A Tactile P300–based Brain–computer Interface Accuracy Improvement

Takumi Kodama and Shoji Makino

Life Science Center of TARA
University of Tsukuba
Tsukuba, Japan

Tomasz M. Rutkowski[1†‡⋆]

†The University of Tokyo, Tokyo, Japan
‡Saitama Institute of Technology, Fukaya, Japan
⋆RIKEN Brain Science Institute, Wako-shi, Japan
tomek@bci-lab.info
http://bci-lab.info/

***Abstract*— In this study we report results of a classification accuracy performance comparison for a novel tactile full–body P300–based brain–computer interface (BCI) paradigm. In the discussed BCI experiments six spatial vibrotactile stimulus patterns are given to the user body entire back and limbs. The acquired somatosensory ERP signals are classified for the BCI purposes using a step–wise linear discriminant analysis (SWLDA), linear (linear SVM) and non–linear (non–linear SVM) support vector machines with features drown from an *electroencephalogram* (EEG) preprocessed signals. The aim of the current project is to determine the most suitable classification methods for a tactile P300–based BCI paradigm and to affirm a validity of vibrotactile stimulus patterns for the user full–body–based interfacing paradigm. The best grand mean averaged accuracies for each classification method result in a rate of 56.33% for SWLDA, 57.33% for linear and 59.83% for non–linear SVMs, respectively.**

Keywords*— *Brain–computer interface (BCI); EEG; tactile P300–based BCI; machine learning.

I. INTRODUCTION

A brain–computer interface (BCI) is a neurotechnology that enables users to express their intention only using their brainwaves [1]. For this reason, in the past decade, several BCI modalities have been eagerly developed in order to communicate with amyotrophic lateral sclerosis (ALS) patients, who have difficulty moving their muscles due to a neuro–motor disabilities [2]. P300 response–based oddball paradigm, which employs of user mental attention modulation, is one of the major modality in the BCI study [1, 3]. The studies of P300 response–based visual and auditory BCI paradigm have been widely investigated [4, 5].

In this study, we examine a novel P300 response–based BCI paradigm using a touch sensation, in other words, a tactile BCI [6]. The tactile BCI could be applicable to locked–in syndrome (LIS) patients who lose their sight and hearing as a late symptom of the ALS [7]. Therefore, an establishment of this alternative paradigm will provide not only a better communication method for care workers, but also a patient quality of life. Recent tactile BCI studies have reported practical feasibility of a tactile stimulus for creating an alternative P300–based BCI paradigm [8, 9].

So far, however, there has been little discussion about classification accuracies of the tactile P300–based BCI. Generally, the tactile BCI paradigm have not been considered as high classification accuracy modality compared to the competitive visual or auditory BCI paradigms. Hence, the more investigation is needed to acquire superior classification results for a widely usage of tactile P300–based BCI paradigms.

[1]The corresponding author.

Figure 1: The fbBCI user lying down on a mattress in which the vibrotactile transducers (shown in left under panel) were embedded. Six vibrotactile stimulus patterns were given to the user full–body throughout the fbBCI experiment. The photograph was included with the user permission.

The main objective in the presented study is to investigate the most suitable classification method for a tactile P300–based BCI paradigm in terms of stimulus pattern classification accuracies. We propose a novel P300–based full–body tactile BCI paradigm (fbBCI) as already tested in a previous pilot study [10]. The fbBCI applied spatial vibrotactile stimulus patterns to the user's entire back and limbs in order to evoke the somatosensory P300 responses. The vibrotactile transducers are placed with larger distances on a mattress in order to give tactile stimulus patterns to the user. The fbBCI was designed for a practical application for bedridden patients so the user could test it with their body lying down on the mattress. The mean stimulus pattern classification accuracy result in the previous report experiment was 53.67% [10].

In the current study, a step–wise linear discriminant analysis (SWLDA), linear and non–linear (Gaussian kernel) SVM algorithms are tested on the acquired EEG data in the fbBCI paradigm. The EEG signal preprocessing steps include filtering, epoching, ERP averaging and decimation. We test several combinations of the above mentioned signal preprocessing steps in order to asses BCI classification methods. The most suitable results of somatosensory P300 responses are determined. Consequently, a potential validity of the proposed P300–based full–body BCI paradigm modality is finally reconfirmed and discussed in the paper.

Table 1: Conditions of the EEG experiments

Condition	Detail
Number of users	10 (5 males and 5 females)
Users mean age	21.9 years old
EEG recording system	g.USBamp active electrodes EEG system
EEG electrode positions	Cz, Pz, P3, P4, C3, C4, CP5, and CP6
EEG sampling rate	512 Hz
Stimulus generators	Dayton Audio TT25-16 transducers
Stimulus frequency	40 Hz
EEG acquisition environment	BCI2000
Target stimulus length	100 ms
Inter–stimulus interval (ISI)	$400 \sim 430$ ms
ERP interval	$0 \sim 0.8$ s after stimulus onsets

II. METHODS

The fbBCI EEG experiment was conducted with ten BCI naive users (five males and females) with a mean age of 21.9 years old (standard deviation of 1.45 years). All the experiments were executed in the Life Science Center of TARA, University of Tsukuba, Japan with guidelines and permission of the institutional ethical committee, as well as in accordance with *The World Medical Association Declaration of Helsinki - Ethical Principles for Medical Research Involving Human Subjects*. All the participating users were paid for their contribution and provided informed consents.

During the experiment, a user laid down on a Japanese–style mattress containing a polyester filling. The user was instructed to distinguish six fbBCI stimulus patterns delivered to arms, shoulder, waist and legs, as depicted in Figure 1. The stimulus patterns were created by eight vibrotactile transducers (Dayton Audio TT25–16 as depicted in a lower left panel of Figure 1). The stimulus carrier frequencies of the transducers were set at 40 Hz. A bio–signal amplifier system g.USBamp from g.tec Medical Engineering GmbH, Austria, was employed to record the EEG signals. Following the 10/10 extended international system, active g.LADYbird electrodes were attached to Cz, Pz, P3, P4, C3, C4, CP5 and CP6 to head locations to cover the primary somatosensory and parietal cortices. A reference electrode was attached to the left earlobe, and a ground electrode to the head FPz position. The EEG recording sampling frequency was set at 512 Hz. The amplifier high– and low–pass filters were set at 0.1 Hz and 60 Hz, respectively. A notch filter was set in a rejection band of 48 to 52 Hz in order to remove power line interferences. The EEG signals were captured by BCI2000 acquisition software. Details of the fbBCI EEG experimental protocol are summarized in Table 1.

In each fbBCI single experimental session 10 targets and 50 non–targets stimulus patterns were randomly presented to the users. The sessions were repeated until each of the six stimulus pattern became targets, namely 60 targets and 300 non–targets were presented overall in a single experimental trial. Each user participated in five trials in a row and the stimulus pattern classification accuracies were calculated by averaging all of the five trials. The vibrotactile stimulus duration was set to 100 ms and the inter–stimulus–interval (ISI) was randomly varied from 400 ms to 430 ms to break rhythmic patterns presentation. In the presented study, the ERP intervals, for a subsequent classifications, were used in latencies covering $0 \sim 800$ ms after the stimulus onsets.

After the EEG experiment, the acquired ERP intervals were post–processed offline using MATLAB software. In this study, the EEG signal processing was divided into three steps. At first, the preprocessing began with a bandpass filtering. The filter passband was set at $0.1 \sim 30$ Hz range to limit interference noise signals from vibrotactile transducers operating at 40 Hz frequency. Secondly, the filtered ERP intervals were decimated by 2 ($f_s = 256$ Hz), 4 ($f_s = 128$ Hz), 8 ($f_s = 64$ Hz), 16 ($f_s = 32$ Hz) and kept intact at the original sampling frequency of $f_s = 512$ Hz in order to test such feature size reduction process on BCI classification accuracy results. Finally, the decimated ERP intervals were averaged using $2, 5$ and 10 ERPs and only single trials to further evaluate the proposed BCI paradigm from a classification speed angle (the less averaged ERPs the faster the classification). The final results of the decimation factors and averaging numbers relations to the BCI classification accuracies have been summarized in the following results section.

Before a classifier training, preprocessed ERP intervals were converted into feature vectors. Single feature vector was comprised of a concatenation of all electrode channel ERP intervals. Namely, a feature vector length was calculated as $l = e \cdot f_s/d \cdot n_c$, where e stood for the duration length of ERP interval (800 ms in this study), f_s represented the sampling frequency (512 Hz in this study), d was the signal decimation factor (selected one from 1, 2, 4 or 8) and n_c was the number of electrode channels (8 in this study). For example, a feature vector length was $e = 824$ when the decimation factor was set to $d = 4$.

The concatenated feature vectors were used for the classifier training. The default numbers of feature vectors were varied from 6 to 60 for targets and 30 to 300 non–targets depends on the number of averaging steps used. The input non–target feature vectors were randomly chosen as many as the number of target feature vectors for the class equivalences (to avoid a classifier overfitting during trainins). For example, 60 target and non–target feature vectors were applied to train the classifier in case of no averaging setting. The same feature selection settings were applied in the classification phase for both the vector length l and input feature vector numbers (varying from 1 to 10 for targets and 5 to 50 for non–targets in a single session).

In the presented study, we adopt three machine learning methods (SWLDA, linear SVM and non–linear Gaussian kernel SVM) to calculate the stimulus pattern classification accuracies. The most suitable classification methods for the tactile P300–based BCI paradigm was assessed by comparing the resulting BCI accuracies. The SWLDA method has been known so far as the most efficient technique for the P300 response classification [11, 12]. The SWLDA was developed as a regression model of the Fisher's linear discriminant anal-

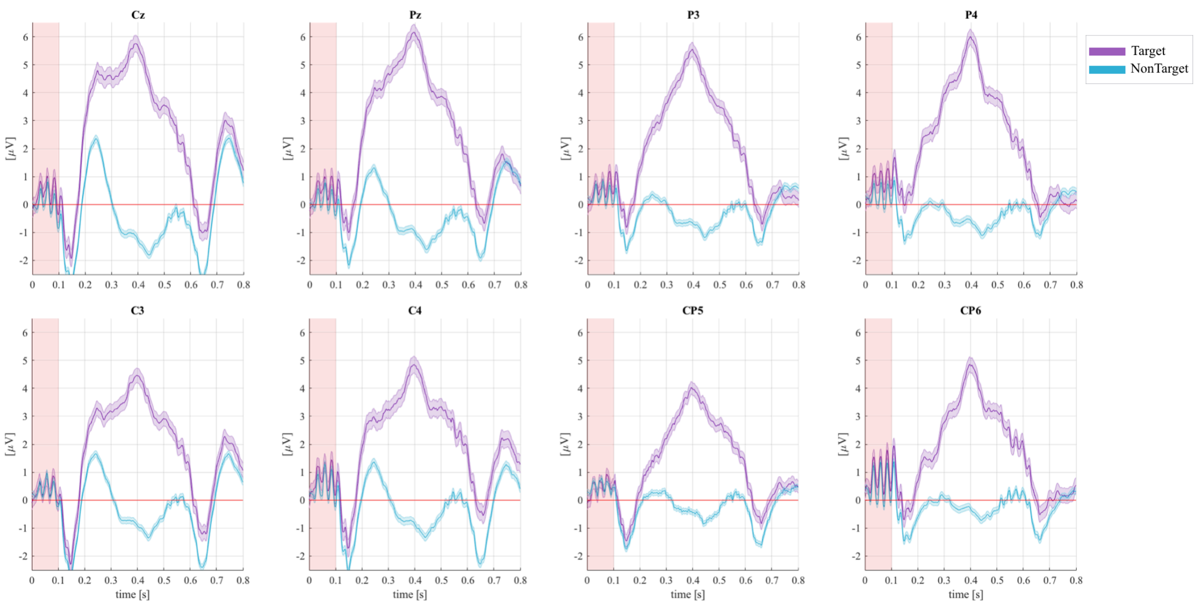

Figure 2: Grand mean averaged ERP results of all ten users in the fbBCI EEG experiment for target (purple lines) and non–target (blue lines) stimulus patterns. The vertical axis of each ERP result shows the electrical potentials, whereas the horizontal the time series after the stimulus onsets. The red covered area represents the vibrotactile stimulus duration (0 $\sim$ 100 ms), where electrical interferences could be spotted in form of EEG oscilations.

ysis (LDA) by repeating adding and reducing features based on resulting statistical tests. The SVM methods have been commonly used not only for brainwaves classification [11] but also in mane general machine learning studies. The SVMs have been achieving their high discriminant performances based on maximization intraclass margins. Moreover, SVM classification could be supported with several kernel functions $K(u,v')$ depending on the machine learning problems. In this study, we tested the linear kernel (linear SVM) $K(u,v') = u^{\mathrm{T}}v'$ and the Gaussian kernel (non–linear SVM) $K(u,v') = exp(-\gamma\|u-v'\|^2)$, where $\gamma = \frac{1}{L}$ for the P300 response classification. The parameter cost for the Gaussian kernel was fixed to $c = 1$.

III. RESULTS

The fbBCI EEG experiment results have been summarized in Figure 2, as grand mean averaged ERP responses of all ten participated users. The above figure presents the ERP intervals after stimulus onsets from 0 to 800 ms in each electrode channels, with clear somatosensory and P300 responses. The most encouraging findings were that the electrical potentials for the target stimulus patterns reached 4 μV or higher potentials for every electrode and their intervals were longer than 400 ms. These characteristics further assisted the superior classification of the proposed vibrotactile stimulus patterns.

The vibrotactile stimulus pattern classification accuracy results using the SWLDA, linear and non–linear SVM classifiers of the fbBCI EEG experiment have been reported in Figure 3 as accuracy comparisons with the decimation factors of $2,4,8,16$ or non decimation. Also the following averaging scenarios were tested using $2,5,10$ or non averaging steps in

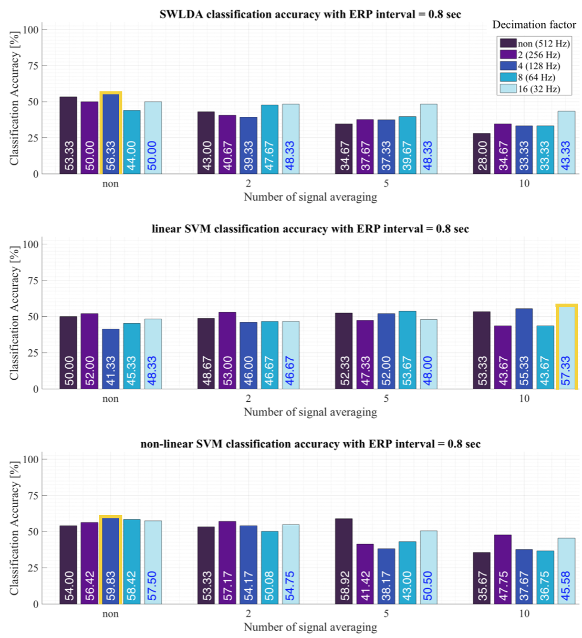

Figure 3: Comparison of the fbBCI grand mean averaged pattern classification accuracies using SWLDA (top), linear SVM (middle) and non–linear SVM (bottom). The vertical axis shows a percentage of the fbBCI classification accuracies. The horizontal axis represents number of signal averaging and each bar shows the signal decimation factor.

EEG signal preprocessing settings. Each bar in Figure 3 represents grand mean averaged pattern classification accuracy over five experimental trials for all ten participating users. The highlighted with yellow columns marked the best BCI accuracies for each classification method with the following achived rates of 56.33% for SWLDA, 57.33% for linear and 59.83% for non–linear SVMs, respectively. The best signal preprocessing settings were those using decimation factor 4 and no ERP averaging settings for the both SWLDA and non–linear SVM, whereas the decimation factor of 16 and number of ERP averaging of 10 for linear SVM. It has been noteworthy that all of the classification accuracies exceeded a chance level rate of 16.7% in the six–command based BCI experiments.

IV. DISCUSSION AND CONCLUSIONS

The purpose of the presented study was to determine the most suitable classification method for a tactile P300–based BCI paradigm. Besides, from the improved classification accuracy results, the potential validity of the proposed full–body tactile stimulation–based modality was also confirmed.

The most encouraging finding in this study was the best classification accuracy result using the non–linear SVM (59.83%) exceeding the mean accuracy result of our previous study using the SWLDA method (53.67%) [10]. Likewise, the both current study best results using SWLDA (56.33%) and using linear SVM (57.33%) exceeded the previously published rate [10], with the similar signal preprocessing settings. The reported in this paper findings have suggested that the non–linear SVM have been so far a more effective classification method for the tactile P300–based BCI paradigm. They also indicated a possibility that the proposed full–body tactile stimulation–based modality shall be applicable for LIS patients who have difficulty using vision or audition sensations due to their disabilities.

The presented study, however, was only conducted on the full–body tactile BCI modality with ten healthy users till now. Therefore, more analyses would be required, for example, more detailed comparison with another results of tactile P300–based BCI studies, or evaluation with disabled users. Overall, the results have reconfirmed that the P300 response–based full–body tactile BCI paradigm shall be a practical method. We expect that in the near future this neurotechnology application will contribute to improve a quality of life for those suffering from ALS and LIS disease patients in need.

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