromatic SSVEP–based BCI which stimulated this project.

This research was supported in part by the Strategic Information and Communications R&D Promotion Program no. 121803027 of The Ministry of Internal Affairs and Communication in Japan, and by KAKENHI, the Japan Society for the Promotion of Science, grant no. 24243062.

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