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Brain–Computer Interfaces Based on the Steady-State Visual-Evoked Response

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***Abstract*—The Air Force Research Laboratory has implemented and evaluated two brain–computer interfaces (BCI's) that translate the steady-state visual evoked response into a control signal for operating a physical device or computer program. In one approach, operators self-regulate the brain response; the other approach uses multiple evoked responses.**

***Index Terms*—Brain–computer interface (BCI), human–computer interface, neural self-regulation.**

I. INTRODUCTION

The Alternative Control Technology (ACT) program of the Air Force Research Laboratory is engaged in the design and evaluation of a variety of hands-free controls. These include eye, head, speech, electromyographic and electroencephalographic (EEG) systems that allow communication with computers while the operators' hands remain engaged in other activities. For example, alternative controls may enable maintenance technicians to manually operate test equipment while accessing schematics on a head-mounted display.

In general, EEG-based control uses selected aspects of the brain's electrical activity. However, this definition does not dictate a specific control methodology. Interestingly, several different EEG-based control devices based on visual evoked responses have been developed in parallel at various research institutions. For example, Farwell and Donchin [1] developed a control based on the "P300," a brain response that varies as a function of stimulus probability and task relevance [1]. Careful design of the task format and procedures allowed these authors to use the natural variance of the P300 for task control. Sutter [2], [3] developed a control device based on the natural variation in cortical visual evoked potentials to determine the user's direction of gaze relative to a matrix of flickering stimuli [2], [3]. This system capitalizes on the cortical magnification that occurs when a flickering stimulus is visually fixated.

EEG-based research in the ACT program has harnessed the steady-state visual-evoked response (SSVER) as an effective communication medium for brain–computer interfaces (BCI's) [4]. Two methods of using the SSVER for control have been employed. In one, operators are trained to exert voluntary control over the strength of their SSVER. In the second, multiple SSVER's are used for control. The latter requires little or no training because the system capitalizes on the naturally occurring responses. The purpose of this paper is to describe these SSVER-based BCI's and to summarize research findings.

II. BCI BASED ON SELF-REGULATION OF THE SSVER

A. Communication Task

Communication between the operator and the computer is binary in the sense that only two control actions are possible. For example, a

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device can be turned on or off, moved left or right, etc. It is also appropriate to describe this BCI as a discrete controller. That is, changes in the SSVER result in control actions occurring at fixed intervals of time.

B. EEG Component

The SSVER is elicited using a visual stimulus that is modulated at a fixed frequency. The SSVER is characterized as an increase in EEG activity at the stimulus frequency [5]. Typically, the stimulus is generated using white fluorescent tubes that are luminance modulated at 13.25 Hz and mounted behind a translucent diffusing panel. With biofeedback training, operators learn to willfully control their SSVER amplitude.

C. Communication Protocol

The EEG is acquired using gold-cup electrodes located over occipital sites O1 and O2 (left mastoid as ground). The differential signal between O1 and O2 is amplified, filtered, and then processed by a lock-in amplifier system (LAS) that provides a measure of the SSVER amplitude. This information is sampled by a computer for feedback and control. Control logic based on thresholds and duration requirements transforms the noisy SSVER into smooth, stable control. The threshold and duration parameters are adjustable for individual operators and specific applications. Typically, two thresholds are employed to achieve binary control; raising the SSVER above the upper threshold for the required duration results in one control action and lowering the SSVER below the lower threshold for the required duration results in a different control action.

D. Results

In general, all operators perform above chance level, although there are large individual differences between operators. While some operators experience difficulty, others achieve nearly perfect control. Specific results are reported below.

1) Flight Simulator Control: The roll position of a simple flight simulator was controlled with this BCI. A display in the simulator presented a series of commands (in 10° increments) requiring the operator to roll right or left. When operators increased their SSVER amplitude above an upper threshold for 75% of the samples in a one-half second interval, the simulator would roll one-half of one degree to the right. When similar duration requirements were met for a lower threshold, the simulator would roll one-half of one degree to the left. When the commanded roll position was reached, a new commanded position was presented. This process continued for two minutes. Most new operators were able to achieve some level and sense of control after a single 30-min training session, and typically demonstrated fairly dramatic learning curves over the course of the next few training sessions. Trained operators were typically able to roll the simulator in the commanded direction 80–95% of the time.

For feedback and control purposes, the simulator display contained a horizontal bar that presented real-time SSVER amplitude. An indicator mark on the bar would move to the right when the SSVER amplitude increased and to the left when it decreased.

2) Muscle Stimulator Operation: A functional electrical stimulator (FES), a rehabilitation device designed to exercise paralyzed limbs, was integrated with this BCI. Operators held their SSVER amplitude above the "on" threshold for one second to activate the FES. Then, the current began increasing, gradually recruiting additional muscle fibers to cause knee extension. Decreasing the SSVER amplitude below the "off" threshold resulted in a ramp-down of the current and lowering of the limb. The control algorithm parameters were adjusted to emphasize accuracy over speed.

Three able-bodied participants with previous SSVER self-regulation experience participated in 3–5 one-hour sessions. A display provided SSVER amplitude feedback, knee angle commands and actual knee angle. Time history data were examined to confirm that the able-bodied participants accomplished the knee extension by controlling the brain—FES interface, rather than voluntary muscle control. Specifically, a change in current level preceded a change in knee angle, and onset of knee angle movement occurred at nearly the same current level each time (i.e., threshold of contraction). Data from each participant's best session were examined. Participants acquired 95.8% of the commanded knee angles with average FES on and off latencies of 4.28 and 5.93 s, respectively [6].

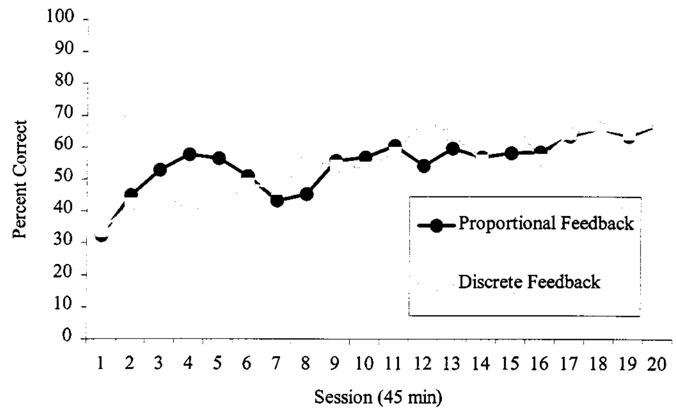

Fig. 1. Learning curves for an SSVER-based switch selection task under two feedback conditions (n = 4 per group). There was no overall difference between the feedback groups. However, the data for sessions 1–5 suggest that the continuous feedback may have supported more rapid initial learning.

3) Effects of Feedback: Eight participants were trained to perform a switch selection task under one of two feedback conditions, discrete or proportional. Three switches were aligned next to three target fields on a display and the task involved selecting the switch next to the field containing a target. To change which switch was selected, participants increased their SSVER amplitude above a threshold to begin cycling through the switches. To stop the progression, the participants decreased their SSVER below the threshold. Changes in the border and fill color of the switches indicated whether the SSVER was above or below threshold in the discrete feedback condition. In the proportional feedback condition, a dynamic vertical bar with a threshold mark displayed real-time SSVER amplitude. Both groups showed significant learning, but there was no overall difference due to feedback type (see Fig. 1).

4) Mechanisms of Control: The control signal in this BCI is derived as a differential measure of SSVER activity at O1 and O2. As a result, operators can change the amplitude of the control signal by self-regulating: 1) the relative amplitude of the SSVER activity at O1 and O2; 2) the relative timing (phase) of the SSVER activity at the two sites; or 3) a combination of both. In one experiment three participants performed a task that required repeated 2-s periods of SSVER enhancement or suppression. Scalp-wide EEG was recorded. Each participant showed interhemispheric shifts of SSVER activity between the enhance and suppress conditions. Data for one participant are shown in Fig. 2. These results suggest that modulation of the relative amplitude of the SSVER at O1 and O2 plays a role in SSVER self-regulation. In a separate study with four participants, monopolar O1 and O2 signals were recorded in addition to the bipolar control signal. Phase and amplitude relationships between O1 and O2 were evaluated during periods of sustained SSVER enhancement and suppression. Each of the participants showed evidence of phase-based control. As in the topographic analysis above, independent regulation of O1 and O2 amplitude was observed as well [7].

Participants were not instructed how to accomplish the self-regulation, however they were not allowed to close their eyes. This was

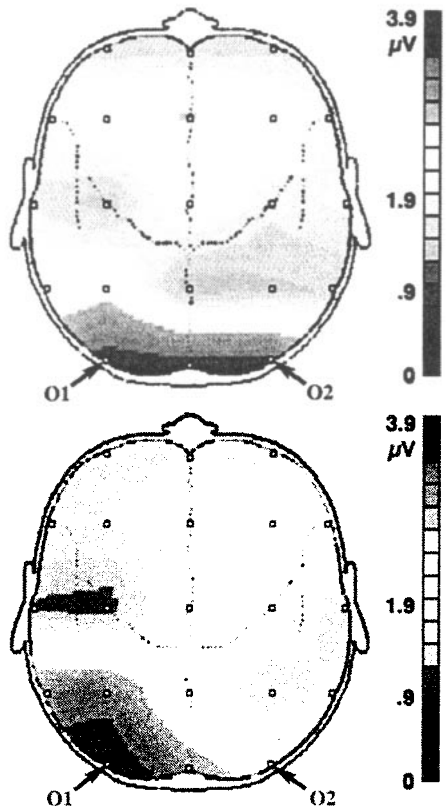

Fig. 2. Topographic maps of 13.5-Hz activity recorded during task-related SSVER enhancement and suppression for Participant 2. Note the evenly distributed activity in the O1 and O2 regions of the top map (suppression) and the asymmetric activity in the bottom map (enhancement).

monitored by the use of a video camera or by electrooculogram (EOG) recordings in some experiments. Interestingly, a variety of eye movement and cognitive-based strategies emerged. In the switch selection task three of the eight participants reported using subtle eye movements to control their SSVER amplitude. These eye movements were also evident in the EOG recordings. In this experiment, the task was projected onto a large screen and the stimulus light source was located behind the participant to illuminate the entire screen. As a result the stimulus covered 83° of the visual field, however, the stimulus was brightest in the center of the screen and decreased slightly toward the edges. Although three of the participants used subtle eye movement, the stimulus remained in their central vision at all times. Interestingly, these participants shifted their gaze slightly away from the brightest area of the stimulus when they wanted to enhance their SSVER amplitude.

III. BCI Based on Naturally Occurring SSVER's

A. Communication Task

The task is to select virtual buttons on a computer screen. A virtual button is a small area of the screen similar to an icon that can have a control action associated with it. The luminance of the virtual buttons is modulated, each at a different frequency to produce the SSVER's. The operator selects the desired button simply by looking at it. At present, a maximum of two virtual buttons is displayed at one time. Therefore, the discussion regarding the binary and discrete nature of the first controller is relevant to this BCI.

B. EEG Component

The SSVER is also the source of control for this system. However, unlike the first BCI, this is a passive system in the sense that operators are not required to actively increase their SSVER amplitude. This system uses the naturally occurring SSVER amplitude at two different frequencies. Cortical scaling as discussed by Sutter [3] plays an important role in this system. As the subject fixates on the desired virtual button, the SSVER amplitude increases at the button's modulation frequency.

C. Communication Protocol

The EEG is acquired using plastic, silver chloride-coated, surface electrodes (with aloe vera gel to improve conductivity). The electrodes are held in place over O1, O2, and Oz (ground) using a headband. The differential (O1–O2) EEG is filtered, amplified, and sampled by a computer. Three software LAS's are implemented for each button. One LAS computes amplitude at the stimulus frequency; the other two compute amplitude at frequencies slightly above (upper frequency) and below (lower frequency) the stimulus frequency. The control algorithm monitors the LAS outputs to determine if a selection should be made. The algorithm requires that two criteria be satisfied for a fixed time duration. First, the amplitude of the center frequency must be above a threshold value to prevent an unwanted selection due to natural fluctuations in the EEG. Second, the amplitude of the center frequency must be larger than the average of the lower and upper frequencies, by a fixed ratio, to ensure that broadband increases in activity do not trigger the system. When these criteria are met, a red border appears around the corresponding button. If these criteria are maintained continuously for 0.3 s, then the button is selected. Individual threshold and amplitude ratio criteria were determined for each operator by a calibration procedure that was performed prior to using the system.

D. Results

Two virtual buttons (2.9 by 3.8 cm) were displayed on the left and right sides of a monitor (separated by 10.3 cm) and modulated at 23.42 and 17.56 Hz, respectively. The buttons were viewed at a distance of 71 cm, resulting in visual angles of 3.0° vertically and 2.3° horizontally. This system was experimentally evaluated using eight participants. Their task was to select the virtual button indicated by a yellow command box. Participants performed 200 trials each, with no training trials. The participants averaged 92% correct selections (range: 83–99) with an average selection time of 2.1 s (range: 1.24–3.02) [8].

IV. Future Plans

Despite the success demonstrated with the self-regulation based BCI, substantial training is required. For this reason, the ACT program will focus its near-term BCI efforts on approaches that use naturally occurring SSVER's. The next step with this BCI will be to compare its performance to that of a standard computer mouse using a Fitts' Law paradigm to evaluate the speed and accuracy of the two controllers [9]. Other studies will explore the number of virtual buttons that can be simultaneously presented and their spatial separation. Although additional buttons and functions will increase usability, this BCI appears ready for near-term application as an assistive technology.

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EEG-Based Communication: A Pattern Recognition Approach

William D. Penny, Stephen J. Roberts, Eleanor A. Curran, and Maria J. Stokes

***Abstract*—We present an overview of our research into brain–computer interfacing (BCI). This comprises an offline study of the effect of motor imagery on EEG and an online study that uses pattern classifiers incorporating parameter uncertainty and temporal information to discriminate between different cognitive tasks in real-time.**

***Index Terms*—Cognitive tasks, electroencephalograph (EEG), pattern recognition.**

I. Introduction

The ultimate aim of this research is to develop an electroencephalograph (EEG)-based computer interface for use by people with severe physical disabilities. This would, for example, facilitate interaction with a word-processor package or manipulation of various environmental controls.

Our approach relies less on biofeedback training [8] and more on the use of pattern recognition methods where cursor movements are generated by the output of a pattern classifier such as a neural network. Our approach is novel in two important technical respects. First, we infer not just the parameters of our classifiers (e.g., weights in a neural net) but also the uncertainty on those parameters. This allows us to estimate the uncertainty associated with each subsequent classification. Second, we use dynamic classifiers such that the cursor movement at a given time step is dependent on cursor movements at previous time steps. Both of these features lead to more robust cursor control [7].

A further aspect of our work is an exploration of the cognitive tasks used to generate the signals which provide a starting point for communication. To date, we have investigated motor imagery and mental arithmetic tasks.

II. Offline Studies

Our research into EEG-based communication began in 1996. At that time, while there was some anecdotal evidence from biofeedback experiments [8] to suggest that motor imagery can be identified from the background EEG, there were no formal experiments to suggest that this is indeed the case. Or indeed, any information on what proportion of subjects these patterns could be detected in or with what accuracy.

To clarify the situation, we recorded EEG from seven subjects performing cued imagined hand movements [5]. Control recordings were also made to ensure we were not picking up stimulus-related activity. The EEG was recorded using a single reference electrode and two 11-electrode arrays placed over the left and right sensorimotor cortex (a total of 23 electrodes).

Laplacian operators were applied to estimate local activity at three sites over left and right sensorimotor cortex. Analysis of mu-rhythm power in the resulting signals showed that imagined hand movements could be discriminated from background EEG in six out of seven subjects with a typical accuracy of 70%. The most discriminative electrode positions were found to be 3 cm posterior to the C3 and C4 positions in the 10/20 system. Extraction of complexity features [6] showed that, in four out of seven subjects, the discrimination accuracy was 80%.

This research was useful in concretely establishing that motor imagery signals could be detected by spectral and complexity features and that, in principle, they could be used to drive cursor movements. It also identified the best position to place a smaller number of electrodes.

III. Online System

The above research informed the design of our "online" EEG-based computer interface. To keep the system as simple as possible our initial prototype uses only three electrodes, a single isolation amplifier and a 266-MHz PC. The electrodes are placed 3 cm behind C3 and C4 and a reference electrode is placed over the right mastoid.

Subjects move a cursor on a computer screen and attempt to hit targets appearing at the top or bottom of the screen. Cursor movements are driven by cognitive tasks and, to date, we have studied two different pairs of tasks; 1) motor imagery versus a baseline task and 2) motor imagery versus a math task. For the motor imagery tasks, subjects were asked to imagine opening and closing their hand (right or left according to handedness), and for the maths tasks subjects were asked to serially subtract seven from a large number. We have also carried out "stationary cursor trials" in which the cursor does not move [4].

Cursor movements were generated by extracting autoregressive (AR) features from the EEG and classifying them using a Bayesian logistic regression model.

A. Handling Uncertainty

The AR features are classified using a logistic regression model trained using the Bayesian evidence framework [7]. This procedure estimates both the classifier weights and the distribution of those weights. The distribution captures the fact that the classifier is not entirely certain as to how to classify some inputs. If this uncertainty is taken into account when making a new prediction (as it should be)

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