The Challenges of Using Scalp-EEG Input Signals for Continuous Device Control

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Abstract. Whether aiming to control a computer cursor, a robotic arm, or a wheelchair, it remains a significant challenge to achieve responsive and reliable asynchronous control via EEG signals. The most promising scalp-recorded EEG signals for this task are sensorimotor rhythms and steady-state visual evoked potentials, which have both been demonstrated to be viable for continuous device operation in controlled laboratory settings. Several issues, such as handling signal nonstationarity and identifying reliable asynchronous modes of operation, must be addressed before these scalp-EEG signals can become practical for controlling devices outside of the laboratory.

1 Introduction

A brain-computer interface (BCI) provides a non-muscular channel for the brain to interact with the world, and is particularly useful for individuals with neuromuscular disabilities. Many such individuals, e.g., those with amyotrophic lateral sclerosis, still have normal cognitive capabilities but are 'locked in' and unable to communicate. These individuals are reliant upon this additional channel for basic communication, control, and a level of autonomy. Current BCIs have only recently been demonstrated for in-home use by disabled individuals [1]. These systems use BCI2000, a general framework capable of performing a variety of BCI paradigms, but have been found to be most practical for home use when operating either the P300 Speller or a sequential-menu driven system using sensorimotor rhythms (SMR). The P300 Speller is capable of performing discrete selections, but requires considerable trial averaging in order to provide accurate results, hence is not suitable for real-time continuous control. The sequential-menu driven SMR is based on 1 or 2-dimensional center-out tasks to make discrete selections from a set of menus. The appeal of these systems is partly that discrete capabilities allow the user to theoretically pause the system with a proper sequence of selections. This provides the user with a primitive form of asynchronous control, but still requires selections to be made in a given time frame.

In order to generate a more natural system for the user, continuous control needs to be implemented in an effective manner, such that truly asynchronous and reliable control can be achieved. Proven methods for continuous BCI control include steady-state visual evoked potentials (SSVEPs) and SMRs. SSVEPs are electrical potentials produced in the brain in response to a repetitive, periodic visual stimulus. SSVEPs

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have been demonstrated in laboratories to provide relatively high bitrates, some with communication rates exceeding 70 bits per minute [2]. Since this is an elicited signal, no user training is believed to be required. However, it is argued that gaze control is still required to obtain these results, which some disabled users may lack. Another possible BCI modality for continuous control includes SMRs, where imagined movement results in measurable power differences in certain EEG frequencies as compared to resting states. Currently, users are required to extensively train to gain adequate levels of control. Training occurs as the user adapts to the system, while the system is simultaneously adapted to the individual. Two of the most significant hurdles to overcome in order to achieve the level of reliable continuous control required for extended BCI home use are the identification of dependable asynchronous control modes and the proper treatment of the nonstationarities in EEG signals of interest. This nonstationarity hinders the training process for SMR control as well as the EEG feature translation and classification capabilities of most BCI modalities.

2 Asynchronous Modes of Operation

Asynchronous BCIs allow for the user to operate a device at his or her own pace, instead of being confined to time-constrained control intervals dictated by the BCI. Asynchronous BCIs are becoming an active area of research [3], with some recent efforts focusing on providing a switch to turn the control state of the device on or off. This method of control requires the user to perform some task, typically with a different BCI modality, to enable or disable the primary method of control. For instance, it has been demonstrated that an orthosis has been controlled by a combination of motor imagery and SSVEPs [4]. In this work, SMRs were used to enable the orthosis, while SSVEPs opened or closed the orthotic hand. Although the orthotic hand was not continuous in operation, these hybrid BCIs provides the first steps toward asynchronous control. A more natural method for continuous, asynchronous control would be to eliminate the need for a control switch. In this case, the no-control state is very important. When dealing within a physical environment (e.g., robotic arm control), minimizing the number of false positives are key to minimizing unwanted collisions within the environment. One key question remains, how to effectively determine the no-control state in a continuous asynchronous environment? Confidence levels, and thresholding of classifiers are possible methods, but can simultaneously hinder the speed of the system, e.g., causing too many false negatives. To further complicate the issue, the relevant signal nonstationarities must be identified, characterized, and effectively countered for such asynchronous approaches to successful.

3 Signal Nonstationarities

The characteristics that describe a user's EEG are continuously changing. These signal nonstationarities can result in significant differences within and across days, and can be attributed to a variety of factors such as: the user’s physical and mental state, the development of new cortical activities, the user attempting to adapt to the system feedback while the system simultaneously adapts to the user (i.e., co-adaptation), changing recording conditions, etc. New and intelligent signal processing methods are required to effectively cope with these nonstationarites. Possible approaches to deal with the nonstationarity include 1) extracting the stationary signal components embedded within nonstationarities [5], or 2) implementing control schemes that adapt to the changing state of the EEG. An example of the first approach is that SMR phase information has been shown to carry additional directional information to supplement the traditional amplitude information, while being stable across several days for encoding hand movement direction [6]. For the second approach, several techniques for unsupervised adaptation have been proposed in [6], including 1) covariate shift adaptation / minimization, 2) feature adaptation, which focuses on adapting the parameters of the feature extraction method to account for subject learning, and 3) classifier adaptation for dealing with shifts in feature distributions in addition to the conditional distributions between features and classifiers.

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