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The Strathclyde Brain Computer Interface

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***Abstract*— Brain-computer interfaces (BCI) offer potential for individuals with a variety of motor and sensory disabilities to control their environment, communicate, and control mobility aids. However, the key to BCI usability rests in being able to extract relevant time varying signals that can be classified into usable commands in real time. This paper reports the first success of the Strathclyde BCI controlling a wheelchair on-line in Virtual Reality. Surface EEG recorded during wrist movement in two different directions were classified and used to control a wheelchair within a virtual reality environment. While Principal Component Analysis was used for feature vector quantiser distances were used for classification. Classification success rates between 68% and 77% were obtained using these relatively simple methods.**

I. INTRODUCTION

Brain computer interface (BCI) technology has shown remarkable promise for providing individuals with severe motor disabilities a means to communicate via computers and to have command and control over their environment [1].

It is well established from primate studies that neurons within the motor cortex show directional tuning during the planning phase of movement [2], [3]. Evidence from single unit recordings demonstrate that the activity of cells in the primate motor cortex is highest for movements in certain directions and lesser when the movement is in other directions. We are able to make use of information from the pre-movement EEG, that relates to direction of intended movement, to predict the direction of intended movement [4], [5]. Some work [6] have used mental tasks rather than motor tasks to develop online BCI. While the study by Leeb [7] presented a single dimensional BCI controlling virtual wheelchair, the current study investigates the possibility of extracting a multidimensional control by using motor potentials relating to wrist movement for real time control of a wheelchair within a virtual environment.

II. MATERIALS

Fig. 1 illustrates the experimental arrangement of the on-line Brain Computer Interface (BCI) experiment. The system comprises a BCI processing workstation and a virtual reality wheelchair simulator, incorporating in total two computers, an EEG/EMG signal acquisition system and an immersive display system. These components are described below.

A. BCI processing workstation

The BCI processing workstation has two major functions: simulator control and data acquisition and processing.

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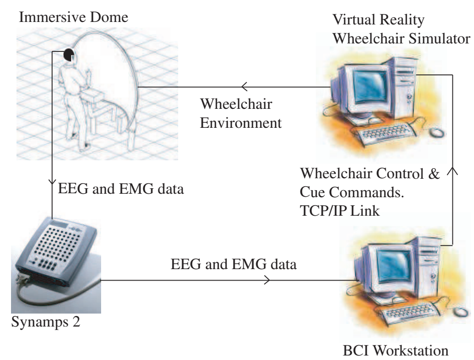

Fig. 1: Brain Computer Interface Block Diagram.

1) Simulator Control: The BCI computer interacts with the VR Wheelchair Simulator through a TCP/IP link (Fig. 1). The BCI workstation sends control commands to the Simulator to present the directional cues to the user and control the wheelchair (after classifying the EEG signal).

2) EEG/EMG Acquisition: Signals were acquired using the Synamps2 EEG/EMG data acquisition system (Compumedics). The software development kit of the system was used to develop a Matlab toolbox to perform data acquisition and classification of movement intention. 14 EEG channels and 2 EMG channels (FCR and ECRL) were acquired at a sampling rate of 2000 Hz during the BCI experiments (Montage shown in Fig. 2). AFz was used as the ground and Cz as the reference electrode. EMG was recorded to verify movement direction.

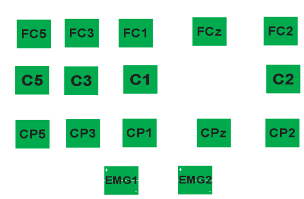

Fig. 2: Electrode Montage.

B. Virtual Reality Wheelchair Simulator

Developing a BCI-controlled wheelchair requires a VR simulator that combines the features of BCI training with realistic wheelchair behavior. Similarly, equipping the wheelchair with smart technology can ultimately reduce the complexity of the BCI task but requires that a viable system should also have the capacity to integrate a variety of sensor technologies [8], [9].

In order to maximize the utility of the simulator a set of objectives has been identified. These include portability, flexibility regarding user input, extendibility to include sensors and simulate smart wheelchairs, support for versatile training scenarios, high degree of immersion and realism, easy set-up and a relatively low cost. The system described here addresses most of these objectives.

1) Hardware: To provide a sense of immersion, the VE is projected on a spherical screen (section of a sphere with 1.5m radius) providing a 160° horizontal field of vision (FOV) using a projector fitted with a wide-angle lens (Elumens VisionStation®). The simulator runs on a dual-core PC with a gaming-standard dual-view graphics card.

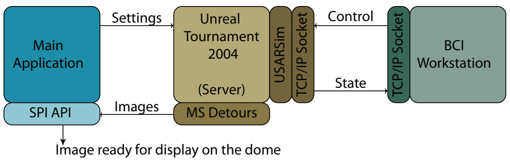

Fig. 3: Software architecture.

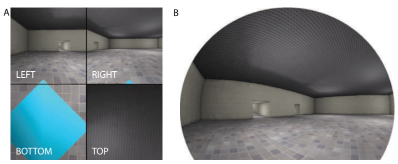

Fig. 4: A: Multiple views from the wheelchair; B: Spherically correct image ready for projection on the dome.

2) Software: Addressing several of the design objectives, the simulator relies on the Unreal Engine 2.5 and the Karma physics engine to, respectively, maintain and render the virtual environment and model the physical behavior of its elements. Unreal Engine is a commercial game engine that ships with the Unreal Tournament 2004 (UT2004) game. This approach was developed by the Urban Search and Rescue Simulator (USARSim) [10] open-source community. USARSim provides a modification to UT2004 that allows placing robots in the game. It employs Microsoft Detours [11] technology to capture backbuffer images from UT2004. Importantly, UT2004 operates as a TCP/IP server, allowing physical separation of the computer running the simulation and any BCI-related hardware, while all communication occurs over the network. Overall software architecture is presented in Fig. 3.

Correct immersive 3D display on the VisionStation is ensured by the SPIClops OpenGL-based API provided by the manufacturer, which requires four orthogonal views of a scene to stitch into a single frame (Fig. 4). To satisfy this requirement, USARSim's use of the Detours technology has been extended to allow greater resolution of the captured images. The average frame rate is above 30 FPS at a resolution of 1024×768 (maximum supported by the projector).

A GUI application has been developed in VisualC++ that integrates UT2004, USARSim and SPIClops. This allows the choice of map, vehicle, and method of control, and provides logging capabilities for debugging purposes. All communication between the application (client) and the game server is recorded, including periodic status information about the wheelchair's position and velocity. This information is saved for offline analysis of user performance. A Matlab toolbox has also been developed providing analogous functionality.

3) Wheelchair Model: The simulator features a simplified 3D model of the Invacare SpectraPlus wheelchair (see

(a) INVACARE® SpectraPlus

(b) 3D model as seen in UT2004

Fig. 5: Wheelchair model and the real wheelchair (image from INVACARE® product brochure).

Fig. 5). This particular wheelchair was chosen as one of the more commonly prescribed indoor/outdoor EPWs in Scotland for which relatively good documentation was available. The 3D model was built in Maya 7.0 PLE based on images available from the manufacturer's website and exported to UnrealEd as separate static meshes using the unEditor plugin available on Unreal Developer Network. The model was then added to USARSim by writing appropriate UnrealScript classes and modifying the USARSim configuration file. The model features fully autonomous castor wheels, a functional curb climber and four orthogonal simulated cameras. Since parts of the wheelchair (e.g. footrests) may come into view on the dome, a human avatar was placed on the wheelchair, but it does not influence the simulation.

An important factor affecting the simulation of any model in UT2004 is its mass distribution and associated inertial properties. These were calculated using estimated masses of the different parts of the chair (since they were not available in the documentation) and literature values for average human body parameters [12], [13]. Thus obtained center of mass and tensor of inertia were used to calculate the torque required for the two simulated motors using the manufacturer's product specification as a guideline.

III. METHODS

A. Experimental Protocol

During the experiments the subject participated in three different sessions which are described below. Each session presented to the subject in the VE lasts about 100s and comprises 20 5s trials. 2s into each trial, the subject is presented with one of the two different directional visual cues. The visual cues projected on the dome are arrows pointing to the right or left. The post-cue EEG is classified and the classification results are sent as control commands to the virtual wheelchair.

1) Visual Only Session: In this session the subjects were presented with the directional cues but were instructed only to observe them. The data recorded from this session will be used to check for the presence of visual evoked responses within the epochs

2) BCI Training Session: In this session the subjects were asked to move their wrist as quickly as possible to the direction indicated by the directional cue. The data recorded in this session will be used as the training dataset for the online BCI session. The data is initially pre-processed to identify which of the EEG channels provided the best classification result.

3) Online BCI Session: As in the training session the subjects were instructed to move their wrist as quickly as possible to the directional cue. The EEG recorded post-cue is then classified and this classification result is provided as a visual feedback to the user by steering the simulated wheelchair along the same direction as the classification result.

B. Data Analysis and Classification

1) Comparing Visual-only Trials vs. Training Dataset: To ensure that the features used for classification of trials are associated with motor related cortical potentials and not visual evoked potentials due to the different visual stimuli presented to the participant time domain averages of the visual only trials were compared with the time-domain averages of the trials recorded during BCI training.

2) Processing the Training Set: After ensuring the absence of visual evoked components in the EEG data, the training data set is processed to extract the classification rates obtained from the different channels. This is done by first splitting the training dataset for each channel into a training and testing subset. PCA [1] is used to extract features from the training subset and averages for the two different movement groups (movements to the right or left) are computed. The PCA matrix is then used to transform each trial in the testing subset. Using the Eigen values from the PCA computation a weighted Euclidean distance between the unclassified trial (from the transformed testing subset). The groups' averages are computed and the new trial is classified to the closest group. In this manner the classification rate for the EEG from each electrode is computed and the electrode with the best classification rate is used to classify the EEG trials during the online BCI trials.

3) Online Classification Trials: Once the electrode with the best classification rate for the participant has been identified the subject participates in the online BCI trials. Prior to starting these trials the training EEG data from the best electrode is transformed using PCA and average feature vectors for the two groups are computed. At the end of each movement trial the PCA transformation matrix is used to extract the feature vector from the new trial and a weighted Euclidean distance based classifier (as described previously) is used to categorize the new trial. The classification result is used to control the wheelchair thus providing the user with feedback of the classification result. The direction cue and the classification result are then compared and this is used to compute the classification accuracy of the online trials.

4) Post-Experiment Processing: The post-experiment processing was performed with an aim of investigating the possibility of improving the classification results. The classification performance was re-calculated with the following modifications:

[1]Refer P.C.A by I.T. Joliffe. ISBN 0387954422

TABLE I: Classification rates (RR) of the training set and online testing experiments.

	Training				Testing			
	Best Ch.		2nd Best Ch.		Best Ch.		2nd Best Ch.	
Subject	RR	Ch.	RR	Ch.	RR	Ch.	RR	Ch.
1	75.2	C2	72.0	FC5	72.7	FCz	72.7	C2
2	71.4	FC2	70.7	FC5	71.4	FC2	71.4	CP2
3	77.0	FCz	71.0	FC2	68.8	FC5	68.8	FCz
4	74.3	CP5	72.1	FC1	71.4	CP5	67.9	C3
5	73.3	FC1	66.7	FC3	77.8	CP1	72.2	CP3

a) Expanding the Training Set: While feedback of the classification is presented to the user during the online BCI trials no feedback is given during the BCI training sessions. It is to be expected that the feedback provided will affect the users performance and hence the features that can be extracted for BCI control which in turn will affect the classification results. To investigate this, half of the online BCI trials were included with the original training dataset and the second half of the online BCI trials were re-classified with features extracted from the new training set.

b) Extracting Frequency Domain Features: In an attempt to investigate if features extracted from the frequency domain would provide higher classification rates the spectrograms of the data was computed. Using ANOVA time-frequency points which were significantly different for the two groups within the training dataset were selected. PCA is then used to further reduce the dimensionality of feature vectors. After computing the PCA average feature vector for the two groups within the training set were computed. A weighted Euclidean distance based classifier is used to classify the unclassified trials and the classification rates were computed for each electrode.

c) Changing the epoch length: In order to increase the information transfer rate of the BCI it is necessary to reduce the length of each trial. To investigate the possibility of using shorter epoch lengths for classification the length of the training and testing dataset were increased in steps of 500 ms from 500 ms to 3000 ms and at each stage the data was reclassified and the classification rates were computed.

IV. RESULTS

Results for five subjects are demonstrated in Tables I, II and III. Table I presents the recognition rates (RR) from the BCI training sessions and online BCI sessions, Table II presents the classification rates obtained by including part of the online BCI trials with the original training set and reclassifying the remaining trials obtained during the online BCI sessions. Table III presents the classification rates obtained by mining frequency domain features which would best help classify the trials into the different groups. In order to study the possibility of increasing the "speed" (information transfer rate) , the epoch length of the data was varied between 500ms to 3000ms in steps of 500ms and the classification results are presented in Fig. 6.

V. DISCUSSION

From the results presented in Table I it can be seen that Strathclyde BCI is capable of classifying in real time

TABLE II: Testing classification rates obtained after including part of the online BCI trials into the training set.

Subject	Best Channel RR	Best Channel Channel	2nd Best Channel RR	2nd Best Channel Channel
1	75.5	C2	71.7	FC2
2	74.1	FC5	74.1	FC2
3	78.0	FC3	72.2	C5
4	73.9	C3	73.9	CP5
5	89.0	C1	83.0	CP5

TABLE III: Testing classification rates obtained by extracting feature from the frequency domain.

Subject	Best Channel RR	Best Channel Channel	2nd Best Channel RR	2nd Best Channel Channel
1	70.0	CPz	65.0	FCz
2	84.0	CP3	76.0	FC1
3	81.3	C5	75.0	FC1
4	78.3	CP1	73.9	C5
5	77.7	C2	72.0	CPz

the movements made by the participant. In all participants (except subject 5) the electrode which performs best in the training set provides the best performance during the online BCI trials while no two subjects sharing the best performing electrode. This supports our strategy of using a high density electrode montage to record the EEG and select the best performing electrode for each subject.

The inclusion of new trials from the online BCI session into the training set significantly increases the classification rates for subjects (Table II). With improvements in the classification rates obtained from best electrode ranging from 2.4% to 11.2%. It can be seen that for all subjects (except subject 1) there is change in the electrode which provided the best classification results, confirming our hypothesis that the feedback provided affects the classifiable features that can be extracted from the EEG recorded from the different electrodes.

While simple and robust classification technique adopted for initial BCI trials provided classification rates higher than chance. Comparing Table I with Table III shows that by using more advanced feature extraction techniques the classification rates for the different subjects (except subject 1 and 5) can be considerably increased, with an overall increase of 5.83% across all subjects(including S1 and S5).

The results presented in Figure 6 show that there is a possibility of increasing the "speed" of the current BCI design by decreasing the epoch length of the EEG trial. It can be seen that the for the different subjects at certain shorter epochs performance of the BCI is equal to or greater than the performance of the BCI when 3000ms (the length used in the online classification trials) of the EEG data is used for classification.

VI. CONCLUSIONS AND FUTURE WORK

We have introduced the Strathclyde BCI. It provides real time classification of wrist movements in 2 directions using surface EEG and a wheelchair simulator. We have demonstrated that the classification rates of the BCI can be improved by including in the training set recent trials and also by using more advanced feature extraction techniques.

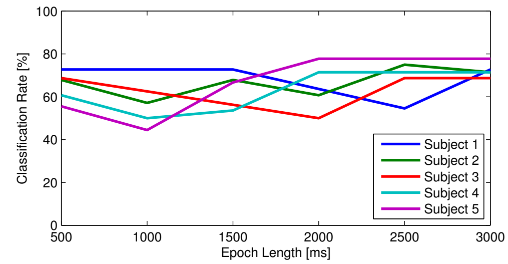

Fig. 6: Effect of changing epoch length on best electrode classification rates in different subjects.

The of "speed" BCI performance can be improved by decreasing the epoch length without loss in the classification accuracy.

While the current study demonstrates the possibility of using movement related cortical potentials for real-time control of a wheelchair within virtual environment further studies have to be carried out to improve the performance of the BCI by 1) increasing the number of movement directions; 2) adapting classifiers in real-time to changes due to visual feedback effects; 3) moving from a cued to a self-paced protocol; and 4) conducting motor imagery trials.

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