# Parallel Man–Machine Training in Development of EEG-Based Cursor Control

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***Abstract*—A new parallel man–machine training approach to brain–computer interface (BCI) succeeded through a unique application of machine learning methods. The BCI system could train users to control an animated cursor on the computer screen by voluntary electroencephalogram (EEG) modulation. Our BCI system requires only two to four electrodes, and has a relatively short training time for both the user and the machine. Moving the cursor in one dimension, our subjects were able to hit 100% of randomly selected targets, while in two dimensions, accuracies of approximately 63% and 76% was achieved with our two subjects.**

***Index Terms*—Brain–computer interface (BCI), communication, control, electroencephalograph (EEG)-processing, machine learning, severe neuromuscular disability.**

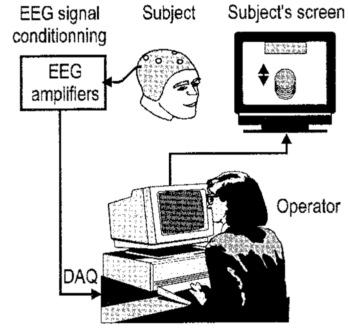


Fig. 1. BCI experimental setup.

## I. Introduction and Communication Task

Assistive devices are essential in enhancing the quality of life for individuals who have severe disabilities, such as quadriplegia and amyotrophic lateral sclerosis, or who have had massive brainstem strokes. However, the effectiveness of most assistive devices is dependent on preserved residual movements or speech. Without any physical channels for control, the only alternative for these people may be in exploring indirect voluntary modulation of electrical fields resulting from neural processes in their brains. This can provide control signals for a simple interface between the user and the computer known as a brain–computer interface (BCI). A frequently used model for a development of a BCI is to control the cursor movements and its positioning on a computer screen. This model requires the subject to learn how to modulate their electroencephalograph (EEG) signals voluntarily by using different thought patterns for different tasks. The problems that remain unsolved even with the most current and successful systems are the slow training of subjects, low spatio-temporal resolution, and poor accuracy in two-dimensional (2-D) control. Precise positioning of the controlled cursor has so far not been achieved. What adds to the difficulty of this research is that a new subject does not know what thought patterns are going to give the best results, so initially the subject and machine are learning in parallel.

Currently there are two main approaches to a subject's training with BCI systems that do not require external stimuli. One approach uses $\mu$- or sensory-motor-rhythm and/or $\beta$ rhythm recorded over sensory motor cortex which are sensitive to physical and imaginary movements of the extremities [1], [2]. The second approach uses a wider distribution of EEG signals and more abstract thought patterns that are not movement related [3], [4]. One example of this approach that is simple for subjects to learn and duplicate is using relaxing thoughts for one direction of cursor movement and stressful thoughts for the other. After several sessions these thoughts will be spontaneously replaced with more direct thoughts representing the subject's desire to move the cursor in one direction or the other. The second approach is more natural because after the first few sessions it does not require indirect movement-related thoughts to control the cursor, which may be difficult to use in practical applications. To achieve the training with the second approach, the training system has to include very fast feedback that will enable the subject to experiment with various thoughts and to quickly see which ones work better for particular task.

The goal of our research is to develop a new training technology that will achieve simple control using various mental activities while taking the advantage of parallel learning process. The control actions that we want to achieve are 2-D (up–down–left–right) cursor movements on the computer screen, with precise positioning. These actions are sufficient to use any computer program in GUI (Graphical User Interface) operating environment (e.g., MicroSoft Windows- or Macintosh-based computers) and previously developed assistive software. To achieve this goal in our Laboratory for Advanced Assistive Technology, we are working on the development of an EEG recording and processing setup, and training methods that will maximize efficiency of extraction of the user's intentions. In order to make future BCI practical, the following three constraints have to be satisfied.

1) Minimize the training time for the final user. Current systems often require weeks of training before reasonable performance is achieved. Long training is usually one of the main obstacles of better acceptance of any new practical assistive system.
2) Use as few EEG electrodes as possible. A BCI with too many electrodes becomes costly, cumbersome, and less feasible for future implantation.
3) Achieve sufficiently high accuracy to provide a reliable interface between the user and the computer.

## II. Methods and Communication Protocol

The subject is comfortably seated in front of a feedback monitor while EEG signals are recorded using up to 28 gel-filled electrodes preinstalled in an ECI electrode cap (Electro Cap Inc.) and arranged according to the 10–20 international electrode system [5], one ground electrode and the linked-ears reference. The electrode cap and EEG-preamplifiers are optically isolated from the rest of the equipment. This provides safety for both the subject and the experimenter. For signal conditioning, i.e., amplification and initial filtering, we use the Brain Imager (Neuroscience Inc.). Analog EEG signals picked up by the electrodes are digitized at 200 samples/s by a data acquisition card AT MIO 64E-4 (National Instruments) inserted in an IBM PC compatible computer. The same computer has special video card splitting the video output into two high-resolution monitors, one for the subject and one for the experimenter supervising the session.

To simplify the EEG-signals and to extract their components that are most relevant to our control task, overlapping windows of digital signals are further processed by an autoregressive (AR) feature extrac-

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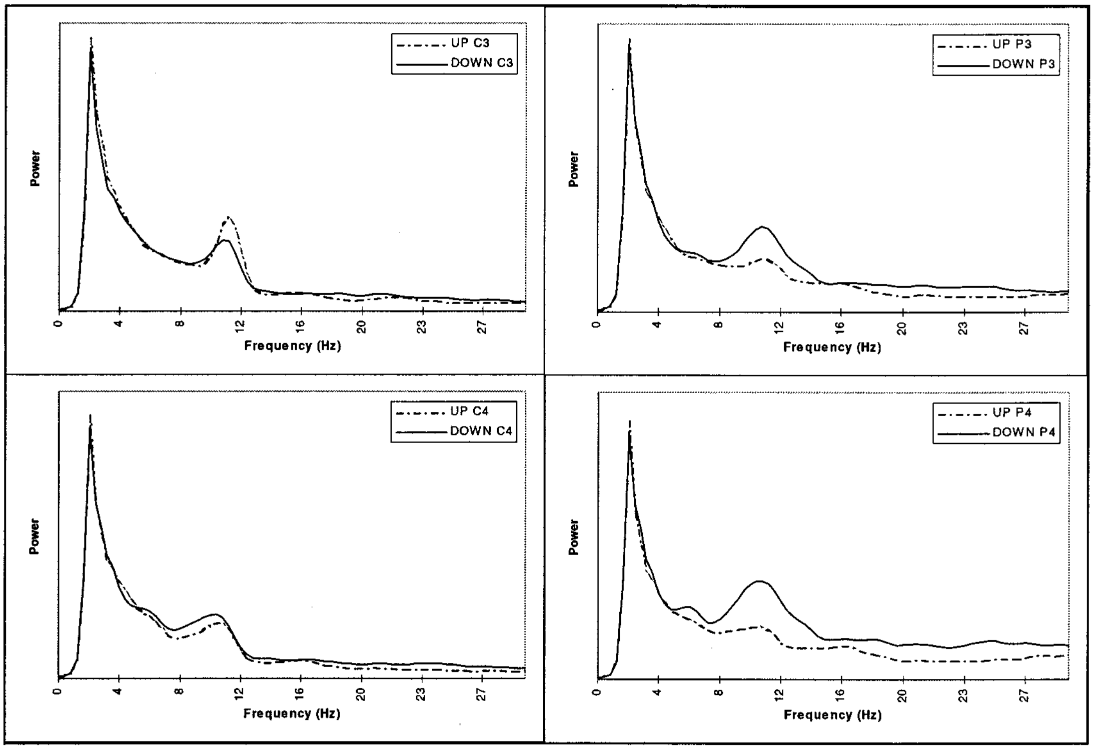


Fig. 2. Averaged FFT spectrum of EEG signals recorded during (1-D) BCI control session.

tion method resulting in a small number of AR coefficients. We experimented with various numbers of AR coefficients and concluded that even only four AR coefficients can represent each voluntarily modulated EEG-signal [6]. Continuous arrays of these coefficients are assigned to particular task (up–down–right–left) and used to train the classifier.

An Adaptive Logic Network (ALN) is the adaptive neural network that we use to classify the EEG patterns in the on-line experiments. ALN is a nonlinear adaptive machine learning system for supervised learning that is capable of approximating any continuous function to any degree of accuracy [7].

During the real-time experiments, selected channels of EEG are digitized and recorded on the computer's hard drive. Our method carries out signal processing on channels used for control, extracts important features from the signals, presents the selected features to the ALN's for training [6], [8], evaluates the ALN to determine direction of cursor movement, and updates the cursor position on the subject's screen. Some subjects use two manual switches to mark sequences of voluntary attempts to mentally control the movement of a circular object on the feedback screen. Since mental concentration is required to produce desired EEG signals, these switches allow the subject to rest during the experiment and avoid fatigue or habituation. The subject's goal is to move the object on the screen to a target. The position of the target is alternated between UP and DOWN in one-dimensional (1-D) setup or between UP, DOWN, LEFT and RIGHT in 2-D setup. When the cursor reaches the target, or misses by reaching the edge of the screen, a new target position is chosen. An example of the subject's screen can be seen in Fig. 1. We chose cursor movement because it is objective, easily implemented, simple for the user to learn, and can serve as a prototype for control of a wide variety of applications.

## III. The Assessment of Results and the Results

We trained several subjects to achieve reasonable control over the object on the screen in one dimension. Acquiring control with our BCI takes some training, but most of our subjects were able to demonstrate some control even after only two 30-min sessions. The first half of each session is used to train a new ALN classifier. During the training phase, the ALN trains in real-time as the subject is attempting to move the cursor toward the target. Once the subject achieves control, the ALN training is halted and the second half of the session is used to evaluate the performance. Performance is evaluated in terms of how many times the target is hit versus missed at various movement speeds of the cursor. During these sessions, the position of the object is updated every 50 ms and the speed of the animated cursor is determined by the number of steps that are required to hit the target, which is set by the operator before the experiment. Once fully trained in 1-D control, our subjects can hit the target close to 100% of the time when 32 full steps are required to hit or miss the target. The spectrum for one of our subjects, calculated by fast Fourier transform (FFT) during off-line data analysis, is shown in Fig. 2. As can be seen from Fig. 2, a large difference in spectral power density exists at around 10 Hz between the EEG recorded while the subject was thinking UP-thoughts as compared to DOWN-thoughts. It is interesting that this effect is reversed at the parietal electrodes, which confirms expectations that the source of this voluntary activity is somewhere underneath central and parietal electrodes.

So far we have been able to train only two subjects to achieve 2-D cursor control. One of the subjects is able-bodied person and the other one has post-polio syndrome. In their latest session, these subjects achieved 2-D cursor control with 70 and 85% of the targets hit, respectively. An average of the latest four sessions for each subject is 63 and 76%.

## IV. Future Plans

Our short term goals are to train a number of volunteers in 2-D cursor movement and positioning, as well as to develop a range of applications for the BCI.

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# Applications of Cortical Signals to Neuroprosthetic Control: A Critical Review

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***Abstract*—Cortical signals might provide a potential means of interfacing with a neuroprosthesis. Guidelines regarding the necessary control features in terms of both performance characteristics and user requirements are presented, and their implications for the design of a first generation cortical control interface for a neuroprosthesis are discussed.**

***Index Terms*—Cortical interface, electroencephalogram (EEG), neuroprosthesis.**

## I. INTRODUCTION

Neuroprosthetic systems provide function by electrical stimulation of paralyzed muscles in a coordinated fashion. The individual using the system can control the stimulation, usually through movement of some nonparalyzed part of the body. For example, in the Case Western Reserve University (CWRU)/VA hand-grasp neuroprosthesis [1], [2], the user controls opening and closing of his or her hand by movement of the contralateral shoulder. This movement is sensed by an external position transducer that is taped to the user's shoulder and chest. The command signal is sent to an external control unit, which converts the signal into the appropriate stimulus level for each muscle. This signal is sent through a radio frequency (RF) link to the implanted stimulator unit, which in turn generates a stimulus pulse train of the appropriate magnitude to each electrode placed on the different muscles of the forearm and hand. By coordinating the activation of each muscle, a functional grasp pattern is achieved.

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The user controls the degree of opening and closing of the hand by movement of the contralateral shoulder—moving the shoulder forward (protraction) results in hand closing, moving the shoulder back (retraction) results in hand opening. The control is proportional, allowing the user to modulate the grasp force for the desired task by adjusting shoulder position. The neuroprosthesis also uses a state control input (typically a chest mounted switch) that enables the user to select different pre-programmed grasp patterns, to turn the device on and off, and to lock and unlock the hand.

Ongoing research and clinical experience has defined limitations that are inherent in the shoulder generated command signal and its hardware implementation. First, shoulder control is restricted to the contralateral arm, thus restricting bilateral implementation of the neuroprosthesis. Second, the external mounting is cumbersome, necessitates external wiring, and performance varies somewhat with mounting differences. Current research is designed to overcome these deficiencies. In particular, an implantable transducer that senses the position of the ipsilateral wrist has been designed and clinically implemented [3]. Also, myoelectric control has been assessed as an alternative command signal, using the EMG signal from retained muscles [4], [5] as the control source. Nevertheless, all of these signal sources are somewhat unnatural and require the user to learn to relate an artificial command with the intended movement. It is in this dimension of natural control that a cortical interface provides the greatest potential.

## II. CHARACTERISTICS OF THE COMMAND CONTROL INPUT

The characteristics of the command signal for a hand neuroprosthesis should enable the user to utilize a natural method to select a grasp pattern, regulate hand opening/closing and the grasp strength, and maintain grasp. The principal feature of the command signal is proportional, single degree of freedom information under user volitional control delivered at a sufficient accuracy and speed to provide appropriate control of the hand. Acceptable factors to achieve this type of control can be separated into performance and user criteria. A partial review of these criteria has been compiled elsewhere [6], [7]. These criteria are shown in the following sections.

### A. Performance Criteria

*1) One Degree of Freedom:* A single degree of freedom input signal will enable control of both hand opening/closing and grasp strength. Control of some other upper extremity movement (e.g., elbow extension, forearm pronation) can be linked to synergistic movements [8], [9], thus reducing the demands of the controller. Other movements (e.g., shoulder) will require a separate control input. For the operation of the contralateral hand, a second control input will also be required since sequential control of the hand is not clinically acceptable.

*2) Stability over Time:* Stability is required to enable day-to-day consistency of the command input. This is addressed further in the discussion section as applicable to cortical signals.