Bakardjian H., Martinez P., Cichocki A., Steady-state visual evoked responses as a reliable tool for an online 8-command brain-machine interface, Proc. of World Multi-Conference on Systemics, Cybernetics and Informatics (WMSCI'08), Orlando, Florida, USA, June 29 - July 2, 2008

Steady-State Visual Evoked Responses as a Reliable Tool for an Online 8-Command Brain-Machine Interface

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INTRODUCTION

Brain-Machine Interface (BMI) research and technology are among the most dynamically developing research areas of neuroscience in the recent decade. As the technology has matured in recent years, more emphasis will be given to applications for healthy users, in addition to its vital basic function to help disabled subjects. A noninvasive approach based on EEG with only a few sensors has been very successful. Even though BMI communication can be achieved in a number of ways, either by using brain responses to externally-driven stimulation, or by recognition of internal brain states, each approach has its own advantages and shortfalls. One BMI paradigm which has the potential to offer superior recognition performance and high number of independent commands is the Steady-State Visual Evoked Potential (SSVEP) approach. In this paradigm, multiple patterns, which flicker or reverse at slightly different frequencies, evoke precisely synchronized steady-state brain activity depending on the subject's selective attention to one of the stimulation patterns [1-4].

BMI SYSTEM DESCRIPTION

One of the implementations of our 8-command SSVEP-based BMI system allows 2-dimensional navigation control of a small car object on a computer monitor screen, which either moves on a closed racing course with a complicated shape, or chases a ball-shaped target (no route limitations). Eight small reversing checkerboard patterns (1.8° arc in size each), controlling the movement, are attached very close to the car object, allowing translation in 8 directions with 45° resolution in 2-D space.

After the user's EEG signals are acquired (6 channels), the ocular and other artifacts are rejected using fast online blind-source separation (BSS) to remove interference from eye blinks, muscle activity and so on. This procedure serves to increase the success rate of the system. The 'cleaned' brain signals are further processed using Kalman filtering and fitted to sine waves with frequencies exactly corresponding to the patterns' reversal rate. The model parameters are optimized using a recursive least-squares procedure, and the model's output signals are adjusted to the shape of the individual spectrum of each BMI user. Statistical comparisons of the extracted signal features allow the final classification of the neuro-command the user intended to send to the machine.

The recognized neural commands are transferred back to the user station and, corresponding to each recognized command, the visual neurofeedback module initiates spatial position changes of the controlled object in two-dimensional space.

All SSVEP stimuli used in this study conform strictly to the guidelines for prevention of photic- and pattern-induced seizures [5].

RESULTS

SSVEP Response Characteristics

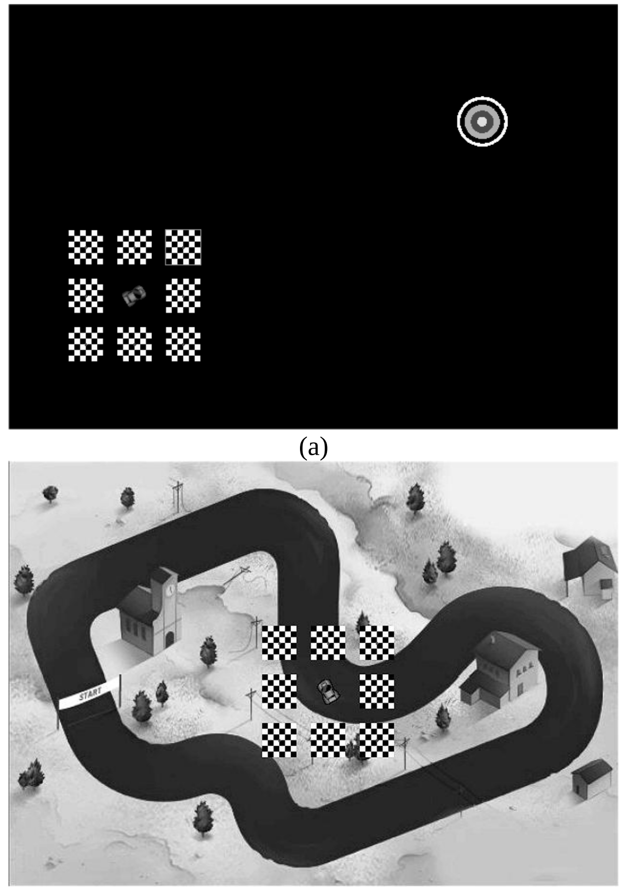
In order to maximize the performance and speed of the BMI system, we studied in detail the whole-head brain responses (128 channels, active electrodes) to SSVEP stimulation with various pattern parameters such as frequency, shape, movement and covert attention. We found that the best frequency response corresponds to visual stimulation of about 12Hz, with several other response peaks as well. Further, we studied the SSVEP time courses as well (in 15-second trials, at 8, 14 and 28Hz), and observed highly dynamic and non-stationary brain responses. The SSVEP onset latency is one important neurophysiological parameter for the evaluation of the BMI system's performance. The minimal mean delay of the first major SSVEP peak was observed at ~1.8s for the medium-frequency range of stimulation (14Hz).

Optimized BMI System Evaluation

The BMI system based on these optimized settings showed a high performance of 98% in the occipital area, 81% in the bilateral temporal areas, and 74% in the frontal area. The mean command time delay for 4 subjects was 2.4±1.0sec These results demonstrated that even though the performance would degrade to some extent, a BMI system based on sensors over other brain areas (temporal, frontal) is feasible and could be developed further for practical use with electrodes mounted on headbands and eyeglass temples.

CONCLUSIONS

Our BMI platform offers several novel points, such as the integration of 8 very small, moving reversing patterns together with the controlled object to improve the overall control by decreasing the long-term attention-related fatigue and by minimizing the necessary eye movements. Other novel features include the application of online BSS for artifact rejection, improved feature extraction through modeling of the signal, and a fast neurofeedback stimulation module for multiple commands. These signal processing features, along with the neurophysiological optimization of the presented multiple simultaneous SSVEP stimuli, allowed our non-invasive real-time brain-machine interface system to reach mean bit transfer rates of over 50 bits/min, among the highest up to date. Future research may probe further possibilities to achieve a similar performance using even smaller patterns, and stimulation without a computer screen such as LED panels attached to wheelchairs, or house walls, in order to control objects with brain power only.



(a)

(b)

Fig.1. Multi-stimulus user neurofeedback designs used in the presented SSVEP-based BMI system. The 8 checkerboard patterns, which reverse at different frequencies, are very small, close to each other, and move together with the controlled object (a car).

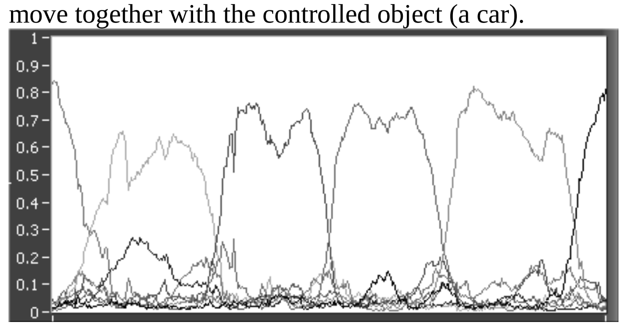


Fig.2. Output signals from the signal analysis module, representing the time evolution of probabilities for recognition of their corresponding commands, as the user attends to different patterns.

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state visual evoked response into a control signal for operating a physical. device or computer program. In one approach, operators self-regulate the.Â imagery on EEG and an online study that uses pattern classifiers incor-. porating parameter uncertainty and temporal information to discriminate. between different cognitive tasks in real-time.Â Brain Computer Interfaces (BCIs) allow a user to control a computer application by acquiring brain activity using Electro Enchephalo Gram (EEG). Non-invasive practical EEG headset available in the market brings more and more research in the field of BCI. BCI applications such as speller device is used both in entertainment field and health industry for typing using brain without using hands. Steady-state visual evoked potentials (SSVEP) brain-computer interface (BCI) provides reliable responses leading to high accuracy and information throughput. But achieving high accuracy typically requires a relatively long time window of one second or more. Various methods were proposed to improve sub-second response accuracy through subject-specific training and calibration. Substantial performance improvements were achieved with tedious calibration and subject-specific training; resulting in the user's discomfort. So, we propose a training-free method by combining spatial-filtering and temporal alignment (CSTA) to recognize SSVEP responses in sub-second response time. Brain computer interface (BCI) is an emerging technology for paralyzed patients to communicate with external environments. Among current BCIs, the steady-state visual evoked potential (SSVEP)-based BCI has drawn great attention due to its characteristics of easy preparation, high information transfer rate (ITR), high accuracy, and low cost. However, electroencephalogram (EEG) signals are electrophysiological responses reflecting the underlying neural activities which are dependent upon subjectâ€™s physiological states (e.g., emotion, attention, etc.) and usually variant among different individuals. The development of classification approaches to account for each individualâ€™s difference in SSVEP is needed but was seldom reported. This paper presents a multiclass support...