

Brain-Computer Interfaces for 1-D and 2-D Cursor Control: Designs Using Volitional Control of the EEG Spectrum or Steady-State Visual Evoked Potentials

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Abstract—We have developed and tested two electroencephalogram (EEG)-based brain-computer interfaces (BCI) for users to control a cursor on a computer display. Our system uses an adaptive algorithm, based on kernel partial least squares classification (KPLS), to associate patterns in multichannel EEG frequency spectra with cursor controls. Our first BCI, Target Practice, is a system for one-dimensional device control, in which participants use biofeedback to learn voluntary control of their EEG spectra. Target Practice uses a KPLS classifier to map power spectra of 62-electrode EEG signals to rightward or leftward position of a moving cursor on a computer display. Three subjects learned to control motion of a cursor on a video display in multiple blocks of 60 trials over periods of up to six weeks. The best subject's average skill in correct selection of the cursor direction grew from 58% to 88% after 13 training sessions. Target Practice also implements online control of two artifact sources: 1) removal of ocular artifact by linear subtraction of wavelet-smoothed vertical and horizontal electrooculograms (EOG) signals, 2) control of muscle artifact by inhibition of BCI training during periods of relatively high power in the 40-64 Hz band. The second BCI, Think Pointer, is a system for two-dimensional cursor control. Steady-state visual evoked potentials (SSVEP) are triggered by four flickering checkerboard stimuli located in narrow strips at each edge of the display. The user attends to one of the four beacons to initiate motion in the desired direction. The SSVEP signals are recorded from 12 electrodes located over the occipital region. A KPLS classifier is individually calibrated to map multichannel frequency bands of the SSVEP signals to right-left or up-down motion of a cursor on a computer display. The display stops moving when the user attends to a central fixation point. As for Target Practice, Think Pointer also implements wavelet-based online removal of ocular artifact; however, in Think Pointer muscle artifact is controlled via adaptive normalization of the SSVEP. Training of the classifier requires about 3 min. We have tested our system in real-time operation in three human subjects. Across subjects and sessions, control accuracy ranged from 80% to 100% correct with lags of 1-5 s for movement initiation and turning. We have also developed a realistic demonstration of our system for control of a moving map display (<http://ti.arc.nasa.gov/>).

Index Terms—Brain-computer interfaces (BCI), electroencephalogram (EEG), kernel partial least squares (KPLS), steady-state visual evoked potentials (SSVEP).

I. INTRODUCTION

NASA astronauts will perform increasingly complex tasks during space exploration, including control tasks in pressurized suits, which do not afford easy access to keyboards or other manual controls. To meet the future demands of these environments, we are evaluating multimodal neuroelectric computer interfaces for hands-free control of displays and devices. Our long-term goals are to: 1) develop new modes of interaction that cooperate with existing modes such

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as keyboards or voice, 2) augment human-system interaction in wearable, virtual and immersive systems by increasing bandwidth and quickening the interface, 3) enhance situational awareness by providing direct connections between the human nervous system and the systems to be controlled.

Research has shown that control signals for graphic devices, such as cursors, can be drawn from specific band-limited electroencephalogram (EEG) signals such as μ and β rhythms [1]. We aim to develop a more flexible processing system, which will automatically select EEG features and adapt to different tasks and users. To do this, we explored several approaches to neuroelectric interface design, including a preliminary design of a brain-computer interface (BCI) [2]-[4]. We examined a range of EEG feature extraction and classification methods, including narrow band filters, adaptive linear combiners, partial least squares classifiers, measures of nonlinear signal complexity, and support vector machines. All of these methods were useful for offline classification of EEG signals measured during various mental tasks or during real and imaginary hand motion. However, in subsequent studies of closed-loop BCI designs for real-time one-dimensional (1-D) cursor control, we found that spectral properties of the EEG were more useful than the EEG time series or measures of nonlinear signal complexity. Although we did not compare time- and frequency-based control signals quantitatively, we observed that transients in the time domain time series were often masked by larger EEG signals and certain artifacts, such as electrooculograms (EOG).

We now describe the design and testing of two systems for real-time EEG-based BCI for control of a computer graphic display. Both systems use a kernel partial-least squares (KPLS) classifier [5], [6] to map frequency spectra of multielectrode EEG signals to motions of a cursor on a computer display. Each system also implements online removal of ocular artifact and control of muscle artifact. Our first BCI, Target Practice, is a system for 1-D device control, in which participants use biofeedback to learn voluntary control of their EEG spectra. Target Practice uses a KPLS classifier to map power spectra of 62 electrode EEG signals to rightward or leftward position of a moving cursor on a computer display. The second BCI, Think Pointer, is a system for two-dimensional (2-D) cursor control. Steady state visual evoked potentials (SSVEP) are triggered by four flickering checkerboard stimuli located in narrow strips at each edge of the display. The user attends to one of the four beacons to initiate motion in the desired direction.

II. METHODS

A. General Methods for BCI Systems

1) *EEG Recording and Preprocessing*: We recorded from 8 to 62 channels of EEG with a QuickCap (Ag-AgCl electrodes) and two calibrated Neuroscan Synamp amplifiers (Neuromedical Supplies, Inc.) using the extended International 10-20 System [7] with linked mastoid references (1000 samples/s, 0.1 to 100-Hz bandpass). We also recorded vertical and horizontal electrooculograms (EOGs) using two pairs of bipolar Ag-AgCl electrodes positioned 2 cm lateral to the outer canthi (HEOG) and 2 cm above and below the left eye (VEOG). Neuroscan Net Acquire software running on a dual-processor Dell computer (Pentium IV Xeon 3.06 GHz processors) broadcast samples of EEG and EOG signals over a TCP/IP network to another dual-processor Dell computer running the Linux operating system. The second computer processed the samples using noduleView, a NASA-developed system for flexible real-time signal processing and control applications. Online preprocessing included digital low-pass filtering (Hamming-windowed FIR, order: 128, -3 dB cutoff: 64 Hz), decimation to 128 Hz, and extraction of EEG features consisting of power spectral density estimates

in the range of 1–64 Hz. We computed a separate power spectrum for each EEG channel, using Welch’s method implemented in C++ code as part of *noduleView*. We cross-validated this code using the *pwelch* function of the Matlab Signal Processing Toolbox (The MathWorks, Natick, MA). We estimated spectral densities from overlapping EEG epochs of 128 points (1 s duration). Each successive epoch overlapped the preceding epoch by 75% or 96 points. Therefore, we obtained a new power spectrum for every channel every 250 ms. The multichannel EEG spectra served as inputs to the KPLS classifier.

2) *Control of Electromyographic Artifact*: Able-bodied subjects may learn to modulate contraction and relaxation of scalp muscles to effect an artifactual control of the BCI using electromyographic (EMG) artifact [8]. EMG signal bandwidth overlaps EEG but extends to much higher frequencies. In pilot studies, nearly all of our subjects tended to learn an initial pattern of EMG-based control. To mitigate EMG artifact, we selected a “control band” of frequencies between 40–64 Hz. If activity in this band exceeded a threshold, based on observations of the normal variation in that band, our EEG-based algorithms were inhibited from adapting or controlling the cursor position. This method has previously used to dissociate EMG and EEG in neurofeedback applications [9]. With this precaution we found that subjects took longer to learn EEG-based control than without the inhibition turned on.

3) *Control of Electrooculographic Artifact*: Eye blinks and eye movements did not serve as a source of artifactual control, but EOG artifacts tended to reduce the accuracy of EEG recordings and inhibit EEG-based control. This proved to be a minor problem for our Target Practice BCI but not significant for our Think Pointer system, which relies on occipital signals less prone to EOG artifact contamination than frontal and central sites. To control for EOG artifact, we used vertical and horizontal EOG recordings to subtract linear regression estimates of EOG signals propagated to EEG electrodes after smoothing the EOG signals using wavelet-denoising methods. Our approach used an established linear subtraction method [10] with an added step of wavelet denoising the EOG signals so that real-time subtraction (no averaging) would minimize subtraction of EEG signals recorded near the eyes [11]. Our method has been submitted for publication in the context of another study [12].

B. Target Practice BCI System

Subjects (two male, one female, ages 20–25) sat in a comfortable chair and viewed a liquid crystal display (LCD) at a distance of 150 cm. A central rectangular region of the display depicted a cross-hair cursor at the bottom edge and a target bar at either the top left or top right edge (Fig. 1). On each trial, the cursor moved at a constant speed from bottom to top, traversing the display in 3 s. The subject’s task was to perform mental activity of one type to drive the moving cursor to the right side when the target was on the right and another type when the target was on the left. The choice of mental activity was left to the subjects, who reported activities such as imaginary cursor motion toward the target side, concentration/relaxation, and imagined speech or sounds. An adaptive machine-learning controller subserved both training and real-time operation of the BCI, using a KPLS classifier of the multichannel EEG spectra as its core algorithm (Fig. 2). At the beginning of each session, subjects practiced a few seconds of each type of chosen activity while the cursor remained and the computer recorded the EEG from 62 electrodes (extended 10–20 system). From these initial data, the BCI system was primed with 50 training examples each of leftward and rightward signals. Following this, the subjects used the system in real time to practice hitting the targets by moving the cursor left or right, in blocks of 60 trials. The order of targets varied

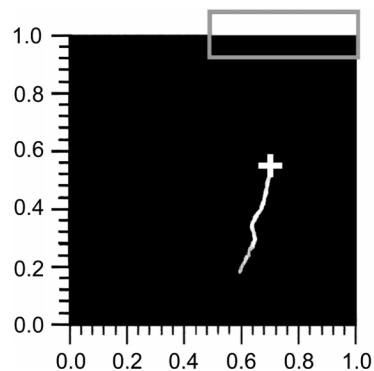


Fig. 1. Screen shot of the display (rendered as a gray scale image) during actual performance of a trial by one subject using the Target Practice BCI. Subject controlled his EEG to drive the crosshair cursor (actually red) right or leftwards to hit the grey (actually green) rectangular target. Vertical speed was constant. A real-time classifier analyzed the EEG and computed the horizontal position of the cursor every 250 ms. As the cursor moved upwards, the computer drew a red trail indicating the path of the cursor. Cursor traveled from bottom to top in 3 s.

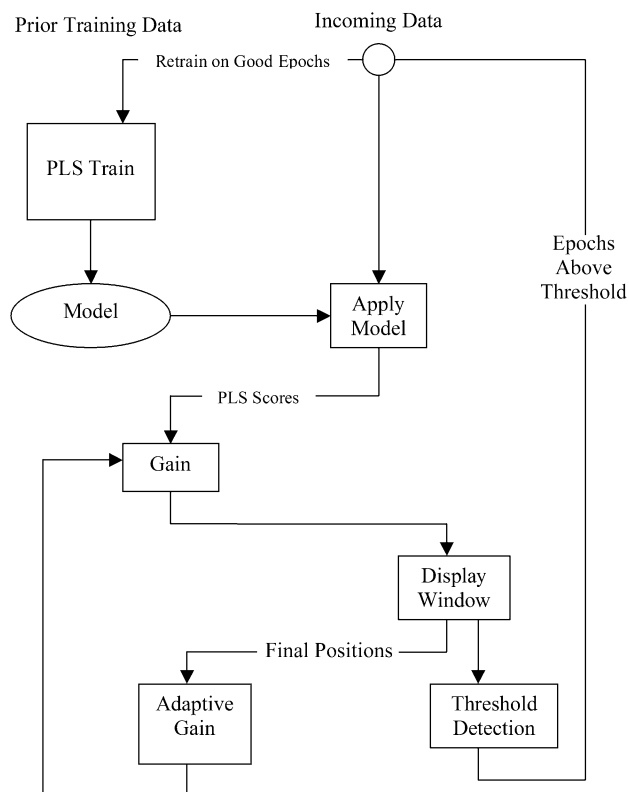


Fig. 2. Adaptive machine-learning system and controller for Target Practice BCI. 50 multichannel EEG spectra from training sessions (25 left, 25 right) filled a buffer of training examples from which a KPLS classifier model was computed. Application of the model yielded scores for each incoming new EEG spectrum, which were scaled by a gain factor to map cursor motion to the display width. Scaled scores were mapped to a horizontal position ranging from the left edge to the right edge of the display. If the position exceeded a threshold distance from the center to either right or left sides of the display (typically 10% of display width), the corresponding epoch was added to the buffer of training data for adaptation of the KPLS model. If final positions were consistently smaller or larger than the display width, the gain was adapted up or down to map the range of scores to the width of the display.

from alternating sets of 1, 4, or 10 rights and lefts, and random order. There was a delay of 2 s between the appearance of the target bar and the engagement of the controller, while the initial data buffer in the controller was filled.

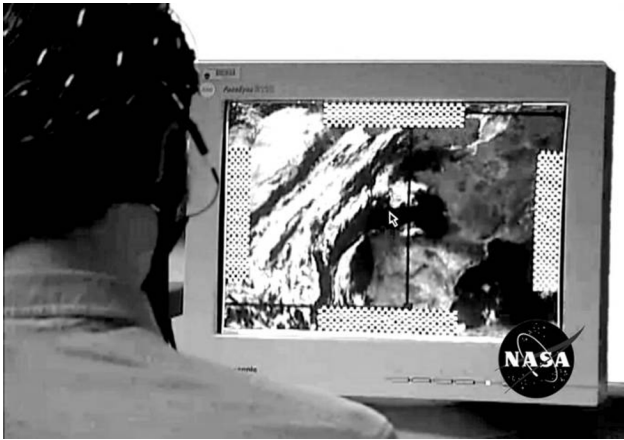


Fig. 3. Photograph of a subject using SSVEP to follow a line drawn on a world map using the Think Pointer BCI. Flickering checkerboards at each edge of the display served to trigger SSVEPs at different frequencies. A real-time classifier analyzed the EEG and chose the direction of motion or a center/stop position every 250 ms.

C. Think Pointer BCI System

Subjects (three male, age 23–35) sat in a comfortable chair and viewed a 21-in LCD display at a distance of 70 cm. A rectangular region of the display (subtending 40° visual angle) depicted a window into a color-coded geographical map of the world, which could be panned left, right, up, or down under computer control (Fig. 3). On each of the four edges of the display, strips of checkerboard stimuli (subtending $16^\circ \times 2.8^\circ$ visual angles) were counter-phase modulated at 100% contrast with temporal frequencies in a range of 5–12 Hz. The spatial frequency of the checks was approximately eight cycles per degree. The flicker produced a SSVEP which we recorded from 12 electrodes referred to linked mastoids: P7, PO7, PO5, PO3, POz, PO4, PO6, PO8, P8, O1, O2, and Oz. A machine-learning system implemented a KPLS classifier of the multichannel EEG spectra for both training and real-time operation.

1) *SSVEP Frequency Response Analysis*: Separate frequencies were used for each checkerboard (5.0, 5.625, 6.4, 6.9 Hz) and corresponding SSVEPs were detected in the EEG for each direction in this sample of training (Fig. 4). The second harmonic of the driving frequency always served as the most reliable feature, but the KPLS classifier also included the SSVEP response at the fundamental frequency.

2) *Training Sequence*: Another adaptive machine-learning controller subserved both training and real-time operation of the BCI (Fig. 5). The first step in adapting the intelligent BCI software is for the user to perform a short training sequence. The four directions of map motion are marked by small flickering checkerboards on the display, each one flickering at a slightly different frequency. As the user views the moving map and attends to the flickering bar for the desired direction, the computer analyzes the EEG recorded and picks out the specific frequencies and sensors that are correlated with the flicker. In less than 3 min, the intelligent software “learns” to understand commands to go up, down, left, and right, and a center-stop command. During the training session for the center/stop condition, the user directs his/her attention towards the center ignoring the four flickering bars.

III. RESULTS

A. Target Practice

1) *Training Time and Strategies*: Three subjects learned to control the cursor in multiple blocks of 60 trials over periods of up to six weeks.

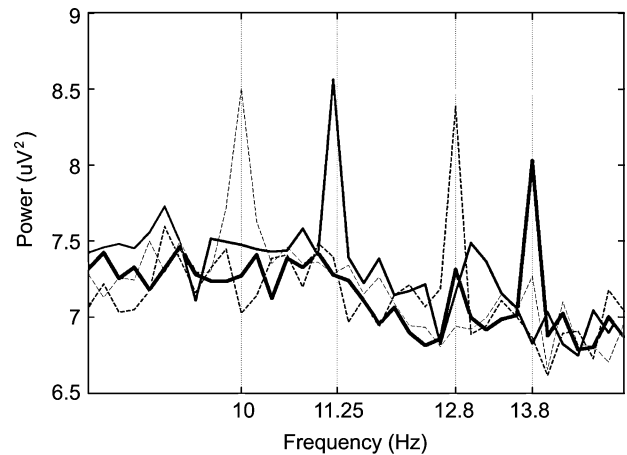


Fig. 4. Second harmonics of the frequency response of SSVEP to four driving frequencies: 5.0 Hz (thin dashed line), 5.625 Hz (light solid line), 6.4 Hz (heavy dashed line), 6.9 Hz (heavy solid line). Each plot is an averaged spectrum, over a 30-s training set, for all four directions of motion. Second harmonics (or twice the base frequency) are the frequencies that produce the most distinctive peaks and are plotted here. For example, the thin solid line plots the magnitude of the EEG when the training direction was down and the corresponding flicker frequency was 5.635 Hz. There is a clear peak at the second harmonic frequency of 11.25 Hz. Peaks of the intended directions are large and clear, and are not confounded with peaks for the unattended directions.

Training time varied greatly among the three subjects, ranging from four to 12 sessions. Each subject selected his or her own strategy for learning mental control via EEG. Some imagined hand motion whereas others imagined symbolic distinctions such as imaginary speech and music. No single method worked for all subjects.

2) *Performance*: The best subject’s average skill in correct selection of the cursor direction grew from 58% to 88% after 13 training sessions. In several sessions, 100% correct performance over 60 random trials was achieved. The worst subject practiced two to three times a week, but never exceeded 65% correct after 12 sessions. The other subject had fewer sessions than these two, reaching 75% average accuracy over six sessions.

B. Think Pointer

1) *Training Time and Strategies*: Training for the SSVEP-based Think Pointer system was rapid and nearly effortless. Other than keeping relatively still and focusing gaze and attention on the flickering bars for training, no special procedures were needed. Use of the BCI reached near-asymptotic performance in one session, with each user obtaining a characteristic and stable accuracy, ranging from 80% to 100%.

2) *Performance*: We recorded two demonstrations of continuous control of the moving map: visual guidance and auditory guidance. In the visual guidance demonstration, the user followed a path defined by a solid line drawn on the map. The solid line contained segments of random lengths and a series of random turns, taking the user “around the world,” with a final stop and hold point. In the auditory guidance demonstration, the user responded to verbal directions spoken by an experimenter. Each command was a random instruction to turn in one of the four directions or stop. Over a range of three to five 30-min practice sessions per subject, we noted all subjects achieved 80%–100% correct control. Chance performance level for this task is 20% correct. The best user was able to consistently obtain 100% accurate turns and stops with both visual and auditory guidance. For all three subjects, visual guidance was more accurate and led to more rapid responses than auditory guidance. The confusion matrices for the four directions and stop command were not systematically measured. However, we kept roughly

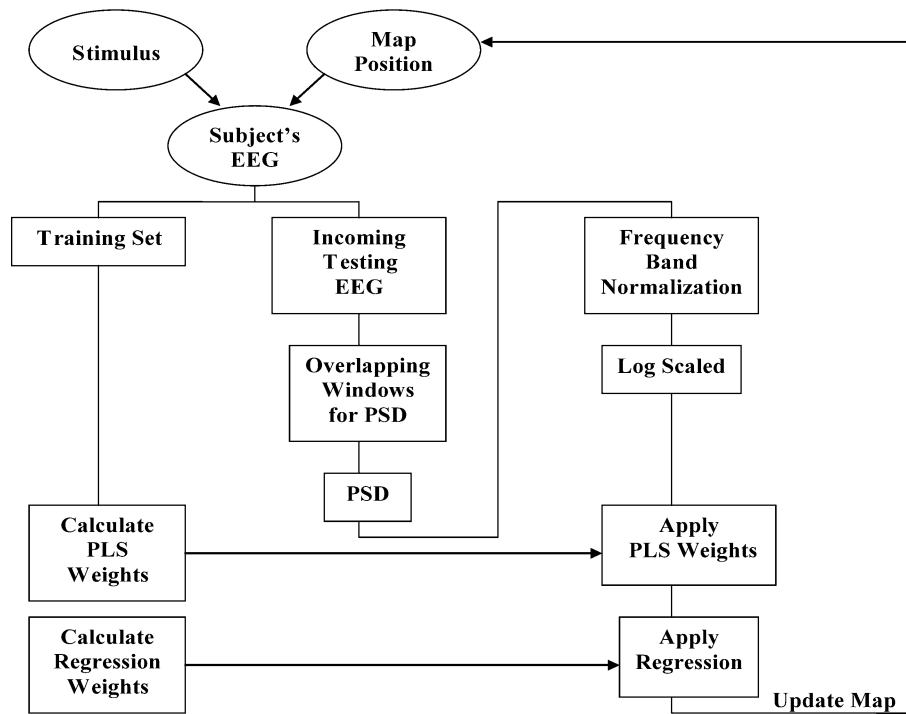


Fig. 5. Adaptive machine-learning system and controller for Think Pointer BCI. Multichannel EEG spectra (power spectral densities, or PSD) from 30 s of EEG recorded for four directions (left, right, up, down) and a stop/center position served as training examples from which a KPLS classifier model was computed. Application of the model yielded KPLS weights for classification of new EEG spectra in real time. Weights were applied to normalized, log-scaled EEG spectra to yield KPLS scores for each spectrum in real time. An additional regression step classified the spectra as one of the four directions or stop by using an exhaustive set of discrete linear regression models and a voting scheme. First, the current KPLS scores were used to compute regression estimates using fixed regression models from the training KPLS scores for all possible pairs (e.g., left/right, left/up, left/down, left/stop, right/up, right/down, etc.). For each training regression model, one direction was coded as -1 and the other as +1. If the estimated regression estimate for a single real-time epoch was positive, it was assigned as a win for the positively labeled direction and likewise for negatively labeled directions. From the full set of regression models, the direction with the greatest number of “regression wins” was selected as the “winner” and determined the direction of motion or stop. This choice served to update the map position with a discrete movement in the winning direction or to stop and hold in the center.

equal occurrences of each command in the training and performance sessions, so as to avoid biasing any class. In a real-world application, the prior probability of stops may be higher than turns, and this bias could be implemented in the classifier. Subjects reported feeling able to compensate for the system lag by anticipating the control needed to make timely turns and stops. We did not measure system lag time directly but used subjects’ assessments and observations of video recordings to estimate lags of 1–5 s per turn. Lags were noticeably longer for auditory guidance than for visual guidance.

IV. DISCUSSION

Our experiments show that 1-D control of a graphic display using artifact-free volitional control of EEG spectra is feasible as a human–computer interface. Our Target Practice system is programmed to allow rapid development of machine learning algorithms for mapping EEG changes to cursor turns and horizontal display excursions. We have demonstrated control of a cursor turning left and right to reach a fixed display target in real time. Limitations of this system stem from inability of some subjects to learn control and lack of adequate training strategies.

Our experiments also show that 2-D control of a moving map display using SSVEP methods is feasible as a human–computer interface. Most previous SSVEP-based BCI designs have used discrete control, as by attending to single flickering regions of a visual display to select an item [13]–[15]. One other design implemented continuous 1-D control using learned self-regulation of the SSVEP [16]. Unlike prior

designs, our Think Pointer system is programmed to allow rapid development of machine learning algorithms for mapping EEG changes to four direction changes and a center/stop position. This system is easy to learn and use and is mainly limited by control lags of 1–5 s. However, at least for visual guidance, subjects may anticipate turns and reduce overall system lags considerably. A visual demonstration of both visual and auditory guidance of a moving map display is currently posted on our website¹.

At least two serious limitations apply to our data. First, the number of subjects is small. This was necessary to allow us time to explore a system designs options and algorithms. Second, our experiments are qualitative and lack statistical and quantitative metrics, such as bit rate or control lags, as used in other BCI studies. For the present, we must present these results as merely being indicative of feasible BCI approaches for device control.

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The Wadsworth BCI Research and Development Program: At Home With BCI

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Abstract—The ultimate goal of brain–computer interface (BCI) technology is to provide communication and control capacities to people with severe motor disabilities. BCI research at the Wadsworth Center focuses primarily on noninvasive, electroencephalography (EEG)-based BCI methods. We have shown that people, including those with severe motor disabilities, can learn to use sensorimotor rhythms (SMRs) to move a cursor rapidly and accurately in one or two dimensions. We have also improved P300-based BCI operation. We are now translating this laboratory-proven BCI technology into a system that can be used by severely disabled people in their homes with minimal ongoing technical oversight. To accomplish this, we have: improved our general-purpose BCI software (BCI2000); improved online adaptation and feature translation for SMR-based BCI operation; improved the accuracy and bandwidth of P300-based BCI operation; reduced the complexity of system hardware and software and begun to evaluate home system use in appropriate users. These developments have resulted in prototype systems for every day use in people's homes.

Index Terms—Augmentative communication, brain–computer interface (BCI), conditioning, electroencephalography (EEG), mu rhythm, P300, rehabilitation, sensorimotor cortex.

I. INTRODUCTION

Conditions such as amyotrophic lateral sclerosis (ALS), brainstem stroke, and brain or spinal cord injury can impair the neural pathways that control muscles or the muscles themselves. People who are most severely affected may lose all or nearly all voluntary muscle control, even eye movements and respiration, and may be essentially "locked in" to their bodies, unable to communicate in any way or limited to slow unreliable single-switch methods. Studies of the past 20 years show that the scalp-recorded electroencephalogram (EEG) can be the basis for brain–computer interfaces (BCIs) [1]–[5] that restore communication and control to these severely disabled individuals.

Since 1986, the Wadsworth Center BCI Laboratory in Albany, New York, has shown that healthy and disabled people can learn to control the amplitude of mu and beta rhythms in the EEG recorded over sensorimotor cortex and that these rhythms can be used to control a cursor on a computer screen in one or two dimensions [5]–[7]. More recently, we have evaluated and refined P300-based BCI operation [8], [9], and also begun to explore BCI applications of electrocorticographic activity (ECoG) [10]. Our primary focus at present is to convert the

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