# Some Steps towards Realtime Control of a Space-craft Simulator via a Brain-computer Interface

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**Abstract**

We explored the possibility of controlling a space-craft simulator in real-time using an analogue Brain-Computer Interface (BCI) for 2-D pointer control. This is an extremely difficult task, for which no previous attempt has been reported in the literature. Our system relies on an active display which produces event-related potentials in the user's brain. By analysing these, it is able to produce control vectors for the user interface at a rate of 10 per second. In tests, users of the simulator were told to pass as close as possible to the Sun. The simulation's initial velocity was randomly selected in such a way that, in the absence of suitable control, the space-craft would almost always miss the Sun. To obtain a successful outcome, users had to control the simulator continuously for approximately one minute in each run. Performance was very promising, on average users managing to satisfy the simulation success criterion in 67.5% of the runs. Furthermore, to study the potential of a collaborative approach to space-craft navigation, we developed collaborative versions of the BCI for pointer control where the system is controlled via the integration of the brain activity of two users. We analysed their performance using the data acquired when training the BCI for use in the simulator. The analysis indicates that a collaborative BCI can produce trajectories that are statistically significantly superior to those obtained in the single-user case. This suggests that the application of both single-user and collaborative BCIs to the domain of space navigation is becoming viable.

# 1  Introduction

## 1.1  Brain-Computer Interfaces

Brain-Computer Interfaces (BCIs) convert signals generated from the brain into control commands for various applications in different areas, like virtual reality and hands-free control of augmentative communication technologies [39, 1, 29]. BCI studies have shown that non-muscular communication and device control are possible and might serve useful purposes for people who cannot use conventional technologies, for example, because they are "locked-in" or lack any useful muscle control [5, 32]. Naturally, BCI systems can also be used by able-bodied users although, at the moment, they are not fast and reliable enough to replace other forms of control.

The signals used in BCI studies to date include P300 waves [13] and other event related potentials (ERPs) [41], evoked potentials (EPs) [24], event-related desynchronization/synchronization (ERD/ERS) [[25], activation patterns induced by mental task strategies [10], slow cortical potentials [4] recorded from the scalp, cortical neuron activity recorded by implanted electrodes (see [31] for a review), neuromagnetic signals recorded through megnetoencelography (MEG) [16], BOLD responses recorded through functional magnetic resonance imaging (fMRI) [37], activity-related, and localised brain oxygenation recorded through near infrared systems (NIRS) [9].

## 1.2  BCI for Pointer and Robot Control

Most of the approaches listed above focus on building BCI spellers. However, over the years, researchers have also focused on another area of BCI, often called Brain Machine Interfaces (BMIs) (see [19] for a review of BMI), which focuses on the *control* of physical systems, such as prosthetic devices, small wheeled robots [23] and autonomous wheelchairs [15]. Attempts have also been made at controlling humanoid robots, in which hybrid architectures integrate human-brain commands with elements of autonomous behaviour pre-implemented in the robot [2, 14]. However, those attempts have met limited success due to the intrinsic difficulty and unreliability of the classification process that transforms the brain signals into symbolic commands for a robot, a vehicle or a prosthesis.

There have also been attempts to develop BCI systems for the control of 2-D mouse pointers. Until very recently, the most successful systems for this purpose have been those based on the detection of $\mu$ or $\beta$ rhythms [40], those using invasive cortical interfaces (e.g., [11]) and those based on steady-state visually evoked potentials (SSVEP) [34, 38]. However, BCIs based on rhythms require lengthy training periods before users can control them; invasive BCIs are not very practical, requiring surgery, presenting risks of infections, etc.; and SSVEP-based BCIs require gaze control.

To overcome some of the above limitations, BCIs for pointer control have been developed based on ERPs. ERPs are relatively well defined shape-wise variations of the ongoing EEG which are elicited by a stimulus and are temporally linked to it [20]. ERPs are rather appealing since, at least in principle, they offer a relatively high bit-rate, require no user training and can be recorded non-invasively. Focus has mainly been on the P300. This is a late appearing positive ERP with a latency of about 300 ms which is elicited by rare and/or significant stimuli. This makes it possible to use it in BCI systems to determine user intentions and commands.

Early work based on the use of P300 include the system in [3], where rather long inter-stimulus intervals led to the pointer moving at the rate of one movement every 10 seconds, and the system in [28], where a speed of one cursor movement every 4 seconds was achieved but accuracy in detecting P300s was only about 50%. Recently, however, performance of P300-based BCIs for pointer control has started improving. A more responsive P300-based mouse was presented in [7]. The reported offline results were reasonably good, but preliminary online tests and further offline analysis showed that the mouse pointer was hard to control. This system was later improved in [30], where a significantly more responsive and robust controller was obtained thanks to a change in the stimuli used to generate P300s. These two systems present one unique feature: they completely dispense with the problem of detecting P300s (a notoriously difficult task) by logically behaving as an analogue device (as opposed to a binary classifier). Also, they use a single trial approach where the mouse performs an action after every trial (once per second in [7] and once every 100 ms in [30]).

## 1.3  BCIs in the Space Domain

Over the last few years there has been some interest in understanding the possibilities offered by BCI technology in space applications. To the best of our knowledge no such system has actually been built, but several researchers and both NASA and the European Space Agency have considered the potential advantages and limitations of BCIs in space. The results of the analyses have been mixed.

For instance, recent reports [22, 21] suggest BCI robotic devices, surface rovers, and semi-automatic manipulators as being the most relevant fields of application [6]. The potential advantages of BCIs for space applications highlighted by these studies include sending commands with minimum delays and high accuracy, astronauts collaborating in the control of machines such as robots and rovers [21], gaining machine control in conditions of restricted mobility and hands-free direct control of cabin instrumentation and equipment. However, as recently pointed out in [8], there are also factors that could limit the efficacy of EEG-based BCIs in a space environment. These include sensory and motor adaptation, microgravity, psychological stress, poor sleep, and vestibular distur-

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bances. Also, current information transfer rates and accuracy of BCIs are still too low for BCIs to be of a real benefit for space applications.

While we do agree that the many potential benefits of BCI technologies are currently limited by the low communication bandwidth, recent advances in neuroscience and collaborative BCI show that BCIs might be improved to an extent that they might become suitable for applications in the space domain.

## 1.4   Collaborative BCI

Recent studies on collaborative BCI seem to suggest that combining brain activity of several users involved on the same decision-making activity might give an advantage compared to decisions made with individual BCIs. In particular, Wang and collaborators [36] have compared the performance of single-user and collaborative (offline) BCIs in a task of movement planning. They proposed a system in which individual BCI subsystems solve the classification task independently and then a classifier integrates individual results. In experiments, through directly extracting information from the posterior parietal cortex and bypassing the motor related procedures, the BCI system could accelerate a motor response by using an artificial limb. The results show that there can be an advantage on the overall performance when brain activity of a group of individuals is integrated, compared to single performance, with the larger the group the better the overall performance (groups of up to 20 people were tested). Similarly [42] have proposed an online collaborative BCI that, using visual evoked potentials (VEP), can accelerate human response to visual stimuli.

Collaborative BCI has been also explored in [26] in an experiment where observers performed a simple visual matching task involving the rapid sequential presentation of pairs of visual patterns and had to decide whether the two patterns in a pair were the same. Visual stimuli were presented for insufficient time for the observers to be certain as to the decision. A composite feature was then developed, which optimally combined behavioural and neural measures in order to predict incorrect decisions. For group decisions, the use of a majority rule and three further decision rules were tested, which weigh the decisions of each observer based on their reaction times and the neural features. Results indicated that the integration of behavioural responses and neural features can significantly improve accuracy when compared with individual performances. Also, within groups of a particular size, the use of decision rules based on such features outperformed the majority rule.

Overall, studies of cognitive neurophysiology and collaborative BCI, such as those described above, seem to suggest that collaborative BCI can potentially provide significant improvements both in accuracy and speed with respect to conventional BCI systems. This seems also due to the fact that information on one's decision can be detected from the neural activity before a conscious decision is made and an overt response is given by an individual (see for example [35, 33]).

Collaborative decisions based on neural activities seem to benefit particularly from this, as shown for example in [12], where sensory-related neural activity could predict collective decisions on a discrimination task as early as 200 ms after stimulus presentation and before an overt response was given, and in [36], as described above.

## 1.5 Contributions of this Article

In this paper we report on the application of a version of the analogue BCI system for 2–D pointer control developed in [30] to a simulated space-craft control task and we study the potential benefits of its extension to a collaborative multi-user BCI system.

In particular, we have coupled the pointer-control system in [30] with a customised version of the Space Commander space-craft simulator [18], where we modified both its galaxy and its controls to make it possible to control the simulator via pointer movements and to present less cluttered and simpler test conditions.

Although the *potential* applications of BCI to the space domain have previously been discussed in the literature (for example [8, 21]), to the best of our knowledge at present there are no published reports of *actual* BCI applications in this domain. Our system, therefore, represents the first attempt at using a BCI to control a space-craft simulator (although, admittedly in a highly simplified environment and with short simulations).

In the present study, we also investigated the possibility of two users jointly controlling the space-craft via a collaborative BCI as a means of making the task less tiring and of increasing the speed and accuracy of the control. As indicated above, also this terrain is largely uncharted as only very recently the first ideas on cooperative BCIs have appeared in the literature [42, 36, 12, 26].

## 2 Methods

Our BCI for the control of a space navigation simulator comprises two systems: simulator itself (suitably adapted to satisfy the requirements of a BCI), and a BCI that converts brain activity into 2–D mouse-pointer movements, which are used for navigation control. Before the simulator could be used, the BCI had to be trained to recognise the ERPs of each user (as normally required in BCI). Experimental sessions, therefore, consisted of a first part where suitable training (and test) data were collected and used to train the BCI, followed by a second part where the trained BCI was used to control the space simulator itself.
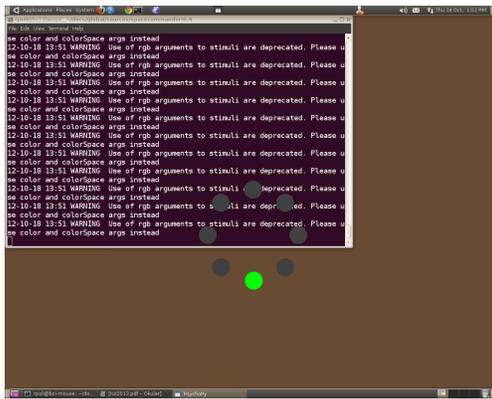
The following sections provide details of the BCI used, the collection of training and test data, the adaptations we made to the Space Commander simulator,
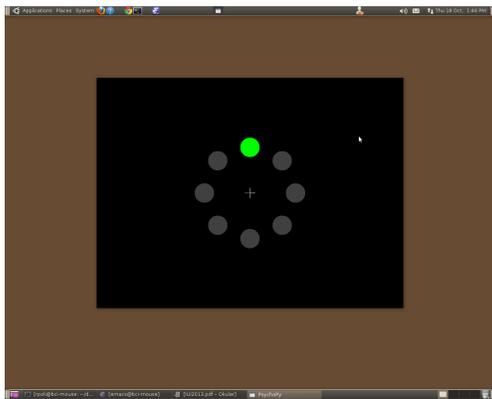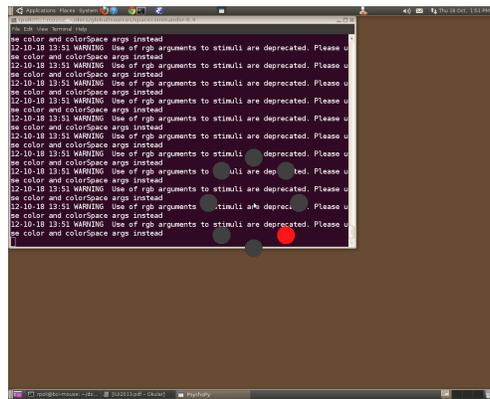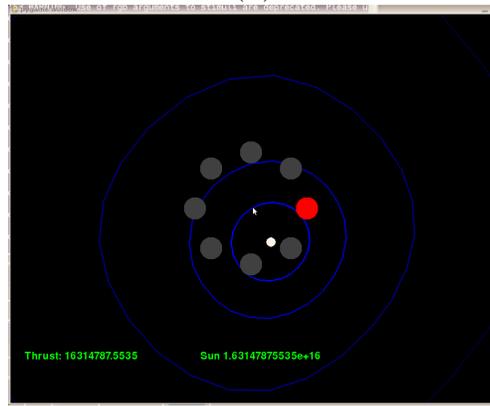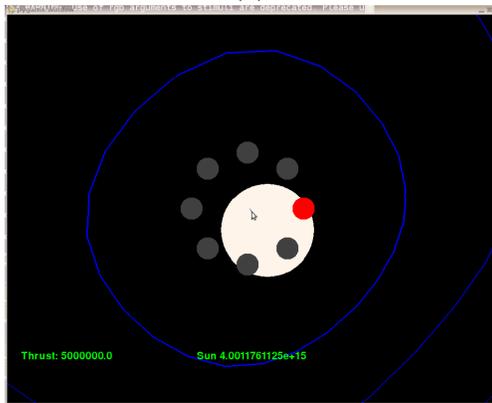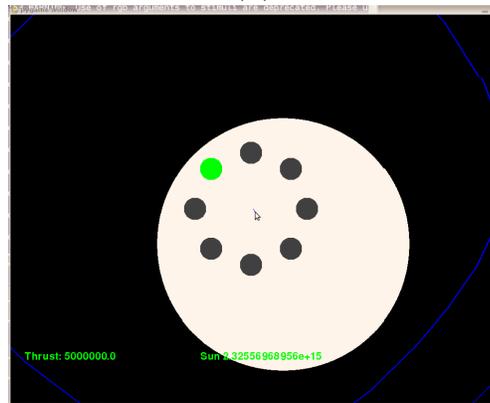
Figure 1: Different modes of operation of the system: (a) offline collection of training data with a static pointer on a black background, (b)–(c) two snapshots of the online collection of training data (and also of an independent test set) where the pointer moves and the background is the standard desktop of the Ubuntu operating system, and (d)–(e) three snapshots of our modified Space Commander simulator while operated by the BCI.

and the methods we used to combine the ERPs from two users for joint pointer control.

## 2.1  BCI Pointer Movement

The BCI mouse we adopted [30] has a large pointer made up of eight circles arranged around an imaginary circle as shown in Figure 1(a). The circles are normally grey, but flash in a periodic clockwise order, a flash of a circle consisting of a momentary change in colour, to either green or red (randomly selected). Each of the eight circles represents a direction. Flashes lasts for 100 ms with no delay in between flashes so that a full revolution is completed in 800 ms. When users want to move the pointer towards a specific direction, they focus their attention on the circle representing that direction (we call this a *target*) and try to mentally identify the colour of that circle every time it flashes, while attempting to ignore the other circles (*non-targets*). As a consequence of focusing attention on a target and identifying its colour, a P300 will be elicited in the user's brain when the target flashes, but not when non-targets flash (thought they might elicit a P300, but of a smaller amplitude). It is precisely this effect that allows the BCI to control the mouse pointer.

In the system, ERPs are represented by a segment of 800 ms of EEG data called an *epoch*. Epochs start when each circle is flashed. Epochs of consecutive flashes, therefore, overlap.[1] Each epoch is passed to an ensemble of two hard-margin linear support vector machines (SVMs). These must be trained for each specific subject (as is traditional in BCI) to guarantee satisfactory performance. However, gathering a training set and training the SVMs takes only a few minutes. The training set is formed by epoch/desired-output pairs. Desired outputs are $+1$ for the epochs starting on the flash of a target (i.e., a circle pointing in the prescribed direction of movement), and $-1$ for the non-targets.

Following [30], after training, the SVMs' raw output was used as a score for ERPs: the higher the output, the more likely an ERP was generated by a target stimulus. The SVMs' score for each ERP was then turned into a vector pointing in the direction of the stimulus and with a length proportional to the score. To produce smoother trajectories, these micro-movements were integrated together using the following analogue integration strategy:

$$\Delta x = \sum_{\phi} (\text{most recent score in direction } \phi) \times \sin \phi$$

$$\Delta y = \sum_{\phi} (\text{most recent score in direction } \phi) \times \cos \phi$$

where $\phi \in \{0, \frac{\pi}{4}, \frac{\pi}{2}, \frac{3}{4}\pi, \pi, \frac{5}{4}\pi, \frac{3}{2}\pi, \frac{7}{4}\pi\}$.

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[1]Naturally, this makes recognising P300s in the noisy EEG data much harder, but, overall, the resulting fast pace of stimulation allows higher information transfer rates.

Furthermore, to counteract the issues associated with eye-blinks and other muscular artifacts (which can generate sudden large movements of the pointer that users are then forced to laboriously correct) we also implemented the additional post-processing strategy evolved in [27].

## 2.2   Training and Test Sets

We gathered data from 3 participants. Participants were seated comfortably at approximately 80 cm from an LCD screen. Data were collected from 64 electrode sites using a BioSemi ActiveTwo EEG system. The EEG channels were referenced to the mean of the electrodes placed on either earlobe. The data were initially sampled at 2048 samples per second. We then band-pass filtered the data between 0.15 Hz and 30 Hz, and sub-sampled it to 32 samples per second. As indicated above, following each flash, an 800 ms epoch of the signal in each channel was extracted. At a 32 Hz sampling frequency, epochs contained 26 data points per channel. Thus, each epoch was described by a feature vector of $26 \times 64 = 1,664$ elements.

The training phase of each experiment was divided into three phases, Phase 1, 2 and 3, each including 8 short sessions with each session lasting approximately 25 seconds. All of the data acquired in one session were associated with the same target direction. Each participant carried out a total of 24 sessions, resulting in each of the 8 possible directions being the target direction for three sessions.

In Phase 1, comprising the first 8 sessions of the experiment, each session started with a blank screen and after 2 seconds the eight circles appeared near the centre of the screen. A red arrow then appeared for 1 second pointing to the target (representing the direction for that epoch). As previously indicated, subjects were instructed to mentally name the colour of the flashes for that target. After 2 seconds the flashing of the stimuli started. This stopped after a random number of trials, from 20 to 24, with a trial consisting of the sequential activation of each of the 8 circles. In other words, each session involved between $20 \times 8 = 160$ and $24 \times 8 = 192$ flashes. During Phase 1, the background remained black (as illustrated in Figure 1(a)), and the circular pointer remained static. The purpose of this first phase was the initial acquisition of a minimalist training set that we could then use to train a first ensemble of SVMs. This would then control the movement of the cursor in Phases 2 and 3, so as to make the conditions in these phases as close as possible to the conditions required in the real-time space-craft navigation task.

After training the BCI with the approximately 1,400 training examples collected in Phase 1, in Phase 2 subjects performed a second set of 8 sessions. The BCI's active stimuli had the same duration and features as in the previous phase, but the background was not black and the mouse pointer was not static. Instead, as illustrated in Figures 1(b)–(c), we used a real desktop environment (as provided by the Ubuntu Linux operating system) and the pointer movement was

controlled in real-time by the SVMs trained with the data collected in Phase 1. All filtering, classification and post-processing operations had to be performed within 100 ms.

In Phase 3 we acquired further data via a third set of 8 sessions. These were in exactly the same conditions as in Phase 2. However, we distinguish this phase from the previous one, because its data have been used for two different purposes in this study.

Firstly, the data were pooled with the data acquired in Phase 2 and used to retrain the BCI's SVMs on a larger and more realistic dataset before the system was used for the online space-craft navigation task. We discarded the data from Phase 1 since these data had been acquired in slightly different conditions than those adopted in the real use of the system.

Secondly, the data from Phase 3 were also used as an independent test set for the analysis of the performance of both the single-user and the cooperative BCI. In this case we had to use the data from both Phase 1 and Phase 2 as a training set as we could not discard Phase 1 without incurring significant over-fitting.[2]

## 2.3   Modified Space Commander

After Phase 3, the subjects had a few minutes of rest and we then started their online sessions with our space simulator. We asked subjects to do up to 21 simulator runs. However, since each of these runs lasted 2 to 7 times longer than the sessions in Phases 1–3, we instructed subjects to feel free to stop the experiment when they felt too tired to continue. On average subjects did 17 such runs.

As indicated above, as a space simulator we created and used a customised version of the Space Commander space-craft simulator (written in Python) [18]. Below we describe the modifications we made to this software for the purpose of our tests.

Firstly, we created a galaxy which only included the Sun. The users' aim was to pass within 0.26 light years from the Sun starting from 10 light-years away from it. So, we modified the code so that it automatically logged trajectories and stopped the simulator as soon as the space craft got within this distance from the Sun. If users failed to hit on the first pass, they had a chance to try to approach it again within a 3-minute simulation limit.

In terms of changes to the default user interface of Space Commander, we disabled all its mouse-button and keyboard controls, disallowed the space-craft from rolling and directly connected the mouse pointer position to the control of the yaw and pitch of the space-craft. Furthermore, we made the simulator's screen go black intermittently, to minimise interference with the active stimuli used in the BCI pointer (which remained visible at all times). The duty cycle

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[2]We discuss the implications of this in the "Results" section.

was such that the galaxy was visible for 800 ms within each 5.6 s period. We also artificially expanded the diameter of the Sun by 5 times and added orbits around it (See Figures 1(d)–(e)) to help users find their way towards the Sun (even if it happened to go off the screen).

In addition, the simulation's initial velocity was randomly selected in such a way that, in the absence of suitable control, the space-craft would almost always miss the Sun. More specifically, the direction of the initial velocity vectors was in the general direction of the Sun but it was off-course in the vertical and horizontal directions by angular displacements randomly selected in the range $[-5°, +5°]$. The magnitude of the initial velocity vector was 0.634 light-years/second. This very high velocity was needed to keep the simulation time reasonably short. However, in preliminary tests we found that approaching the Sun at such velocity was almost a shock for the subjects, so we introduced a velocity reduction mechanism which progressively slowed the approach speed down. The minimum this was allowed to drop was 0.032 light-years/second (corresponding to the artificial thrust of 5,000,000 units shown in Figures 1(e) and (f)). As a result of this, simulations lasted anywhere between 50 seconds (when the Sun was "hit" at the first pass) and 3 minutes (when time ran out).

## 2.4   Cooperative BCI

In order to test the potential benefits and drawbacks of a cooperative BCI approach to the problem of space navigation, we created two methods for combining the ERPs of pairs of users. Our objective was to understand which method provided better performance and to see whether any of these would be superior to single-subject pointer control.

Both methods use exactly the same filtering and signal manipulation techniques of the BCI for 2–D pointer control for single users described previously. Also, both rely on the subjects having been exposed to exactly the same stimuli in exactly the same order in all the sessions of the three phases of collection of training and test data, which we ensure in our experiments. Timing information was also recorded in our EEG data files so that the ERPs from two subjects could be synchronised with sub-millisecond accuracy. In this way we were in a position to simulate exactly the conditions of two subjects performing our experiments together.

The first method combines the *input signals* to the BCI by averaging the ERPs from each subject before they are passed to a single ensemble of SVMs. This method presents the advantage of reducing the stochastic noise which always hampers the trial-by-trial recognition of target ERPs in EEG data by a factor $\frac{1}{\sqrt{2}}$ (i.e., by approximately 30%). However, there is always a significant variability in the shape and delay of ERPs in different subjects and averaging their ERPs may introduce significant distortions, which may in turn make their classification harder.

The second method combines the *outputs* of the single-user version of the BCI for the two subjects and averages the pointer movement vectors before they are executed. An advantage of this method is that the ERPs from each subject are processed by a ensemble of SVMs which was specifically trained on the data from that subject. This normally results in better classification accuracy (and this is why per-subject training is ubiquitous in BCI). Also, since the output vectors are noisy (due to the noise and variability in ERPs), averaging the vectors produced by two subjects produces a noise reduction (of the same magnitude as that of the first method), that is likely to result in better trajectories. However, we do not benefit from any reduction of the noise in input to the BCI, while the first method does.

# 3   Results

## 3.1   Single-User Control of Pointer Movement

Let us start with the analysis of the performance of the BCI for pointer movement (on its own) when a single user controls it (we will test it in the Space Commander control task in the following section). This is important as in [30] all tests were performed with offline data and static displays (such as the one in Figure 1(a)), while here we are attempting to achieve online control (as in Figures 1(b)–(f)).

As we explained above, in these tests we used the data from Phase 1 and 2 as a training set and the data from Phase 3 as an independent test set. The data from Phase 1 were acquired in slightly different conditions than the other data (static vs dynamic pointer and black vs ordinary-desktop background). However, we had to use the data from both Phase 1 and Phase 2 as a training set as we could not discard the data from Phase 1 without incurring significant over-fitting.[3] Because of this misalignment between training and test set, the test-set results reported in this subsection and in the last subsection of this section are actually *lower bounds* on performance.

There are a number of ways of evaluating performance of the BCI controller of pointer movements. We adopted three: *AUCs*, *normalised path lengths* and *absolute angle deviations*. These are described in the remainder of this section.

We used the *Area Under the Curve* (AUC) of the Receiver Operating Characteristic (ROC) to assess the performance of the machine learning component of the system — an ensemble of two SVMs. The AUC is a well known summary

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[3]We did considered the option of asking our subjects to acquire more training data, but we eventually discarded it to avoid their under-performing in the Space Commander task due to tiredness. When subjects start becoming tired, their attention levels drop and, as a consequence, their brain signals start changing. These changes include much reduced or even absent P300s where one would normally have robust ones. Also, as subjects become tired they tend to produce more muscular artifacts. So, after about one hour of experimentation (excluding subject preparation, which takes approximately 30 minutes) subjects wear out.
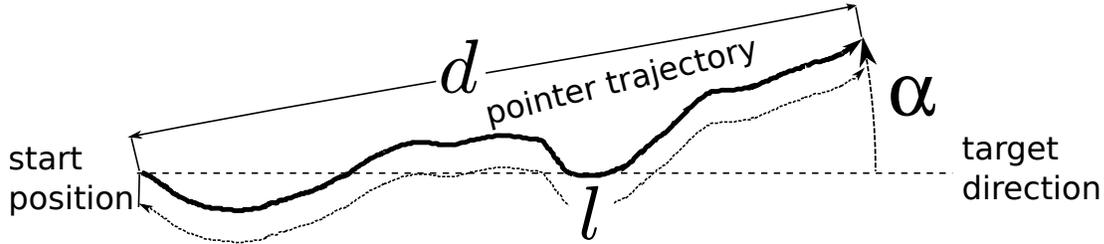
Figure 2: The overall performance of the BCI for pointer movement is evaluated based on the extent to which the pointer trajectory produced (thick line) is straight (the normalised path length, which, in the figure, is equivalent to $\frac{l}{d}$, where $l$ is the length of the trajectory measured by "walking" along it) and by how much it deviates from the ideal direction (the absolute angle deviation, represented by the angle $\alpha$ in the figure).

for ROC curves that has been used widely in machine learning. It essentially characterises the behaviour of a classifier from the point of view of the trade off between producing false alarms and missing targets. A perfect classifier is one that never produces false alarms and never misses any targets. Such a classifier would have an AUC score of 1. A (useless) random, classifier, on the other hand, would have an AUC of 0.5. So, the closer the AUC to 1, the better a classifier. In our work, AUCs were calculated using the efficient method proposed in [17].

The normalised path lengths and absolute angle deviations were introduced to evaluate the performance of the whole system. This requires an analysis of the trajectories produced by adding together the displacement vectors produced by system after the integration and post-processing phases. The *normalised path length* indicates how straight a trajectory is. This can be assessed by looking at how different a trajectory is from the line segment connecting its extremes. As indicated in Figure 2, this difference can be measured by simply comparing the path length of the trajectory (denoted as $l$ in the figure) with the segment's length ($d$ in the figure). The normalised path length is defined as the ratio between the two. The closer the normalised path length to 1 the better.

The *absolute angle deviation*, instead, indicates how well a trajectory points towards the target direction. This can be assessed by measuring the angle between the line segment that we used to evaluate the straightness of the trajectory and the axis denoting the target direction ($\alpha$ in the Figure 2). Since it is not important whether the angle is positive or negative, we take its absolute value to represent performance, resulting in an absolute angle deviation. We measure this in degrees.

Table 1 reports the values of AUC score, normalised path length and absolute angle deviation on a subject by subject basis for the test data gathered in Phase 3. Normalised path lengths and absolute angle deviations were evaluated on the full trajectory produced by concatenating (after appropriate rotations) all of the outputs produced by the system for the sessions acquired in Phase 3

Table 1: Single subject test-set performance at controlling pointer movement (see text for explanation of the three measures of performance).

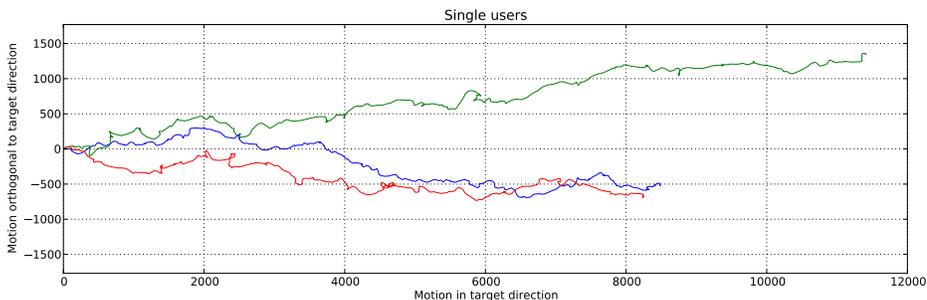| Subject | Absolute angle deviation | Normalised path length | AUC |
|---|---|---|---|
| 1 | 3.505 | 1.249 | 0.948941 |
| 2 | 6.727 | 1.275 | 0.879715 |
| 3 | 4.650 | 1.388 | 0.931228 |



Figure 3: Trajectories produced by the BCI pointer control system for each of the three users when using the test data acquired in Phase 3.

(approximately 1,400 movements). The full trajectories are shown in Figure 3.

It is clear from these results that all three subjects were able to control the mouse to a significant degree. Absolute angle deviations were small in all cases, normalised path lengths were reasonably close to 1, and AUC scores were on average above the 90% mark, which indicates very good performance (for BCI standards).[4]

## 3.2 Space Commander Runs

In the tests with Space Commander, we measured the success rate of our subjects (the fraction of runs where they were able to pass near the Sun) and we also studied their passage distances from the Sun.

We compared the results obtained by our subjects when using the system against two alternatives: (a) a static controller that does not steer the space-craft at all thereby always producing a rectilinear trajectory, and (b) a random-drifter which behaves as if the mouse pointer drifted randomly by a tiny random displacement at every simulation cycle (i.e., every $\frac{1}{60}$ of a second). This displacement was a zero-mean stochastic vector uniformly distributed in $[-1, +1] \times [-1, +1]$ (i.e., typically a sub-pixel amount).

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[4]We will perform a deeper statistical analysis of single-user trajectories when we compare them to those obtained with cooperative control in a later section.

Table 2: Comparison of the success rates and mean passage distances from the Sun (in light-years) of the static controller (210 runs), the random-drifter (210 runs) and the controller based on our BCI mouse (51 runs).

| Controller type | Success Rate | Passage Distance |
|---|---|---|
| Static | 9.5% | 0.671549 |
| Random-drifted | 6.2% | 0.758904 |
| BCI | 66.7% | 0.387318 |

Table 2 shows a comparison of the success rates and mean passage distances from the Sun of the static controller, the random-drifter and the controller based on our BCI mouse. It is clear that in the absence of intelligent control only between about 1 in 16 (for the random-drifter) and 1 in 10 (for the static controller) trajectories actually pass sufficiently near the Sun to trigger the system's stopping criterion. On the contrary on average our subjects were able to satisfy the criterion in 2 out of 3 runs. Mean passage distances confirm this observation with the mean distance for the BCI controlled runs being approximately 51% and 58% less than in the absence of control. Also, when we applied the one-tailed Kolmogorov-Smirnov test for two distributions to the passage distance data, we found that the BCI controlled runs resulted in passage distances which are highly statistically significantly superior to those obtained with both the random-drifter and the static controller (both $p$ values being $< 10^{-17}$).

## 3.3 Cooperative Control of Pointer Movement

Let us now turn our attention to the analysis of the performance of the BCI for pointer movement when two users jointly control it. To the best of our knowledge cooperative control in such a complex task has never been attempted with a BCI.

As for the single-user analysis, also in these tests we used the data from Phase 1 and 2 as a training set and the data from Phase 3 as an independent test set. Also, as before, the misalignment between training and test set implies that the results reported here are actually *lower bounds* on performance.

We start from reporting our three performance indicators — AUC, normalised path length and absolute angle deviation — for each possible pair of subjects and for the two methods of achieving joint control: averaging the ERPs of the two subjects and passing them to a single ensemble of SVMs, or processing the ERPs of the two subjects independently through two separate ensembles of SVMs and then averaging the output vectors produced by the system.

Tables 3 and 4 show the results of these tests. Again normalised path lengths and an absolute angle deviations were evaluated on the full trajectory produced by concatenating the outputs produced by the systems for the trials in Phase 3. The full trajectories for the two approaches to cooperative BCI control are shown in Figure 4.

Table 3: Cooperative BCI test-set performance at controlling pointer movement when using the average of ERPs and one ensemble of SVMs.

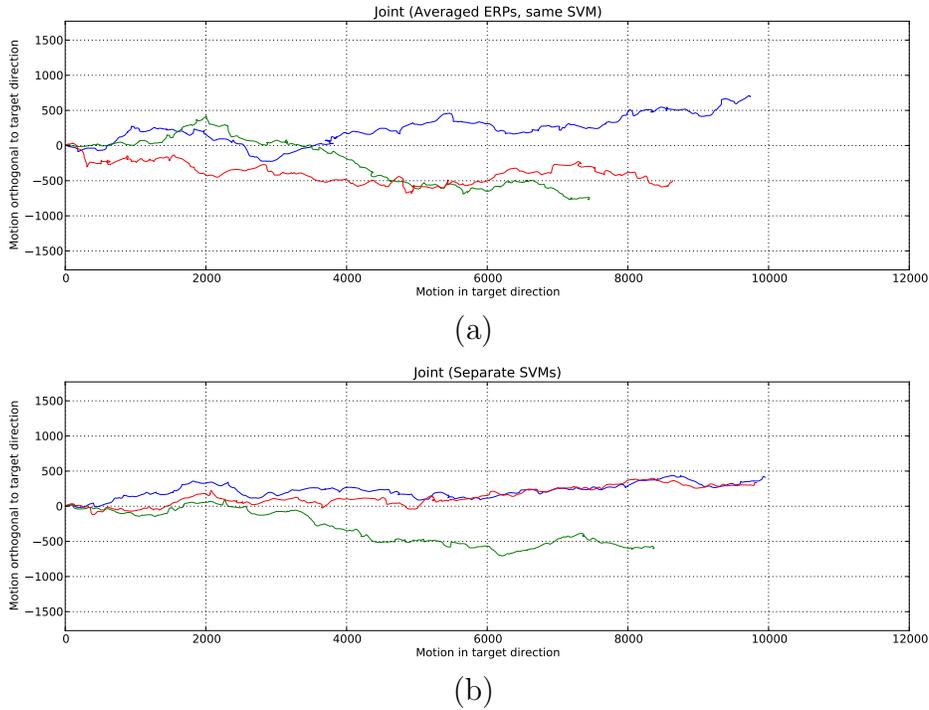| Subject | Absolute angle deviation | Normalised path length | AUC |
|---------|--------------------------|------------------------|-----|
| 1 & 2 | 4.075 | 1.264 | 0.920215 |
| 1 & 3 | 5.853 | 1.276 | 0.966195 |
| 2 & 3 | 3.322 | 1.322 | 0.938081 |



(a)



(b)

Figure 4: Trajectories produced by the system in the two cooperative-control configurations: (a) joint control obtained by averaging the ERPs of the two subjects and feeding them into a single (common) ensemble of SVMs, and (b) joint control obtained by sending the ERPs of the two subjects through two separate ensembles of SVMs and averaging the output displacement vectors produced by the system.

Table 4: Cooperative BCI test-set performance at controlling pointer movement when using two separate ensembles of SVMs

| Subject | Absolute angle deviation | Normalised path length | AUC |
|---------|--------------------------|------------------------|-----|
| 1 & 2 | 2.376 | 1.127 | 0.911615 |
| 1 & 3 | 4.070 | 1.165 | 0.940064 |
| 2 & 3 | 1.965 | 1.146 | 0.902924 |

It is clear from these results that, for all pairs of subjects, cooperative control of the BCI was either on par (for the ERP-averaging method) or very advantageous (for the separate SVM ensembles) over the single-subject tests. In particular, absolute angle deviations and normalised path lengths appear to be significantly better for the second form of cooperative control than for single subjects. This can also be seen by visually comparing Figures 3 and 4(b). Also, AUC scores on average are comparable but have significantly smaller variance in the cooperative BCIs, implying greater consistency in performance.

To verify if the differences observed in the cumulative performance indicators reported above are statistically significant, we segmented the trajectories produced by the single-user method and our best cooperative method (based on independent SVMs) into their component trials (remember each trial represents a complete revolution of the flashing stimuli which correspond to 800 ms of data: 8 mouse movements, one every 100 ms). This gave us 176 trajectory segments. We then measured the absolute angle deviation and the normalised path length for each segment. Since the segments are paired across subjects and pairs of subjects (during training all subjects were presented with exactly the same sequence of stimuli), so are the values of these performance measures. Therefore, we could compare the distributions of performance for the segments with the one-tailed Wilcoxon signed rank test (which is a non-parametric test for paired data) to establish if the distribution of trial-by-trial trajectories was better for cooperative control or for single-user control.[5]

Table 5 shows the $p$ values returned by the test when comparing the normalised path length and the absolute angle deviation of pairs and single subjects. All comparisons show that pairs produced statistically significantly better trajectories under both performance criteria than single subjects.

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[5]Naturally, since we performed multiple pairwise tests, we applied the Bonferroni correction to the standard 5% significance level.

Table 5: Wilcoxon $p$ values for comparisons based on normalised path length (top) and on absolute deviation (bottom). Values in bold face are statistically significantly superior at the 5% confidence level (after Bonferroni correction). Values in italics are significant at a 10% confidence level (again after Bonferroni correction).

| *Performance measure* | **Are these ...** | ...better than these? | | |
| --- | --- | --- | --- | --- |
| | | Subject 1 | Subject 2 | Subject 3 |
| Normalised path length | Joint 1 & 2 | **$6.37502 \times 10^{-8}$** | **$1.31414 \times 10^{-7}$** | **$9.36245 \times 10^{-5}$** |
| | Joint 1 & 3 | **$2.7696 \times 10^{-8}$** | *$0.00879649$* | **$8.39675 \times 10^{-6}$** |
| | Joint 2 & 3 | **0.000142919** | **0.000502456** | **0.0002320074** |
| Absolute angle deviation | Joint 1 & 2 | **$1.76193 \times 10^{-7}$** | **$4.04779 \times 10^{-11}$** | **$8.16628 \times 10^{-11}$** |
| | Joint 1 & 3 | **0.000185374** | **0.00270251** | **$1.10938 \times 10^{-10}$** |
| | Joint 2 & 3 | **0.00254564** | **$1.75272 \times 10^{-5}$** | **$1.05116 \times 10^{-10}$** |

# 4 Discussion and Conclusions

In this paper, we have studied the possibility of navigating a space-craft via a BCI as well as the potential benefits of a collaborative BCI over a single-user one in relation to this task.

Although there have been previous reports analysing the potential benefits and drawbacks of BCI technology in the space domain [8, 21, 6], to the best of our knowledge this is the first paper that describes an implementation and its actual testing in this domain. We would also like to note that only very recently the first explorations of cooperative BCIs have appeared in the literature [42, 36, 12, 26] and none of these have attempted to achieve anything as difficult as finely controlling a 2–D pointer on a screen in real-time as we have done in this article.

In tests of the single-user space-craft navigation system, we have found that users managed to satisfy the success criterion for the simulation in more than $\frac{2}{3}$ of the runs. While this performance level is clearly inferior to what can be achieved using an ordinary mouse to control the space-craft (where users would "hit" the Sun in 100% of the runs), it is actually a very good result considering the bandwidth and accuracy limits typical of brain-computer interfaces. This indicates that while BCI technology is still not quite ready for immediate deployment in space, it is inching its way towards becoming competitive and there is certainly ground for optimism for future space applications.

This study also provides an important contribution to collaborative BCI. Previous studies have shown that collaborative systems can outperform single-user BCIs. However, in those studies this was achieved only when combining at least three users [36, 42, 26]. On the contrary, in our study we have found that combining the brain activity of two users already provides considerably improved performance over single-user BCI. This has important implications for cooperative BCI from a practical point of view, since wiring up more than two users is very impractical, expensive and requires difficult setups (in terms of space, screen technology, networking, etc.). Also, previous attempts used much simpler tasks and users were not actively and directly controlling a user interface (as we did).

In the future we will implement and test a cooperative form of BCI for real-time space-craft navigation and we also want to explore its potential applications in robotic control.

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