PARALLEL MAN-MACHINE TRAINING IN DEVELOPMENT OF EEG-BASED CURSOR CONTROL

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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 amyotrophyc lateral sclerosis, or who have had massive brainstem strokes. However, the effectiveness of most assistive devices are 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 simple interface between the user and the computer known as Brain-Computer Interface (BCI). Frequently used model for development of BCI is to control the cursor movements and its positioning on computer screen. The problems that remain unsolved even with currently most successful systems are very slow training of subjects, low spatiotemporal resolution, and poor accuracy in two-dimensional control. Precise positioning of the controlled object 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. The goal of our research is to develop new training technology that will achieve simple control using various mental activities. The control actions that we want to achieve are two-dimensional (up - down - left - right) object movement on the computer screen, and precise positioning of the controlled object. In order to achieve our goal, we are working on the development of EEG recording and processing setup and training method that will maximize efficiency of extraction of user's intentions. In order to make the BCI practical, the following three constraints must be met:

1. Minimize the training time of subjects. Current systems often require weeks of training before reasonable performance is achieved. Long training is usually the main obstacle in acceptance of any practical assistive system.
2. Use as few EEG channels as possible. A brain-computer interface with too many electrodes becomes costly, cumbersome, and less feasible for implantation.
3. Achieve high enough accuracy to provide reliable interface between man and machine.

II. Methods and Communication Protocol

The subject is comfortably seated in front of a feedback monitor while EEG signals are recorded using an electrode cap with 28 gel-filled electrodes arranged according to the 10-20 international electrode system, one ground electrode and the linked ears reference. The electrode cap and EEG-preamplifiers are electro-optically isolated from the rest of the equipment. This provides safety for both the subject and the operator. For signal conditioning, i.e. amplification and initial filtering we use the Brain Imager (Neuroscience Inc.). Analog EEG signals are then digitized at 200 samples/s by a data acquisition card (DAQ) 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 operator supervising the experiment.

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 non-linear adaptive machine learning system for supervised learning which is capable of learning any continuous function to any degree of accuracy [1].

During the real-time experiments, selected channels of EEG are processed 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 ALNs for training [2,3], evaluates the ALN to determine direction of cursor movement, and updates the cursor position on the subject's screen. The subject uses 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. The subject's goal is to move the object on the screen to a target. The position of the target is switched between UP and DOWN in one-dimensional setup or between UP, DOWN, LEFT and RIGHT in two-dimensional setup. New position of the target is decided at the end of each run when the object reaches the target or the opposite end of the screen is hit. 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.

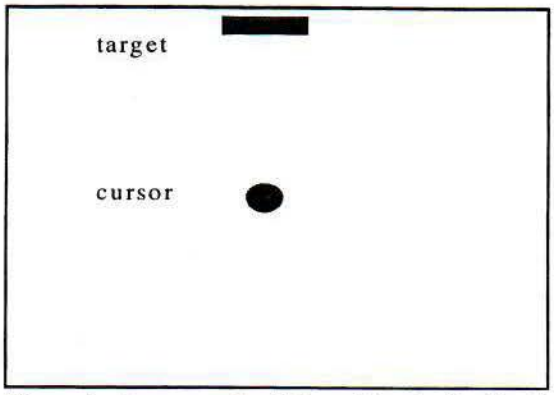

Figure 1: An example of the subject's feedback screen during an on-line experiment. The subject's goal is to move the cursor to the rectangular target.

III. THE ASSESSMENT OF RESULTS AND THE RESULTS

We had several subjects so far who learned to have reasonable control over the object on the screen in one dimension. Acquiring control with the BCI takes some training, but most of our subjects were able to show control after two sessions. Each of the sessions lasts approximately 30 minutes. The first half of each session is used to train a new classifier and the second half is used to evaluate the performance. Performance is evaluated in terms of how many times the target is hit versus missed at various movement speed of the object. During these sessions, position of the object is updated every 50 milliseconds and the speed of the animated object 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 one-dimensional 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 FFT calculated spectrum for one of our subjects during BCI cursor control 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 clearly shows that the source of this activity is somewhere underneath central and parietal electrodes.

So far we have been able to train only two subjects to achieve two-dimensional cursor control. One of the subjects is able-bodied person and the other one has post-polio syndrome. The two-dimensional cursor control that these subject can achieve is approximately 80% of targets hit.

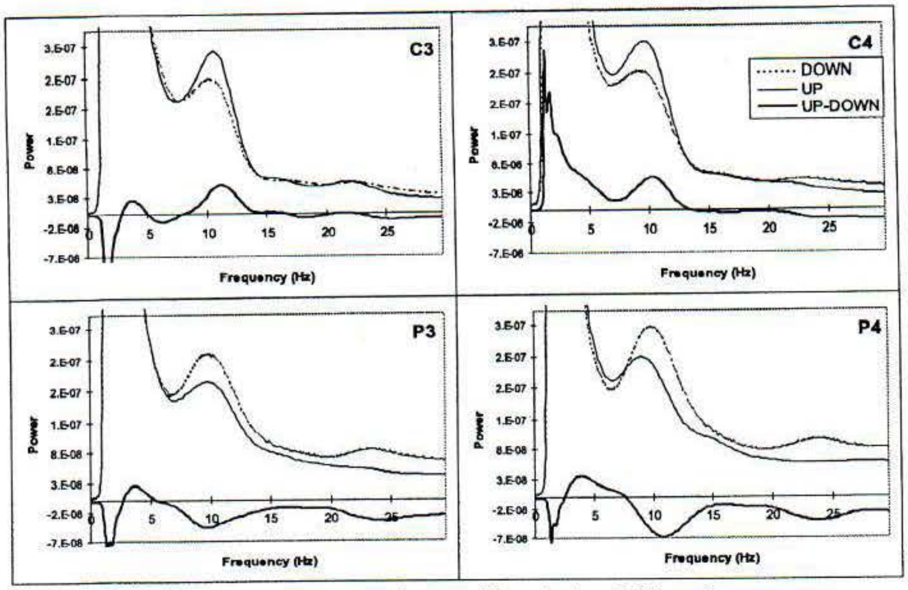

Figure 2. Averaged FFT spectrum of one subject during BCI session

IV. Future Plans

Our short term goals are to train a number of volunteers in two-dimensional cursor movement and positioning, as well as to develop a range of applications for the brain-computer interface.

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