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A Brain-Computer Interface Based on Multi-Modal Attention

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***Abstract*—The amplitude of steady-state evoked potentials (SSEP) can be modulated by switching spatial attention within one modality. In this article, we show that switching attention between different sensory modalities also modulates SSEP amplitude. This could be used to combine classifications in each modality into a multi-modal brain-computer interface (BCI) system. We present the result of combining visual and tactile stimulation. Our investigation also revealed an attention-related power change of the mu-rhythm. Taking this as an additional feature into account results in a three-class BCI system with the same accuracy like an SSSEP-based system with only two classes.**

I. Introduction

A brain-computer interface (BCI) is a system providing a direct communication channel between the human brain and a computer using suitable brain signals [1, 2]. The main goal of BCI research is to develop prosthetic devices that allow physically disabled or paralyzed people to operate a computer and control devices, thereby giving them the ability to perform simple tasks autonomously. An important type of BCI system is based on SSEP. In a typical steady-state visual evoked potential (SSVEP) based BCI system, the subject looks at targets flashing at different frequencies on a screen [3]. The SSVEP, measured at occipital electrodes, follows these frequencies. This can be used to select an action. The amplitude of steady-state somatosensory evoked potential (SSSEP) can also be modulated. If the subject focuses attention to stimulation at the left or right hand, the amplitude of SSSEP at the contralateral hemisphere increases [4]. A recently proposed BCI system based on modulation of SSSEPs reached 70-80% accuracy classifying left and right spatial attention after 5 days of training with online feedback [5].

The amplitude of evoked potentials is not only modulated by switching attention within one modality, but also by switching it between modalities. Such effects have been shown for vision and touch, for example [6, 7]: attending to one modality can modulate the modality-specific ERP component compared to unattended conditions.

Here we investigate if switching attention between modalities can also modulate SSEPs and whether this phenomenon can be applied in a BCI system. First we analyze the modulation of SSSEPs when switching attention between a tactile and a visual task. Then we compare the strength of the effect to the modulation when switching spatial attention within the tactile modality. Finally, we perform an offline analysis to determine the classification accuracy of the multi-modal BCI system.

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II. Methods

A. Subjects

Eight subjects (three female and five male, graduate students from Hamburg University and Tsinghua University), aged from 20 to 30 years, participated in this study. Five of them were naïve to this experiment. All of them showed normal or corrected to normal eyesight and touch sensation.

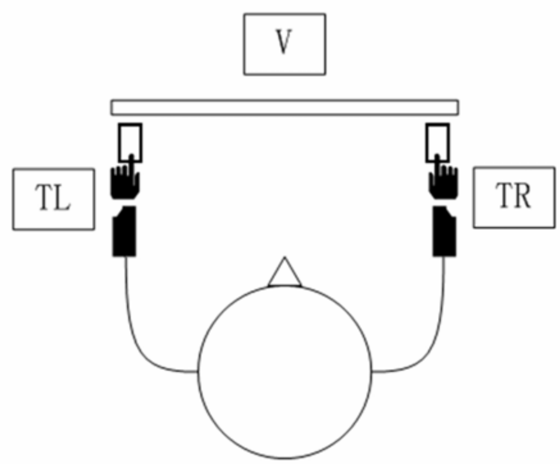

Fig. 1. The experimental setup. TL, TR and V indicate tactile-left, tactile-right and visual stimulus respectively. During the experiment these stimuli are presented simultaneously.

B. Stimulation

1) Tactile stimulation: Tactile stimuli were applied by two Braille elements attached to the distal segments of both index fingers. The 8 pins (1 mm in diameter) of each element were laid out in a rectangular area (3mm×8mm) and driven by Piezo-elements. All pins of each element were driven by the same signal. The elements were controlled by a programmable stimulator (QuaeroSys, Germany). The amplitude of the pins moving up and down could be varied between 0 and 1.5mm. Within one trial, subjects were

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stimulated with the maximum amplitude. The target event was a short (100ms) decrease in stimulation amplitude. In order to make the subjects really focus attention on the tactile stimulus, the amplitude change was minimized. The discrimination threshold was determined in a test before the experiment for each subject individually to make the reported accuracy of targets about 80%. Stimulation to the left and right hand was frequency tagged. The optimal frequencies were determined in a test before the experiment to yield maximal SSSEP amplitude. They ranged between 20 and 40Hz. The frequency resolution of the stimulator was 1Hz. To mask the noise emanating from the stimulators, the subjects wore earphones playing white noise.

2) Visual stimulation: Visual stimuli consisted of 5 capital letters (A through E) displayed on an LCD monitor (Dell, USA) with 60Hz refresh rate. They were presented centrally at 2.4° visual angle. Stimulation sequences consisted of 1 to 7 presentations of each letter in random order (total 25 letters in one sequence). Each letter was flashed for 116ms with the same time of blank screen between them, resulting in a 4.3Hz steady-state visual stimulation.

C. Experimental paradigm

The experimental setup is shown in Fig. 1. During the experiment, the subjects had to focus attention to the visual stimulus (V) or the tactile stimuli either at the right (TR) or at the left hand (TL). The visual task was to count the number of occurrences of a certain letter and the tactile tasks were to detect if there was an amplitude decrease or not. Subjects reported the results orally and their response was logged by the experimenter. Before each trial a cue was displayed on the screen instructing the subject which stimulus to attend to. After the cue the visual and tactile stimuli were presented simultaneously for 5s. Each session consisted of 60 trials (20 for each task) in random order. Each subject participated in 5 sessions, resulting in a total of 100 trials per task per subject. Presentation of the stimuli was programmed using the software package Presentation (Neurobehavioral Systems, USA).

D. EEG and EMG recording

A 32-channel EEG (ActiveTwo system, BioSemi Instrumentation, Netherland) was recorded at the scalp with a sampling rate of 1024Hz. The locations of the 32 electrodes were selected according to the 10-20 system. In addition, two electrodes were placed on each hand for bipolar recording of the EMG signals of finger movements.

E. Data analysis

The classification process is shown in Fig. 2. First a CAR (Common Average Reference) spatial filter was applied to enhance the signal-to-noise ratio of the EEG signals. In this method, the signals of all electrodes are re-referenced to the mean value of all channels. This approximates a reference-free EEG recording. Because it emphasizes the signal components that are present in many electrodes, CAR reduces singular components and functions as a high-pass spatial filter [8].

After spatial filtering, all trials were transformed to the frequency domain and averaged within each task. The amplitudes at the frequencies of the visual and tactile stimulations constitute three feature values for classification. Two other features used are the averaged power values of the mu-rhythm (8-14Hz) at peri-central electrodes C3 and C4.

In order to find the EEG channels with the strongest task modulated response, we computed the squared Pearson product-moment correlation coefficient (r^2) between the feature values for each trial and the task. Coefficients close to 1 indicate a linear relationship between the feature and the task, whereas for values close 0 there is no such correlation.

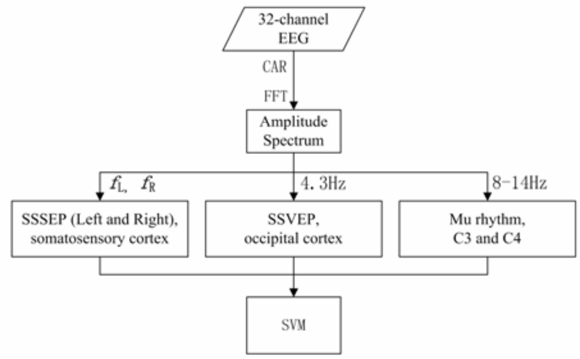

Fig. 2. Flow chart of the classification process. f_L and f_R are subject-specific frequencies (20-40Hz) for tactile stimuli.

To investigate the possibility of building a BCI system based on multi-modal attention, we performed an offline classification using the support vector machine (SVM, [14]) algorithm and the features from the electrodes with the highest r^2 values. The SVM classifier was trained using 10×10-fold cross-validation.

All analyses were carried out using Matlab (The Mathworks, USA).

III. Results

The spatial mappings of r^2-values in the three conditions are shown in Fig. 3. When switching attention between the two tactile tasks, the highest r^2 values based on SSSEP are observed over fronto-central electrode locations contralateral to the attended finger (Fig. 3a). This is consistent with previous findings on attention modulated SSSEPs [4]. In Fig. 3b the SSSEP is shown when attention switches between the visual and the tactile task. The change in amplitude is statistically significant in 5 out of 8 subjects (t-test and =0.05). Fig. 3c shows that the SSVEP can also be modulated by switching attention between modalities. The change in amplitude is statistically significant in all subjects (t-test and =0.05).

An interesting observation is the attention-related power change of mu-rhythm over peri-central cortex (Fig. 4, the change in amplitude is statistically significant in all subjects, t-test and =0.05). The resulting correlation coefficients (r-value) were Fisher z transformed before averaging over subjects, then retransformed, squared (r^2 value) and plotted on

Fig. 4b. Depending on the baseline, this change can be seen as either a decrease during task TR/TL or an increase during task V. Since the mu-rhythm is associated with motor planning and execution, and attention typically increases amplitude of evoked potentials [4], this change was not expected. The correlation between the task (TR/TL vs. V) and the EMG at stimulation frequencies of tactile stimulus is very low (Table 1), verifying that the classification was not affected by finger movements relative to the stimulators.

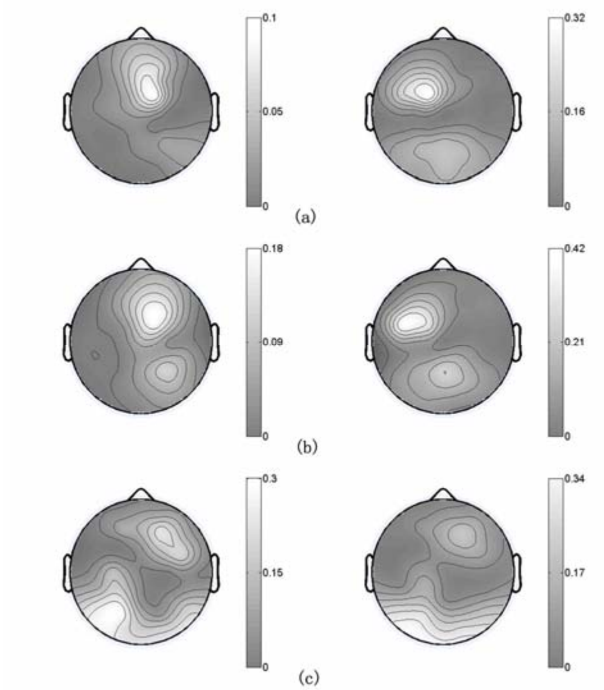

Fig. 3. Averaged spatial mappings of r^2 values of subject WA: (a) task TR vs. TL, based on SSSEP features (left figure for EEG components at stimulation frequency of the left finger and right figure for EEG components of right finger); (b) left: task TL vs. V, based on SSSEP feature at stimulation frequency of left finger; right: task TR vs. V, based on SSSEP feature at stimulation frequency of right finger; (c) left: task TL vs. V, based on SSVEP feature; right: task TR vs. V, based on SSVEP feature.

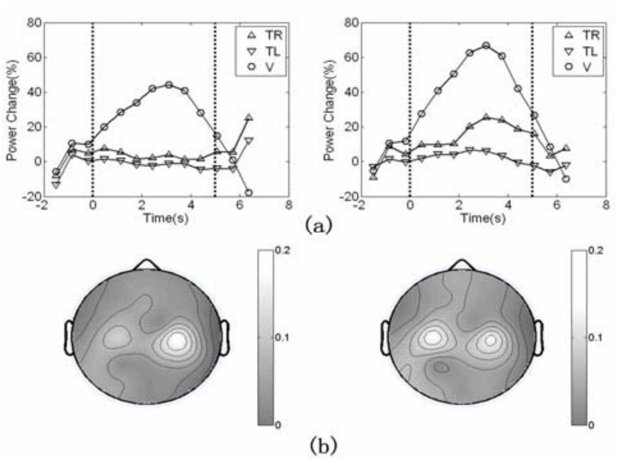

Fig. 4. (a) Averaged power change during task TR, TL and V, left/right for channel C3/C4, using averaged power of all interval time as baseline, subject CL (t=0 indicates onset of trials); (b) Spatial mapping of r^2 values based on mu-rhythm energy (left/right for TL/TR vs. V), averaged over all subjects.

TABLE I
CORRELATION OF THE EMG SIGNALS AND THE TASK

Subject	Left hand r^2	Right hand r^2
CL	0.0010	0.0003
IN	0.0003	0.0002
NI	0.0027	0.0001
ZH	0.0098	0.0426
WA	0.0006	0.0018
CO	0.0076	0.0003
AL	0.0049	0.0114
TI	0.0003	0.0001

Low r^2 values indicate less correlation of the EMG signals and the task (TR/TL vs. V). All subjects show corresponding p-values >> 0.05.

TABLE II
CLASSIFICATION ACCURACY IN DIFFERENT CONFIGURATIONS

Subject	TR vs. TL	TR/TL vs. V	TR vs. TL vs. V
CL	55.8±4.1%	90.7±1.8%	63.9±3.2%
IN	63.8±4.2%	81.7±4.0%	56.9±3.2%
NI	63.1±3.5%	89.2±2.3%	61.8±3.7%
ZH	69.4±2.1%	83.2±4.7%	65.9±0.9%
WA	78.5±3.7%	90.2±3.1%	80.1±2.4%
CO	48.8±2.1%	76.2±3.3%	46.1±3.7%
AL	64.3±1.8%	83.5±2.9%	61.9±3.2%
TI	60.4±3.3%	70.6±4.6%	57.3±3.2%
Average	63.0±8.8%	83.2±7.2%	61.7±9.7%

The classification capabilities of the features were tested in three different configurations. Using only the SSSEP feature yields 63.0±8.8% accuracy over all subjects for classifying the left and right tactile task. This is consistent with previous results [5]. Switching attention between the visual and tactile task and using all features, i.e. SSSEP, SSVEP and mu-band power, increases the two-class (TR/TL vs. V) classification accuracy to 83.2±7.2%. Since there are two conditions in the tactile modality and one condition in the visual modality, we can distinguish 3 classes. In this configuration 61.7±9.7% accuracy can be obtained. For single subject results, refer to Table 2.

IV. DISCUSSION AND CONCLUSION

Switching attention between visual and tactile stimulation and using the ensuing modulation of SSSEP and SSVEP results in a BCI system with a performance that compares well with other SSSEP-based systems [5]. By combining two input modalities, however, a larger number of classes can be distinguished. Compared to BCI systems based on motor imagery [15, 16], our system obtains a similar classification accuracy for between modality classification but without any training of the subject. This clearly is an advantage for the practical application. Training the subjects can be expected to further improve the results.

One reason for the unexpected decrease of mu-band power when attending to the tactile task might be event-related desynchronization (ERD) in the motor cortex due to the occurrence of finger movements. The EMG recording and the missing correlation with the task exclude this possibility. ERD in mu-band has also been observed under tactile stimulation [13] and during motor imagery [10]. Our hypothesis is that the attention-related ERD observed in our experiment and motor imagery ERD could have a common underlying mechanism. This will be investigated in a future experiment.

An alternative way of interpreting such effect is to consider it as event-related synchronization (ERS) during the visual task. ERS may correspond to an idle state of motor or somatosensory cortex. Due to limited resources, when focusing on the visual task, the attention system may switch somatosensory areas into this idle state. Vice vesa, focusing on the tactile task could be considered as a reduction of attention to visual stimulation. Our results show that this modulates the amplitude of SSVEPs. Likewise, it has been shown that changing the strength of attention to a visual stimulus can modulate the SSVEP amplitude. This mechanism has been applied in a practical BCI system [11]. We hypothesize that the SSVEP modulation in our experiment is caused by similar mechanism.

In summary, we investigated the modulation effect of attention on steady-state brain response. The results show that SSSEP can be modulated by switching spatial attention but also by switching attention between modalities. We found mu-band ERD during attending to tactile stimulation, which is an interesting discovery. The accuracy of the offline classification confirms that the multi-modal approach is suitable for a BCI system. Taking the auditory modality into consideration could be the next step. Furthermore, we propose the idea of combining spatial attention in every modality and the attention between modalities, which could result in a new type of BCI systems.

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