Fig. 1 illustrates one of the patterns computed by means of the SSP method. In order to facilitate visual interpretation, the pattern has been derived from all 26 electrodes. Also, for the sake of simplicity, only the features related to the α peak are visualized. The figure shows the distributions of the features in the subject RA01 for the imagined right and left movements when using SL-transformed potentials.

The simplicity of the classifier we have utilized suggests that it is still possible to increase the recognition rates if SSP is combined with more powerful classifiers. In particular, SSP can be used either as a preprocessor for an artificial neural network, or to classify data using patterns obtained through Self Organizing Maps. This is subject to ongoing research.

Results obtained in this first year of the ABI project also indicate that SL electrodes return waveforms correlated with the numerically computed surface Laplacian. A new design of these electrodes, which is easier to place and less noisy, is under study. In the context of a Brain Computer Interface a few SL electrodes can improve the quality of the acquired signals.

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A Virtual Reality Testbed for Brain–Computer Interface Research

Jessica D. Bayliss and Dana H. Ballard

***Abstract*—Virtual reality promises to extend the realm of possible brain–computer interface (BCI) prototypes. Most of the work using electroencephalograph (EEG) signals in VR has focussed on brain–body actuated control, where biological signals from the body as well as the brain are used. We show that when subjects are allowed to move and act normally in an immersive virtual environment, cognitive evoked potential signals can still be obtained and used reliably. A single trial accuracy average of 85% for recognizing the differences between evoked potentials at red and yellow stop lights will be presented and future directions discussed.**

***Index Terms*—Brain–computer interface (BCI), P3, virtual reality (VR).**

I. Introduction

Recent brain–computer interface (BCI) work has shown the feasibility of online averaging and biofeedback methods in order to choose characters or move a cursor on a computer screen with up to 95% accuracy [1]–[4]. Previous research in virtual reality (VR) has looked at brain–body actuated control [5] or steady state visual evoked potentials [6]. VR promises to extend the realm of possible BCI prototypes through allowing individuals to interact directly with an environment rather than a computer monitor while still maintaining the environmental control necessary in research. The safety of VR also makes it an excellent candidate for BCI research on real-time tasks and VR can serve as a motivational tool for people because it is often perceived as an interesting environment.

BCI's are most often used for augmentative communication by individuals with locked-in syndrome. The P3-evoked potential (EP) is a positive waveform occurring approximately 300–450 ms after an infrequent task-relevant stimulus [7], [8]. It has been shown that even when the P3 evoked potential (EP) component disappears after a brain stem injury, it can be regained [9]. Thus, this particular EP is a widely available signal that does not heavily depend on the problems of a particular patient.

II. Materials and Methods

A. The System

The VR environment is rendered on a SGI Onyx. For immersion, subjects wear a binocular head-mounted display (HMD) containing a camera-based eye tracker. While collecting EEG data, eye tracking data is also collected and overlaid onto a videotape of the virtual scene. This dual data collection enables a comparison of what an individual is looking at with what the BCI is doing and can be used to find BCI recognition errors that could not be found by looking at the EEG data alone.

The heart of this system is the NeuroScan commercial package on a Pentium PC. A dynamic linked library (DLL) provided by NeuroScan enables locally written software to have access to all unprocessed data

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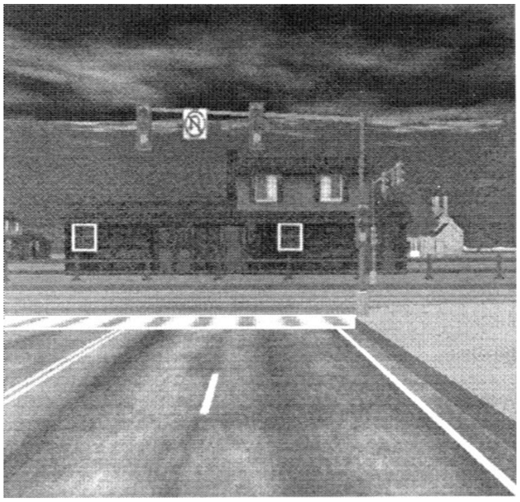

Fig. 1. A typical stoplight scene in the virtual driving environment.

and trigger codes. Signal processing is done in Matlab in order to enable maximum algorithm flexibility. Feedback to the virtual world is done through a serial port interface between the SGI and the PC.

B. Virtual Driving

VR allows subjects to make on-line decisions in a dynamic environment. Thus, the best tasks for this environment involve interaction with virtual objects. To this end, we have used the driving environment shown in Fig. 1 to look at on-line cue recognition during a stoplight detection task.

In order to test the feasibility of on-line recognition in the VR environment, we recognized the P3 EP. Previous P3 research has concentrated primarily on static environments such as the continuous performance task [10]. In the traditional visual continuous performance task, static images are flashed on a screen and the subject is told to press a button or count the occurrences of a rare stimulus when it occurs on the screen. This makes the stimulus both rare and task relevant in order to evoke a P3. As an example, given red and yellow stoplight pictures, a P3 should occur if the red picture is less frequent than the yellow and subjects are told to press a mouse button only during the red light. A similar response occurs in a VR driving world when red stop lights are infrequent and subjects are told to stop their virtual cars at the red light. In order to make yellow lights more frequent, both green and red lights were preceded by yellow lights.

Subjects were instructed to drive in a virtual town and stop at red stop lights while ignoring both green and yellow lights. The subjects used a modified go cart with brake, accelerator, and steering output to control the virtual car. Go cart driving is more like a "natural" driving task than driving and stopping with a mouse. While this choice could cause more artifacts in the signal collection (due to muscular activity during turning and braking), the most significant artifacts observed in the data were due to eye movement as determined by visual inspection and correlation between eye and other channels.

Whenever a traffic light in front of the subject changed color, a trigger pulse containing information about the color of the light was sent to the NeuroScan system. While an epoch size from -100 ms to 1 s was specified, the data was recorded continuously. Eight electrodes sites (FZ, CZ, CPZ, PZ, P3, P4, as well as two vertical EOG channels) were arranged on the heads of five subjects with a linked mastoid reference. Electrode impedances were between 2–5 kΩ for all subjects. The EEG signal was amplified using Grass amplifiers with an analog bandwidth from 0.1 to 100 Hz. Signals were then digitized at a rate of 500 Hz and stored on a computer.

TABLE I
SUMMARY OF CLASSIFICATION RESULTS OVER FIVE SUBJECTS OVER THREE DIFFERENT ALGORITHMS

	Average % Correct		
	Correlation	ICA	Robust Kalman Filter
Red	82	74	71
Yellow	60	80	90
Total	67	78	83

TABLE II
CLASSIFICATION RESULTS OVER FIVE INDIVIDUAL SUBJECTS FOR THE ROBUST KALMAN FILTER AS WELL AS RESULTS FOR TWO RETURN SUBJECTS ($p < 0.01$)

	Robust Kalman Filter % Correct			
Subjects	Red	Yellow	Total	Return Total
S1	55	86	77	--
S2	82	94	90	--
S3	74	85	81	--
S4	65	91	82	85
S5	78	92	87	80

To determine that the P3 EP occurred only at red stoplights, we calculated the averages over red light and yellow light trials with trials where the subject ran a red light (approximately two per subject) removed. As expected, the data obtained while driving contained artifacts. To reduce these artifacts before averaging, we preprocessed the data and subtracted a combination of eye and head movement artifact using the linear regression technique described in [11]. Results show that a P3 EP indeed occurs at red and not yellow lights [12].

III. RESULTS

While averages show the existence of the P3 EP at red lights and the absence of such at yellow lights, we needed to discover if the signal was sufficient for single trial recognition as the feedback needed by a BCI depends on quick recognition. We tried three methods for classification of the P3 EP: correlation, independent component analysis (ICA) [13], and a robust Kalman filter [14]. We summarize the data over five subjects for all algorithms in Table I. All algorithms performed significantly better than correlation, but ICA did not perform significantly different from the robust Kalman filter.

We classified approximately 90 yellow light and 45 red light data epochs from each subject. The P3 EP existed at red lights and represented a BCI code for a "stop" action. The P3 did not exist at yellow lights and thus represented a code that no action should be performed. It is more important that the yellow lights be classified as non-P3 than the red lights classified as P3. As an example, if an individual uses the P3 to control a TV, it would be acceptable to have to try twice to turn on the TV, but it would be unacceptable to have the TV turn on and off randomly because of falsely recognized P3's. As shown in Table I, the percentage of red light P3's classified correctly (true positives) steadily declines from correlation to the Kalman filter while the percentage of correctly classified yellow lights steadily improves (true negatives). This shows a trade-off between recognizing all P3's (the red lights) and rejecting the majority of the non-P3's (the yellow lights).

Each subject's data for the best performer (the robust Kalman filter) is shown in Table II. Data was preprocessed with the method described in the previous section. The robust Kalman filter was trained using red and yellow light averages from the maximal electrode site for obtaining the P3 for each subject. We used the whole trial epoch for recognition because it yielded better recognition than just the time area around a potential P3. In order to look at the reliability of the robust Kalman filter two of the Subjects (S4 and S5) returned for another VR driving session. The results of this session using the robust Kalman Filter trained on the first session are shown in the last column of Table II. The recognition numbers for red and yellow lights between the two sessions were compared using correlation. Red light scores between the sessions correlated fairly highly: 0.82 for S4 and 0.69 for S5. The yellow light scores between sessions correlated poorly with both S4 and S5 at around -0.1. This indicates that the yellow light epochs tend to correlate poorly with each other due to the lack of a large component such as the P3 to tie them together.

IV. Future Work

The recognition rates presented make it practical to use the P3 EP as an interface to devices such as TV's, radios, and other appliances. The ease of swapping user interfaces in this BCI system facilitates such environmental control work. We expect that the most useful BCI will rely on a variety of brain signals. For example, if a patient can develop μ-rhythm control, they might want to use it to control the volume on a TV with a P3 being used to control the on–off functions. Contextual information, when available, should also be used. Environmental control provides many ready opportunities for this because of the different physical locations of items.

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The Thought Translation Device (TTD) for Completely Paralyzed Patients

Niels Birbaumer, Andrea Kübler, Nimr Ghanayim, Thilo Hinterberger, Jouri Perelmouter, Jochen Kaiser, Iver Iversen, Boris Kotchoubey, Nicola Neumann, and Herta Flor

***Abstract*—The thought translation device trains locked-in patients to self-regulate slow cortical potentials (SCP's) of their electroencephalogram (EEG). After operant learning of SCP self-control, patients select letters, words or pictograms in a computerized language support program. Results of five respirated, locked-in-patients are described, demonstrating the usefulness of the thought translation device as an alternative communication channel in motivated totally paralyzed patients with amyotrophic lateral sclerosis.**

***Index Terms*—Electroencephalogram (EEG), language support program, locked-in, operant learning, slow cortical potentials (SCP's).**

I. Introduction

A communication device for the completely paralyzed was developed using an operant learning approach for the self-regulation of EEG signals. The procedure was tested in locked-in patients with amyotrophic lateral sclerosis (ALS) [1]–[4]. The thought translation device (TTD) uses slow cortical potentials (SCP's) to select letters or words from a language support program. SCP's are shifts in the depolarization level of the upper cortical dendrites which are caused by intracortical and thalamocortical afferent inflow to neocortical layers I and II. Negative SCP's are the sum of synchronized ultraslow excitatory postsynaptic potentials from the apical dendrites. Positive SCP's result from a reduction of synchronized inflow to the apical dendrites or may be caused by inhibitory activity or by excitatory outflow from the cell bodies in layers IV and V. Positive SCP's lasting from 300 ms to several seconds or minutes are correlated with a disfascilitation of the involved cortical networks. Behavioral and cognitive performance is improved after subjects or patients have learned to increase the negativity of the SCP, while cognitive and

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