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Multimodal Brain-Computer Interfaces*

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Abstract: A critical parameter of brain-computer interfaces (BCIs) is the number of dimensions a user can control independently. One way to increment this number without increasing the mental effort required to operate the system is to stimulate several sensory modalities simultaneously, and to distinguish brain activity patterns when the user focuses attention to different elements of this multisensory input. In this article we show how shifting attention between simultaneously presented tactile and visual stimuli affects the electrical brain activity of human subjects, and that this signal can be used to augment the control information from the two uni-modal BCI subsystems.

Key words: steady-state evoked potentials; SSVEP; SSSEP; attention; EEG; support vector machine

Introduction

Causing effects by mere thinking is a dream of mankind that has not yet turned into reality, but research into brain-computer interfaces (BCIs) has demonstrated some potential for technical feasibility. In general, a BCI consists of components for the acquisition of signals from the brain's activity, for the analysis and classification of these signals, and for driving a computer or other device based on the classifier output. This effectively constitutes a direct communication channel between the brain and a computer[1]. A BCI in the narrower sense bypasses any muscular activity of the user, like limb moving, speaking, eye movements, or jaw clenching, a definition that is based on the original motivation for development of BCI techniques as a rehabilitation method for patients suffering from severe motor impairments. In recent years several applications of BCI technology for feedback and assistance systems, games, and person authentication and identification have emerged, which are used mainly by healthy humans. In a wider sense any system that translates brain activity into control signals for a device can be considered a BCI. Today information transfer in BCIs is one-way, from the brain to the computer. Methods for sending information in the opposite direction, i.e. from the computer into the brain, bypassing all sensory organs, are beginning to emerge[2].

The acceptance of technical solutions for extracting information from human brain activity depends on two main factors: reliability and ease of use. A well-established BCI paradigm that satisfies both factors employs steady-state evoked potentials (SSEPs) — oscillatory brain activity caused by and phase-locked to rhythmic sensory stimulation[3]. This rhythm can be reliably detected in the electrical brain activity, recorded by amplifying the weak electrical potentials that can be measured on the surface of the head (electroencephalogram (EEG)).

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1 SSEP-Based BCIs

An evoked potential is a change in the electrical potential of the brain that is caused by a transient in the sensory stimulation of the subject, for example by switching on a light. Evoked potentials show at a fixed delay relative to the stimulus. If the stimulation is repeated at regular intervals, individual evoked potentials are superimposed, which composes a steady-state response. Alternative theories consider transient phase resetting of ongoing activity[4,5] or baseline shift of ongoing activity[6] as causes.

Figure 1 illustrates the principle for generating SSEPs by visual stimuli. These so-called steady-state visual evoked potentials (SSVEP) are normally elicited by light that flickers at frequencies between 3 and 50 Hz. They can be detected in the human EEG and exploited for BCI applications[7]. In a similar manner SSEPs can be caused by repetitive sounds (evoking auditory steady-state responses (ASSR)) or vibro-tactile stimuli (evoking somatosensory steady-state evoked potentials (SSSEPs)).

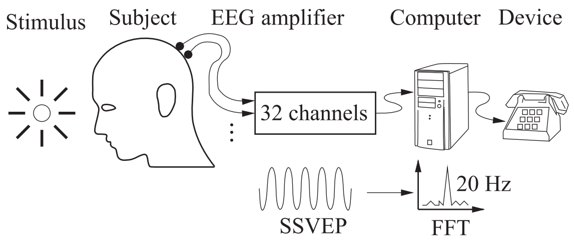

Fig. 1 Schematic of an SSVEP-based BCI. Looking at a flickering light (e.g., at 20 Hz) causes SSVEPs in the electrical brain activity of the subject. SSVEPs are prominent over occipital brain areas, and can be registered by an EEG amplifier. The signal is then processed on a computer for extracting features (e.g., Fourier spectrum) and classification. The output of the classifier is used to control a device. In this example the subject can dial a number on the phone by looking sequentially at lights flickering at different frequencies corresponding to the digits on the key pad.

Three properties of SSEPs have made them a popular approach to BCI sytems: First they can be well distinguished from the ongoing or background activity of the brain, typically considered as noise, by virtue of a high signal-to-noise ratio. Second and more importantly, the SSEP frequency reflects exactly the stimulation frequency, opening the possibility for tagging different stimuli by different frequencies. For SSVEPs, for example, when several lights are simultaneously presented, the highest SSVEP amplitudes will be registered at the frequency of the light currently fixated by the subject. This frequency-coded type BCI (also called f-VEP BCI[8]) using visual evoked potentials has been extensively studied, and is one of the most successful paradigms for BCI control[9-14]. Third, higher-order cognitive functions, like attention, can also modulate SSEP amplitudes[15-17]. BCI systems based on this attentional modulation of SSVEP[18-20] and SSSEP[21,22] amplitude have been developed.

However, all SSEP-based BCI till now utilized only one type of SSEPs in the respective BCI system. Recently, the idea of combining different approaches to implement hybrid BCIs has become more and more popular[23]. Combining two or more paradigms into one BCI implementation potentially multiplies the number of commands at the disposal of the user. Moreover, the BCI users do not have to spend more mental effort to benefit from the integration of different paradigms.

In the following sections we present a study that shows how a BCI system can exploit changes in SSVEP and SSSEP amplitude when switching attention between visual and tactile modalities.

2 Bi-modal BCI Using SSVEPs and SSSEPs

2.1 Experimental setup

A detailed description of the experimental setup is given in Ref. [21], but a short summary is reproduced here. Visual stimuli consisted of 5 capital letters (Latin characters A through E) flashing at 4.3 Hz on an LCD monitor. A stimulation sequence consisted of 1 to 7 presentations of each letter in random order (total 25 letters in one sequence).

Tactile stimulation was applied to the distal segments of both index fingers using two computer-controlled Braille elements. Subjects had to detect a transient (100 ms) drop in stimulation amplitude. This decrease was adjusted to the individual discrimination threshold, making the task challenging. 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. Stimulation frequencies ranged between 20 and 40 Hz.

The experimental setup is shown in Fig. 2. During the experiment, the subjects had to focus attention on 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 task was to detect if there was an amplitude decrease at the respective hand or not. Subjects reported the results orally, and their response was logged by the experimenter. Before the start of each trial a cue was displayed on the screen instructing the subject which stimulus to attend to. After the cue, visual and tactile stimulation was switched on for 5 s. Each session consisted of 60 trials (20 for each task) in random order.

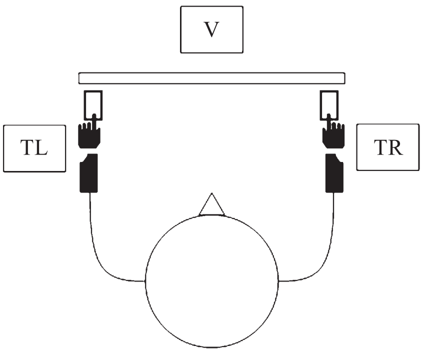

Fig. 2 Schematic view of the experimental setup. TL, TR, and V indicate tactile tasks on the left and right hands, and the visual task respectively. During the experiment tactile and visual stimulation was presented simultaenously.

2.2 Data analysis

The 32-channel EEG data recorded during each trial were first processed by a common average reference (CAR) spatial filter to enhance the signal-to-noise ratio. After spatial filtering, all trials were transformed to the frequency domain and averaged within each task. The SSEP amplitudes at the frequencies of the visual and tactile stimulations constitute three feature values for the classification that followed. Two other features were the averaged power values of the mu-rhythm (8-14 Hz) 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 reliable change of the feature value with the task, whereas for values close to 0 the feature is unaffected by the task.

To investigate the possibility of building a BCI system based on multi-modal attention, we performed an offline classification using the support vector machine algorithm (SVM[24]) and the features from the electrodes with the highest r^2 values.

3 Results

The spatial distribution of correlations between tasks and changes in SSEP amplitude are shown in Fig. 3. The strongest correlation of the attention switching between right and left hand with the SSSEP amplitude at the stimulation frequency of the left hand, for example, appears at fronto-central electrodes over the right hemisphere (see Fig. 3a, left panel). Systematic power changes at the stimulation frequency of the right hand with the attention switching between the two tactile stimuli appear at fronto-central electrodes over the left hemisphere (see Fig. 3a, right panel). At these positions a statistically significant power change can be observed when trials with attention to the right hand are compared to trials with attention to the left hand.

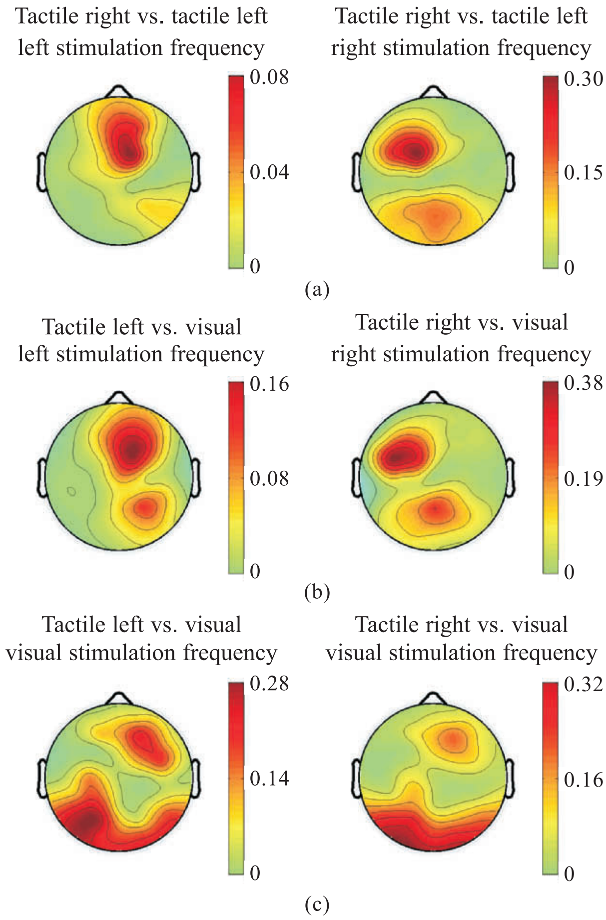

Fig. 3 Topographies of correlations (r^2-values) between attentional task (left/right column: attention to the left/right tactile stimulus) and SSSEP (a and b) and SSVEP power (c) for a representative subject.

Contrasting the tactile tasks with the visual task (Fig. 3b) shows an additional systematic change of SSSEP amplitude over contra-lateral parietal areas at the respective stimulation frequency. The strongest task-related modulation of the SSVEP is observed over occipital areas (see Fig. 3c).

An interesting observation is the attention-related power change of mu-rhythm over peri-central cortex (see Fig. 4). Depending on the baseline, this change can be seen as either a decrease during task TR/TL, or an increase during task V. Significant correlations can be observed over both hemispheres (electrodes C3 and C4), but they are strongest on the contra-lateral side of the attended finger. Since the mu-rhythm is associated with motor planning and execution, and attention typically increases amplitude of evoked potentials[15], this change was not expected.

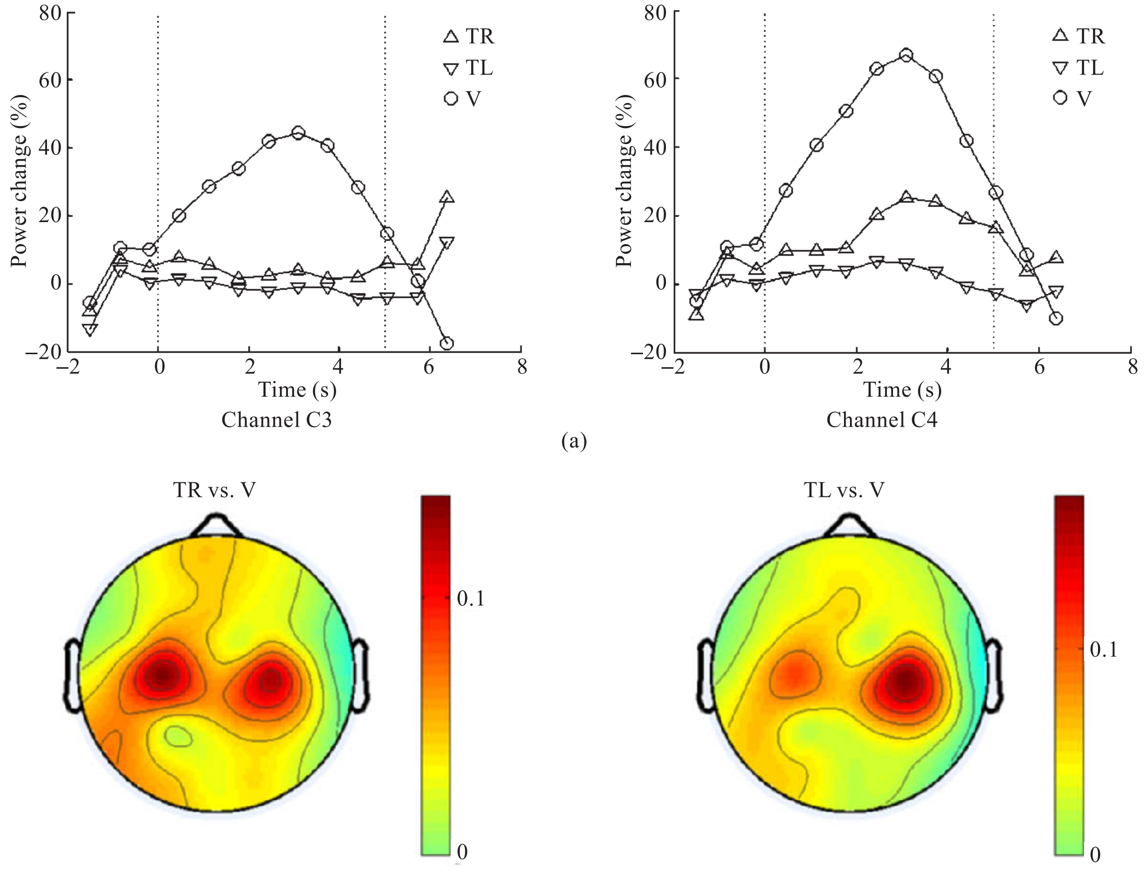

Fig. 4 (a) Average power change during TR, TL, and V at electrodes C3 (left) and C4 (right panel) compared to average power over time as baseline (subject CL). (b) Topography of r^2 values showing the correlation between task and power of the mu-rhythm: TL-V (right) and TR-V (left).

To investigate if the correlations between attention and observed power changes are a simple effect of electrical activity of finger or arm muscles, we computed r^2 values for the correlation between the task (TR/TL vs. V) and the EMG amplitude. These correlations were very low (typically below 0.01) and not statistically significant[21].

The observed attentional modulation of SSSEP amplitude, SSVEP amplitude, and mu-power were used as features in a classification system for automatically recognizing to which element of the stimulation the subject directed his/her attention. Figure 5 shows a schematic view of the processing stages. By comparing for each trial the classifier output to the target of attention as requested from the subject by the cue, the correctness of the recognition method was evaluated. Three configurations were investigated. Using only the SSSEP feature yielded 63.0%±8.8% accuracy over all subjects for classifying attention to the left vs. right hand. This result is consistent with previous studies[22].

Switching attention between the visual and tactile task and using all features, i.e., SSSEP, SSVEP, and mu-power, increased 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, the system can distinguish 3 classes. In this configuration the accuracy was 61.7%±9.7%.

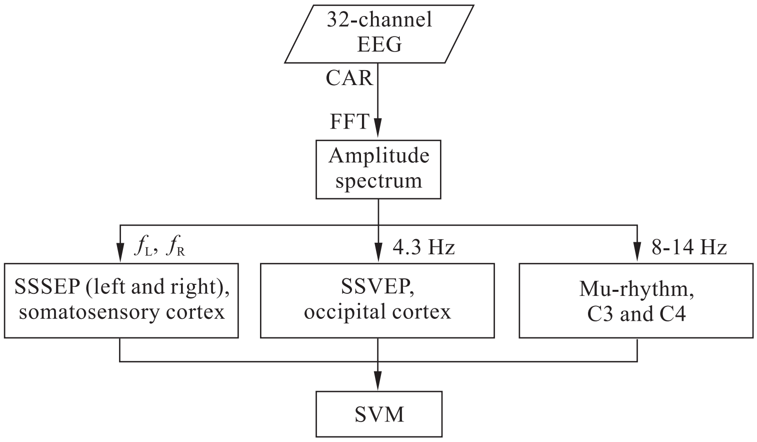

Fig. 5 Flow-chart of the classification process. f_L and f_R are subject-specific frequencies of vibro-tactile stimuli yielding maximal SSSEP amplitude.

4 Discussion

The results show that the amplitudes of SSSEPs and SSVEPs can be selectively modulated by the subject shifting attention voluntarily to different elements of a multisensory stimulation. For SSSEPs we observed a negative modulation, i.e. a reduction of SSSEP amplitude when attention was directed to the respective stimulus. Positive modulations have also been observed in a different experimental setup[15]. A systematic investigation of attentional SSSEP modulation showed that the direction depends on the depth of processing of the stimulus at the attended location, and is highly dependent on which properties of the stimulus are currently task relevant[25]. For SSVEP we observed an increase in amplitude when attention is directed to the visual stimulus, which is consistent with previous findings[26].

The SSEP amplitudes from the different modalities were used as features for a classification system that can automatically detect to which element of the stimulus the subject currently pays attention. This effectively constitutes a BCI that the user can control by directing attention to different stimulation elements. Recognition of attention switches between modalities (TR/TL vs. V) is more reliable than attention switches within the tactile modality (TR vs. TL). More importantly, the accuracy of recognizing all three attentional states (TR vs. TL vs. V) is only marginally lower than the accuracy of the two-class system using only the tactile stimulation. This shows that combining several uni-modal BCI systems is an efficient way of increasing the number of control dimensions without increasing cognitive or training requirements from the subject, maintaining reliability of the combined system relative to the reliability of the uni-modal systems.

Various extensions that further increase the number of control dimensions of the proposed system are straightforward. Instead of using only a single visual stimulus, several frequency-tagged stimuli can be simultaneously presented to the user. The attentional modulation of the SSVEPs at the corresponding frequencies allows to distinguish several visual classes (e.g., visual left vs. visual right)[27] in addition to the two tactile classes (tactile left vs. tactile right). Extending this system by auditory stimulation has the potential to further increase the number of control dimensions. Modulation of the auditory steady-state response (ASSR) by attention has been shown in Refs. [17,28], and the same data analysis methods used for detecting these modulations in SSSEPs and SSVEPs can be applied to detect ASSR modulations. Finally, a combination of this multi-modal SSEP-based BCI with other reliable BCI paradigms, e.g., based on P300 or ERD/ERS, into a hybrid BCI[23] is conceivable.

How multi-modal BCIs will be accepted by the users remains to be assessed. On the one hand, the majority of devices we operate in our daily lives leave a genuinely multisensory impression (think of driving a car, or operating a hand blender). Therefore, multisensory BCIs may receive better acceptance for the more “natural” way of operating them. On the other hand, we are used to multi-tasking in daily routines, like answering the phone while driving or handling the blender. Blocking too many modalities by a BCI might hence lower the acceptance to use such a device routinely.

In conclusion we would like to point out that the attentional modulation of SSEPs cannot only be exploited for technical applications as described here, but can be employed for investigating the neurophysiological basis of attention in general[29].

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