Augmenting Gaze Control with a Brain-Computer Interface

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Abstract

We present a hybrid brain-computer interface (HBCI) composed of a motor imagery-based brain switch and a headtracking device. Normal gaze-only (either head or eye gaze) interfaces suffer from a Midas Touch problem where unwanted selection of commands is triggered by subjects gazing at objects for too long. We use a BCI to provide a nontouch communication channel. Subjects were able to select and move objects in a fully immersive virtual environment. Object pick up and drop off was carried out by looking at the target object whilst using the BCI-based brain switch; object movement was controlled by the head-tracker. The HBCI was compared with a control condition where gaze dwell time (DT) was used to pick up and drop off objects. Overall, the HBCI was just as fast and accurate as the DT condition, which highlights the potential for a HBCI to be used as an interaction device in a variety of user interface situations.

1 Introduction

A brain-computer interface (BCI) is defined as a control system where "commands do not depend on the brain's normal output pathways of peripheral nerves and muscles" [1]. The most commonly used form of BCI is based on electroencephalography (EEG) as it is generally considered to be the least expensive and most practical method. BCIs are primarily used by people with severe motor disabilities, such as amyotrophic lateral sclerosis (ALS), to interact with a computer to improve their quality of life.

Our work is targeted at users with limited motor control such as head gaze or eye gaze. Thus the main users would be disabled users, but we can envisage situations where a BCI can add an additional channel of communication in situations where the hands and voice might be occupied. In particular we look at integrating a *brain switch* which is defined as a BCI where only one brain pattern in the EEG signal is detected and used as a switch [2].

Our work is an example of a hybrid BCI (HBCI). A HBCI is a system composed of one BCI and one other system. The HBCI that we present is composed of a head-tracker and a ERD-based BCI. We demonstrate our HBCI in a CAVE-like immersive display system (UCL CAVE), but this is just as an example, the system could equally be used with desktop displays or other forms of interactive environment such as smart homes.

Eye-gaze or head-gaze based interfaces are good examples of interfaces that can benefit from an additional communication channel such as a BCI. Normally the gaze has to dwell on the interface object of interest for a period of time before selection or activation. This suffers from the "Midas Touch" problem where the user selects items without meaning to creating user frustration. We compare the performance of our HBCI with that of eye-gaze dwell time (DT) to select and move objects in a 3D environment. BCIs are quite low bandwidth and provide noisy data. Thus the main challenge in the study is to demonstrate that a HBCI can have similar efficiency as a gaze dwell-time interface.

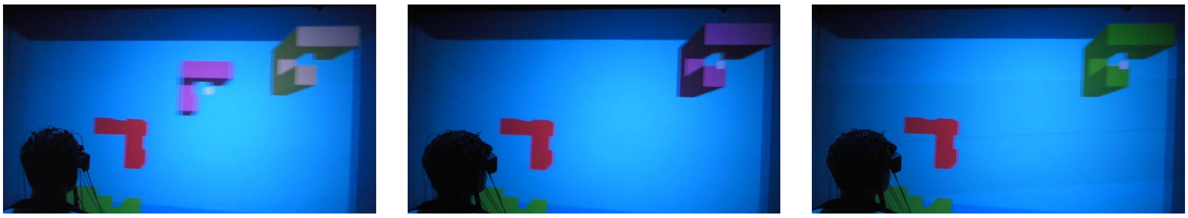

Figure 1: Left: Participant has selected correct object and is moving it towards the target object. Centre: Object is placed on top of the target object. Right: Object has now been dropped off by the participant and has been turned back to green.

2 Methods

2.1 Spatial Reasoning Task

To compare the performance of the HBCI and DT conditions we created a spatial reasoning task based on the rotation of 3D objects. The aim of the task was to select and manipulate the object matching the target object. There were four objects to choose from (figure 1). The correct object was set to a different rotation angle from the target object. Participants had 45 seconds in which to carry out the trial, after which there was a timeout, whether they had completed the task or not. They received a 5 second rest between trials and completed 9 trials in total.

The aim of the task was to pick up the correct object, move it and drop it off on top of the target object. Participants were able to select an object by placing the white cursor on the bounding box of the object they required. When the correct object was selected, its colour turned to purple and it rotated to the correct rotation angle automatically. Once dropped off, it changed back to its original colour. If an incorrect object was selected it turned red and did not move.

The task was displayed on the UCL CAVE, which comprises three 2.2m by 3m walls, and a 3m by 3m floor. The head was tracked with in Intersense IS-900 tracker. Graphics were generated with the UCL software, running on a four node self-built PC cluster. Imagery was generated at 85Hz in time-sequential stereo, at 1024 by 768 pixels per display surface.

2.2 Dwell Time Condition

Participants selected and de-selected an object by looking at it for 3.5 seconds. The DT was determined by pilot studies to find the best match to the level of difficulty of the task. Our DT was longer than those used in Sibert and Jacob [3] (150ms) and Ware and Mikaelian [4] (450ms) because we wanted to investigate tasks that had a cognitive load rather than just a simple selection of a basic target. This was supported by Vilimek and Zander's [5] findings, which is the closest study to ours. Their work was based on a hybrid eye-gaze BCI to perform selection of words on a screen. They found that a short DT reduced accuracy rates of their more difficult tasks to 51.1% whereas a longer DT provided accuracy rates of 75.6%. Interestingly, they also found that the highest accuracy rates were in the longer DT condition for the easy task, and in the BCI condition for the difficult task. This may suggest that BCIs may be of assistance in more difficult tasks.

2.3 HBCI Condition

Participants selected and de-selected an object by carrying out hand motor imagery (figure 1). In our experiment we used the g.tec g.MOBIlab+ 8 channel EEG system which is wireless and portable. Electrodes were placed at: Fz, Cz, P3, Pz, P4, PO7, Oz, PO8 based on the international 10-20 system. The reference was placed on the right ear-lobe and the ground on the forehead. We used the BCI2000 software [6] to carry out the EEG signal detection and filtering. We relayed the motor imagery data to the CAVE application over a UDP socket.

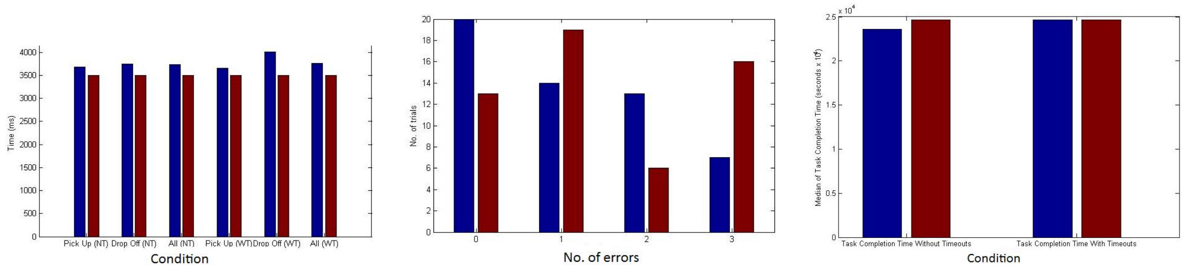

Figure 2: Blue denotes the HBCI system, red denotes the DT system. Left: Median time to pick up or drop off objects. Centre: Error rates (out of 54 trials). Right: Task completion times.

2.4 Overall Procedure

We examined the time taken to pick up and drop off objects, the error rate and the overall time taken and compared this to the performance of the DT system. Six participants took part (all male; age range 21-23 years) and were compensated for taking part. They were all students at UCL. We used a within-subjects design, which allowed us to both compare the performance with previous literature and also compare each participant's performance on the HBCI and DT systems.

Participants were individually trained with the BCI2000 software using hand motor imagery for one hour. On a different day, participants took part in the main experiment in the UCL CAVE. Each participant performed a series of 9 trials in the UCL CAVE in both the HBCI and DT systems. Half the participants used the HBCI system first, whilst the other half first used the DT system. Overall, the experiment lasted one hour per participant.

3 Results

During most trials there were no significant differences between the HBCI system and the DT system. The Wilcoxon matched pairs test was carried out between different conditions, some including timeouts. Overall, there were five timeouts during the HBCI system whilst there were none during the DT system. Four of the timeouts were outliers from the data, therefore the statistical analysis was carried out with and without them. Table 1 shows the results of the analyses where the two significantly different conditions are highlighted in bold. There were no significant differences in error rates (p=0.1063) and time taken to complete a task (p=0.8741) (figure 2). Interestingly, the medians of the HBCI system, with and without timeouts, were slightly faster than the DT condition (figure 2).

	Pick Up	Drop Off	Pick Up & Drop Off Rate
Without Timeouts	0.4544	0.0610	0.0613
With Timeouts	0.5611	**0.0095**	**0.0200**

Table 1: p-values of Wilcoxon matched pairs tests, where the pairs are the HBCI and DT for each participant

4 Discussion

There were no significant differences between the HBCI and DT conditions for the time taken to pick up and drop off objects (excluding two timeouts), in error rate or in task completion times. There were 4 timeouts in the HBCI system which did not affect the overall significance of the results, but do suggest that some time-critical tasks might need slightly different mechanisms.

The only comparable study we know of in the literature is that of Vilimek and Zander [5]. They created an eye-gaze HBCI and had 10 participants perform a search-and-select task by presenting them with stimuli consisting of words made up of consonants only. They had an “easy” and “difficult” task with shorter or longer words respectively. They compared the performance of shorter (1000ms) and longer (1500ms) DTs with their HBCI for each task. Interestingly, their task completion times showed that the BCI condition was statistically slower than the DT conditions. In contrast, we found no significant difference in task completion times, in fact, the medians of our HBCI system were slightly faster, however we did have longer dwell times.

Vilimek and Zander [5] also found the highest accuracy rates in the longer DT for the easy task, and in the BCI condition for the difficult task. In our experiment, we found no significant difference between accuracy rates. We had expected the DT system to render more errors as participants selected unintended objects. However some participants commented that the level of difficulty of our spatial reasoning task was too high. This could have led them to select each object randomly in both systems until they selected the correct one. This would correlate with the results found in the error rates (figure 2).

We believe that it it possible to make this HBCI even better and possibly surpass the performance of a pure DT technique. Firstly, the BCI could be made asynchronous, i.e. the user can carry out the motor imagery whenever they wish. With the cycle of the BCI2000 software, a participant could wait up to a maximum of 6 seconds before their motor imagery was picked up by the software, which is a considerable disadvantage especially since the length of DT was 3.5 seconds. Secondly, the participants could be given real-time feedback about the strength of their motor imagery before it is strong enough to hit the target. Participants had received such feedback during training but not in the CAVE. Some participants reported that it was harder when you did not know how well you were doing before the target was hit. This factor could certainly improve the BCI's performance.

In conclusion, we present the beginnings of an alternative to dwell time interfaces for situations where the user has limited motor control. We feel that there is much potential in building and developing HBCIs in and outside of immersive virtual displays.

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