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UAV BCI

Comparison of manual and pedal control systems for 2D flight performance of users with simultaneous BCI control

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Contents

1	Abstract	2
2	Introduction	3
2.1	BCI Hardware	3
2.2	BCI Signal to noise	3
2.3	Project	3
2.3.1	Research Question	4
3	Literature Review	4
3.1	User tasks	4
3.1.1	Spatial navigation	5
3.1.2	Auditory imagery	6
3.1.3	Physical task	6
4	Methods	7
4.1	Experimental session	7
4.1.1	Calibration Phase	7
4.1.2	User training (mental task)	8
4.1.3	User training (physical task)	8
4.2	2D experiment	9
4.3	Subjects	9
4.4	Equipment	9
4.5	Software and Hardware	10
4.6	User Performance	10
5	Results	10
5.1	Classifier Performance	10
5.2	User Performance	11
5.2.1	Vertical BCI control	11
5.2.2	Horizontal BCI control	13
5.2.3	Hand vs. Foot	13
5.2.4	Inverted dimensions	14
6	Discussion and Conclusions	14
6.1	Summary of Results	14
6.2	Future Research	15
6.3	Conclusion	15

1 Abstract

In this study, physical tasks used in combination with a BCI in order to achieve 2D control are compared. One subject was trained in achieving 1D BCI control using the auditory imagery and spatial navigation mental tasks. This control was then combined with either a joystick (hand task) or a buttonbox placed on the ground (foot task) to achieve 2D control. In the main condition, the BCI controlled the vertical direction and the physical task controlled the horizontal dimension. Another condition was set in which the control dimensions were reversed; the BCI controlled the horizontal dimension and the physical task controlled the vertical dimension. There were no differences found in any condition.

2 Introduction

A *Brain Computer Interface* (BCI) is a stack of hardware and software enabling interaction between the brain and the outside world without the use of a peripheral nervous system. To be more precise, hardware collects brain signals from the brain using measurements linked to neuronal activity such as electrical potential. These signals are then often amplified and sent to a computer. On the computer, algorithms related to the BCI application are used to process the signals and retrieve information of interest. This information is then used for various purposes, again BCI application dependent [van Gerven et al., 2009].

Early research into BCIs has mainly focused on developing and improving means of communications for patients suffering from neuromuscular disorders (e.g. *Amyotrophic Lateral Sclerosis* – ALS) [Farwell and Donchin, 1988, Wolpaw et al., 1991, Wolpaw et al., 2002, Wolpaw and McFarland, 2004, Townsend et al., 2010]. More recently, applications have been targeted at enabling patients with neuromuscular disorders to move again [Philips et al., 2007], as well as applying BCIs to healthy people to aid them or extend their abilities [LaFleur et al., 2013].

2.1 BCI Hardware

Several types of hardware can be used in BCIs. The most common being *electroencephalography* (EEG), *magnetoencephalography* (MEG), *functional Magnetic Resonance Imaging* (fMRI), *electrocorticography* ECoG and *functional Near-Infrared Spectroscopy* fNIRS.[van Gerven et al., 2009]

Of these types of hardware EEG, MEG and ECoG measure brain signals by means of the electrical potentials caused by neural activity.

fMRI and fNIRS measure blood oxygen levels in the brain linked to increased oxygen requirement of firing neurons.

Most BCI hardware is *non-invasive*, i.e. it does not 'invade' the body of the user. Of the mentioned hardware, only ECoG is invasive, requiring direct access to the brains surface.

2.2 BCI Signal to noise

The signal to noise ratio in BCIs is unfortunately rather low [Wolpaw et al., 2002]. As physical movement causes large amounts of neuronal activity in the motor cortices, any physical movement can result in confounding factors in the recorded brain data. Additionally, muscles receive electrical signals from the brain to excite movement. Thus, movement near recording apparatus can result in confounding factors if electrical potentials are used to record brain data. Finally, muscle movement in itself also generates electrical potentials, resulting in further confounds.

2.3 Project

This thesis is part of a larger project, comprising of 4 theses in total. The goal of the project is to implement *two dimensional* (2D) control of an *Unmanned Aerial Vehicle* (UAV) using a BCI similar to the setup used by [LaFleur et al., 2013]. A BCI will be constructed, using various combinations of physical and mental tasks, to operate a Parrot AR.Drone 2 quadcopter (hereafter referred to as drone or quadcopter) [Parrot SA., 2012]. EEG will be used for mental tasks, in combination with a joystick and foot buttons for the physical tasks. Several linear and nonlinear classifiers will be used to classify brain data into continuous commands to change the drone's *gaz* (movement on the vertical axis) and *roll* (movement on the horizontal axis) while it flies forward with a constant velocity. A shared control system will be developed in an attempt to overcome incorrect predictions from the classifier output.

2.3.1 Research Question

The purpose of this specific study was to look at the best way to combine the BCI with physical control. In the past, most applications were aimed at patients not capable of performing motor tasks. However, as the field progressed, the attention partially shifted towards applications for healthy users. The aim of this project was not to find the optimal way of controlling a drone. High performance can be easily reached with a joystick or a remote control of some sort. The aim of this project was to see how physical control can be best combined with BCI control, to see if multitasking is possible. If multitasking is possible, it may become possible one day to have a 'third limb' in the form of a BCI that can be controlled independently of arms and legs. This project can then serve as a basis on which to expand the research on multitasking with BCIs. This leads us to three potential research questions:

- 1): *Is it possible to combine physical and mental control?*
- 2): *What combinations of physical and mental tasks are subjectively easiest for users?*
- 3): *What combinations of physical and mental tasks are easiest for the BCI, i.e. work well together from the point of view of the brain signals?*

In this thesis, we have selected a fixed pair of tasks for the BCI control, because not all mental tasks work well in combination with physical tasks. For example, motor imagery will not work because the actual physical task will cause interference, but more on that later (see chapter 3.1, User tasks). Based on prior literature, we have chosen the mental tasks *spatial navigation* and *auditory imagination*.

Given the fact that the mental tasks are fixed, the specific research question is about the optimal pairing of mental and physical tasks. More specifically: *Out of a joystick and foot buttons, which motor task is best suited for 2D drone control when paired with the mental task spatial navigation + auditory imagination?*

My hypothesis is that a joystick would give better performance because humans are more used to manipulating objects with their hands. Humans spend every day driving cars and bicycles and steering with their hands, so controlling a drone with hands seems only natural.

Another question I will try to answer is *Does it matter if the dimensions are switched, i.e. when the physical task controls the up/down movement?*

3 Literature Review

3.1 User tasks

The user needs to perform different mental tasks to control the BCI. Mental tasks need to differ in at least one of two criteria: signal frequency and signal location. One set of tasks used very often is motor imagery [Curran et al., 2004]. The user is instructed to imagine moving either their right or their left hand without actually moving it. This elicits an induced brain response (response induced by the users themselves, not timelocked to a stimulus) located in the motor cortex, which can be detected by the BCI system. However, users need to use actual movements, which also elicit brain responses in the motor cortex, in this study to control the drone in one dimension so motor imagery is not the best fitting task. Having motor imagery control the BCI will result in the BCI firing when actual movements are being performed, causing interaction between the two control dimensions. Mental tasks that are not located in the motor cortex needed to be selected. [Curran et al., 2004] mentioned the tasks auditory imagery and spatial navigation.

Auditory Imagery requires the user to "listen" to a familiar tune in his/her head. The user is to avoid mouthing the words in order to minimize the motor activity.

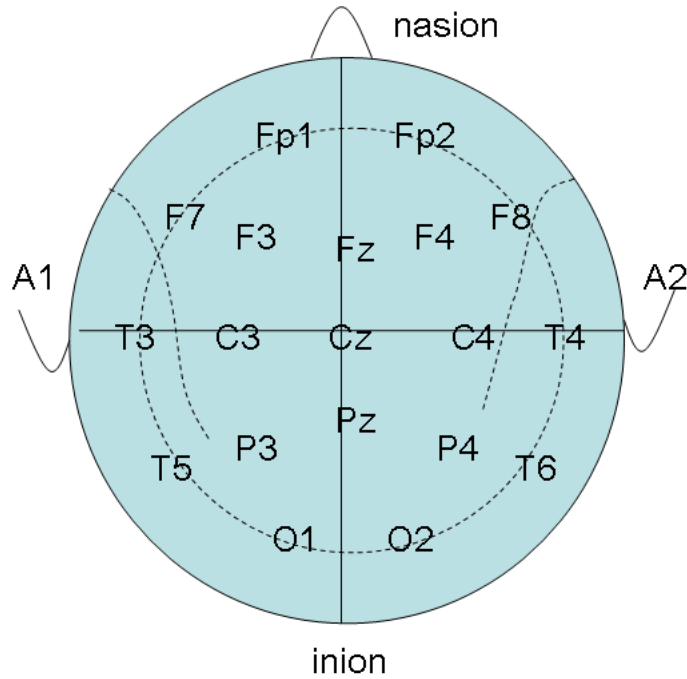


Figure 1: 10-20 system for electrode placement

Spatial Navigation is performed by navigating through a familiar environment, e.g. the subject's own house, moving from room to room and around rooms. Visualizing what is seen while navigating through the rooms is important. The subject has to avoid imagining to walk to again minimize the motor activity.

Both of these tasks have their prominent signal location somewhere other than the motor cortex, which is why I opted for the following mental tasks: Auditory Imagery and Spatial Navigation. The user will perform the Auditory Imagery task to move the drone downwards, and the Spatial Navigation task to move the drone upwards.

[Curran et al., 2004] focused on electrodes at positions P4 and T4, in the right temporo-parietal area, to measure activity elicited by auditory imagery and spatial navigation (see figure 1). They found that the task pair spatial navigation-auditory imagery actually had a significantly better classification performance than motor imagery (74% vs. 71%, $p = 0.013$).

3.1.1 Spatial navigation

[Ghaem et al., 1997] investigated which brain areas are active during mental simulation of routes. Their experiment involved participants walking along a path with several landmarks, once while a guide was with them and a second time in which they could walk on their own. Their task was later to imagine walking along that same (memorized) path and try to produce the sequence of

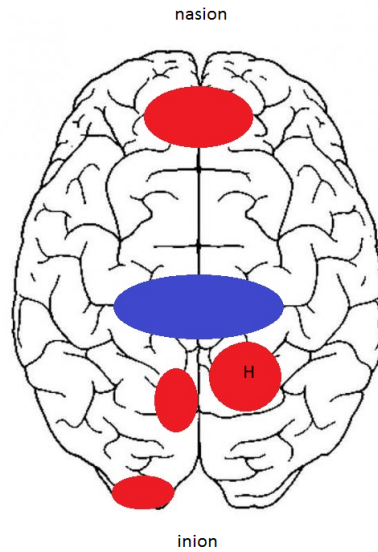


Figure 2: Location of the active brain areas during the mental tasks, spatial navigation (red) and auditory imagery (blue). The location of the hippocampus is denoted with an H.

left/right hand turns needed to cover the path. [Ghaem et al., 1997] found that during this task, the following brain areas were active: posterior right hippocampal regions, left middle occipital gyri, left precuneus, and the bilateral dorsolateral prefrontal areas. This mental task has its activity in the frequency band of 4-10 Hz. See figure 2 for the location of these areas. The hippocampus is located very deep within the brain, so it is not easy to detect with EEG. Because of the poor spatial resolution of an EEG measurement, it may be that the hippocampal activity that does get measured will be spread out across the cortex rather than appear in the small location shown in figure 2.

3.1.2 Auditory imagery

[Janata, 2001] considered auditory imagination. The experiment consisted of three consecutive conditions. In one of these conditions, participants were presented with a melody consisting of eight musical tones, one in which only the first five were presented and the participant had to imagine the last three, and one where the participant was presented with three tones and the other five were to be imagined. [Janata, 2001] states that "...the auditory imagination [is] characterized by a strong centro-parietal positivity...". This mental task is active at a frequency of 8-12 Hz. Figure 2 shows the location again.

3.1.3 Physical task

The user's control in the horizontal dimension will differ, with either a joystick or foot pedals to move the drone left/right.

4 Methods

4.1 Experimental session

A high level overview of one experimental session can be seen in table 1. A session consists of preparatory steps, multiple training phases and a testing phase. The different phases are described below.

From	To	Duration	Activity
0	10	10	Subject instruction
10	40	30	Attaching the EEG cap
40	51	11	Classifier training
51	61	10	User training (mental tasks)
61	63	2	User training (joystick)
63	65	2	User training (foot pedals)
65	95	30	2D simulated experiment

Table 1: Session time line (times in minutes)

4.1.1 Calibration Phase

This phase is done before every experiment session. In this session, the user is asked to perform the mental tasks a few times to generate data on which we can train the classifier for the predictions used in the experiment. During the calibration phase, the participant was presented with a signal indicating which mental task needs to be performed. This signal is an icon showing either a house or a musical note. The house corresponds to the spatial navigation task and the musical note corresponds to the auditory imagery task. Figure 3 shows what the screen looks like during this phase. It starts with a fixation cross, and after one second the fixation cross will disappear and either one of the two icons will be shown in its place. The subject’s task is then to perform the cued mental task for as long as the icon is shown. The top of the window shows how many epochs have been completed so the subject knows how much of this session is left. The detailed time line for classifier training can be found in table 2.

The duration of this phase was around ten minutes per session. The length of the breaks at the end of each epoch are randomized, with a value between 0.5 and 2.5 seconds. The average length of one epoch (including the break) is 6.5 seconds. During this phase, the subject will perform a total of 80 epochs, 40 for each task. The order in which the cues are shown is randomized for every session. The epochs are divided into 16 blocks of 5 trials. After each block, the subject gets a 10 second break. Halfway through the training - after 8 blocks - the subject gets a slightly longer break of 30 seconds.

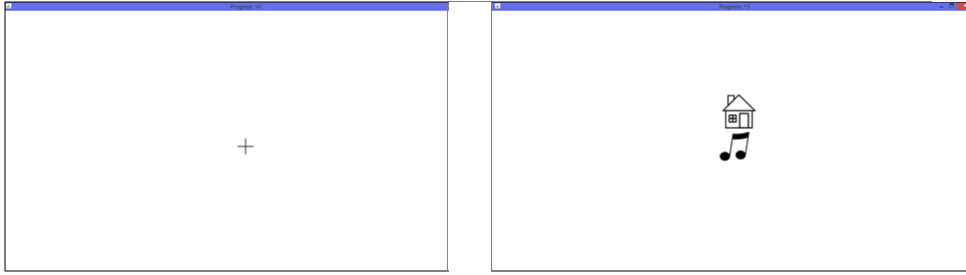


Figure 3: The screens during the classifier training. First a fixation cross is shown for one second, after which one of two pictures will be shown for three seconds. A break of varying length (between 0.5 and 2.5 seconds) follows, after which the screen resets to the fixation cross

4.1.2 User training (mental task)

Training the user in the mental task is very important. Not only will the user be better at the specific task through practice, but the brain signals elicited by the user will be stronger if the user has more training [McFarland et al., 2005].

The first training session consists of only one dimensional control. Figure 4 shows the screens for the experiment. During this training session, the user will be shown a screen that contains a red (or green) rectangle and a small black circle. The black circle is the cursor/drone, which the user can move up or down, and the rectangle is the target to which the cursor needs to be moved. For this training session, the cursor will only spawn in the horizontal center of the screen, so the participant does not need to worry about any left/right movement. The cursor can only be moved once the rectangle has turned green (after 2 seconds). The top of the screen shows a black bar filling up from left to right, showing the user how much time is left to complete the current trial. The total trial time is 5 seconds. If the cursor is inside the rectangle as the trial time runs out, it will count as a hit, otherwise it will count as a miss. When the target has been hit, the next trial will feature a smaller rectangle whereas a miss will result in a larger rectangle. It is not enough to merely hit the target once during the trial, it will only count as a hit if the cursor is inside the target at the end of the trial.

The reason for the resizing of the target was inspired by a study performed by [Hill et al., 2014]. In their study, instead of measuring the performance by measuring the amount of hits or misses, they dynamically resized the target and set a convergence parameter deciding the size of the increase or decrease. The final target size would then give a performance measure. The specifics of resizing was described by [Kaernbach, 1991], but more on that later.

This phase also takes a little over 10 minutes per session. The length of the breaks at the end of each epoch are again randomized to a value between 0.5 and 2.5 seconds. The average length of one epoch (including the break) will be 6.5 seconds. During this phase, the subject will perform a total of 80 epochs. The epochs are divided into 16 blocks of 5 trials. After each block, the subject gets a 5 second break. Halfway through the training - after 8 blocks - the subject gets a slightly longer break of 30 seconds.

4.1.3 User training (physical task)

This training session is similar to the previous one. The drone/cursor will now be controlled by using a joystick or foot pedals and the number of trials is reduced, since this task is a lot easier. The movement direction is now horizontal instead of vertical.

From	To	Duration	Activity
0	1	1	Fixation cross is shown
1	5	4	Visual cueing of mental task
1.5	5	3.5	Subject performs mental task
2	5	3	Training data is collected
5	5.5 to 7.5	0.5 to 2.5	Break

Table 2: Classifier training epoch time line(times in seconds)

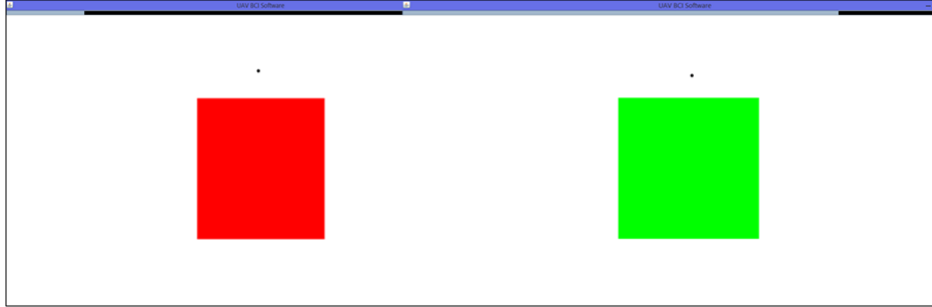


Figure 4: The screens during the experiment. The drone cannot be moved while the target is red; it turns green after two seconds

The subject will perform a total of 3 blocks (with 5 trials each) to familiarize himself with the controls and the drone/cursor movement.

4.2 2D experiment

The final experiment will consist of two dimensional control. The user has two control tasks at the same time, and the target rectangle resizes dynamically.

This phase consists of 32 blocks of 5 trials (160 total). The physical task, joystick or foot pedals, changes every 8 blocks. As in training, the subject gets a 5 seconds break after every block and a longer break (30 seconds) after 4 blocks. The experiment is spread out across four sessions of two blocks each to prevent the subject from becoming too tired. Between blocks, the subject decided for himself how long a break he would like.

4.3 Subjects

Only one subject was used. This subject was male, 20 years old and had very limited to no previous experience with operating a BCI.

4.4 Equipment

A biosemi EEG system with 64 channels was used for measuring EEG. We did not place eye trackers to correct for artifacts during the training, because the subject will most likely not sit still during the actual experiment because he or she will be flying a drone. To prevent the drone from crashing

into walls, the sides of the screen need to be watched as well as the center, so eye movements will be inevitable. We wanted to simulate the actual experiment as best we could.

4.5 Software and Hardware

The software was implemented in Java. As was mentioned before, the software features a rectangle as the target and a small black circle as the cursor. The number of pixels the cursor moves can be changed to account for different screen sizes. The step size has been set to 100 pixels per step. The cursor spawns at a random position on a circle around the target. This circle has a radius of 4 times the step size. The size of the target also changes dynamically, with the smallest possible size being one step size and the largest possible size being the distance at which the cursor spawns.

For the physical task concerning hand movement, a joystick was used to control the drone/cursor. Tilting the joystick to the left or right would result in a movement of left and right respectively. In the other condition, the participant had to use a buttonbox, placed on the ground so it could be reached with the participant’s feet, containing 5 buttons of which only the two outer-most were used. The left-most button was used for moving the drone to the left and the right-most button was used for moving the drone to the right.

4.6 User Performance

The user’s performance is measured in a way inspired by [Hill et al., 2014]. During the experiment the difficulty of the task (i.e. the size of the target) is adjusted by use of the weighted-up-down procedure proposed by Kaernbach [Kaernbach, 1991]. In Kaernbach’s study, the difficulty increased with a set value S_{up} every time the target was hit, and the difficulty decreased according to the formula $S_{up}/S_{down} = (1 - p)/p$ where p is the target hit rate on which the procedure converges. We set $p = 0.8$, $S_{up} = 20$ (one fifth of the step size), and S_{down} was computed as described earlier. The size of the target after the last trial will determine the user’s performance.

5 Results

5.1 Classifier Performance

The subject was trained to become better at generating relevant brain signals. Table 3 and figure 5 show the classifier performance after each calibration session. It should be noted that after the second and fourth session, the subject reported to have been restless and itchy during the training phase (denoted by a * in the table), which may have caused the slight dip in performance during the fourth training session. A regression test was performed to see if this is a real learning effect. The test did not show a significant effect ($p < 0.5$), which is most likely due to the low number of datapoints. From session 5 onwards, the AUC graph showed notable differences in location and frequency compared to the first session. As seen in figure 6, the subject was already able to generate sufficient brain signals in the first training session. The red bars in the figure denote the location and frequency the classifier uses to classify the spatial navigation class. The blue bars indicate the auditory imagery class. The location of the red bars roughly correspond to the locations found by [Ghaem et al., 1997], with the left middle occipital gyri showing the strongest class relevance. The active frequencies are at around 15Hz, which does not coincide with the findings of [Ghaem et al., 1997]. The auditory imagination task shows its class relevance in the centro-parietal area, just as it was in the research by [Janata, 2001]. These frequencies did correspond to the 8-12 Hz range. The fifth session showed notable differences in activation in terms of both location and frequency band (see figure 7). It

Training session	Performance
1	84%
2	85%*
3	87%
4	75%*
5	91%
6	92%

Table 3: Classifier performance after each training session. The performances denoted by a * indicate training sessions in which the subject reported restlessness and itchiness

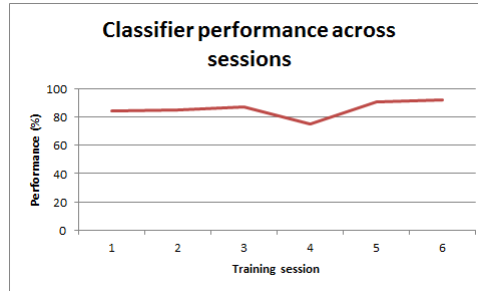


Figure 5: Line graph showing the classifier performance across training sessions

may be possible that there were some muscle artifacts present during this training sessions, seeing that those frequency bands (around 20 Hz) had never shown a significant effect in earlier sessions. It could however be that the subject simply became more adept at generating the relevant brain signals and thus allowed for more frequency bands to show activity during the specific task.

5.2 User Performance

As mentioned earlier, the user performance measure was inspired by [Hill et al., 2014]. The user’s performance is indicated by the size of the target at the end of the last trial. The total amount of targets hit is also some measure of performance, albeit not as good as the size of the target. The amount of hits is not a good a measure because ideally, the amount of hits is always 80% of the total trials because of the convergence parameter ($p = 0.8$).

There were two experimental sessions, one in which the user would use the BCI to control the drone in the vertical direction and one in which the BCI would be responsible for the horizontal direction. Consequently, the physical task would control the drone in the horizontal and vertical directions respectively. The final measure of the user’s performance was given by the size of the last target. This means that a high value corresponds to a low performance score and vice versa. As mentioned before, the smallest possible size for the target was 100 (the size of one step in the experiment), and the largest possible size was 400 (4 times the step size).

5.2.1 Vertical BCI control

160 trials were performed, 80 for each physical task, split into four blocks of 40 trials each. See table 4 for an overview of the results. It can be seen that all blocks had very low performance, and

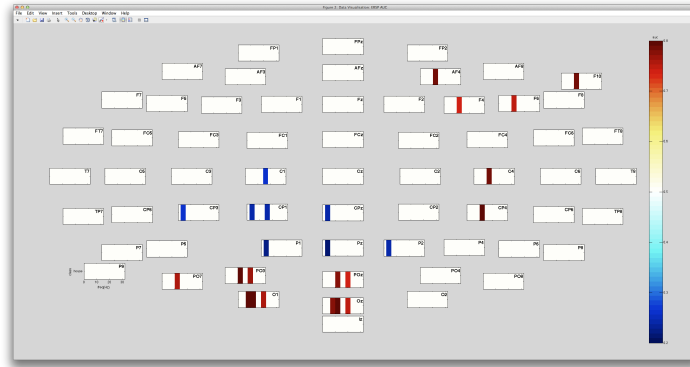


Figure 6: AUC graph corresponding to the first training session. The x-axes show frequency bands from 0 to 50 Hz. Red bars show locations and frequencies where the spatial navigation task is more active, blue bars show locations and frequencies where the auditory imagery task is more active

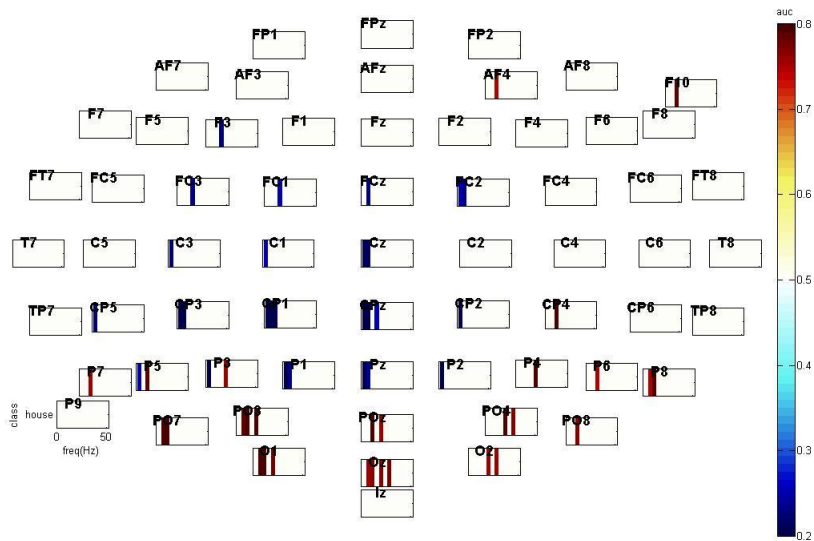


Figure 7: AUC graph corresponding to the fifth training session. The x-axes show frequency bands from 0 to 50 Hz. Red bars show locations and frequencies where the spatial navigation task is more active, blue bars show locations and frequencies where the auditory imagery task is more active

not nearly the 80% hit-rate we would expect. The performance is much lower than what we would expect, because the target’s size would converge so that 80% of the targets would be hit. However, there was a maximum size that prevented the target from taking over the whole screen. This is an indication that the task was still too difficult even when the target’s size was maximal.

Additionally, the classifier did have a hit rate of more than 80% (closing in on 90% in the final sessions), so we would expect reasonable control. There was one difference between the calibration phase and the experimental phase: in the calibration phase, the user did not have to switch between tasks during one trial. When a cue was shown, the user only had to perform one mental task for the following three seconds. During the experiment, however, both mental tasks needed to be performed for the cursor to stay inside the target. This was an added difficulty for the user, which was not present during the calibration phase.

Block	Physical task	Final size/Max size	Hits/Total trials
1	Foot	340/400	19/40
2	Foot	400/400	17/40
3	Hand	400/400	20/40
4	Hand	380/400	12/40

Table 4: User performance and total hits for each block of 40 trials (vertical BCI control)

5.2.2 Horizontal BCI control

The same setup was used as in the vertical BCI control condition. The order of the physical tasks was changed to balance the fact that the subject got more practice during the experiment. Table 5 shows the results for these blocks. These performances are also really low, even worse than the previous results. Again, the 80% hit rate was not achieved, and the final target size was never lower than maximum.

Block	Physical task	Final size/Max size	Hits/Total trials
1	Hand	400/400	19/40
2	Hand	400/400	20/40
3	Foot	400/400	16/40
4	Foot	400/400	15/40

Table 5: User performance and total hits for each block of 40 trials (horizontal BCI control)

5.2.3 Hand vs. Foot

The main research question was to compare flight performances when the drone was controlled by hand or by foot. Table 6 shows the average results for both conditions. This is just the average of the previous two tables, so the performance is still rather low.

Physical task	Average final size/Max size	Total Hits/Total trials
Hand	395/400	71/160
Foot	385/400	67/160

Table 6: User performance: hand vs. foot performance

5.2.4 Inverted dimensions

Another research question was to compare control dimensions to see if the direction of the BCI control had any influence on performance. Table 7 shows the comparison of performance regarding BCI control directions. The same for this table, it is an average of the first two so all performances are low and hit rates are not what we expected.

BCI control direction	Average final size/Max size	Total Hits/Total trials
Vertical	380/400	68/160
Horizontal	400/400	70/160

Table 7: User performance with inverted dimensions

6 Discussion and Conclusions

6.1 Summary of Results

To summarize the results: the subject had a low performance in every block of the experiment. The performance was so low that there were no clear differences for any of the conditions.

The measure of user performance is primarily taken from the final size of the target. The smaller the target’s final size, the higher the performance. However, seeing that the overall performance was not very high, most of the times the final target size was maximal for all conditions. In these cases, the number of hits can give some insight in which condition had a higher performance. Ideally, this would not give any insight because the weighted up-down method is constructed in such a way that the hit rate is always the same, regardless of the user’s performance. The hit rate would be equal to the convergence parameter p .

The main research question was about comparing flight performance when controlling the cursor with hands or feet. As shown in table 6, the performance of the user when performing foot task was slightly better (385 vs. 395). When looking at individual blocks of 40 trials however, it becomes apparent that there really only was one block (merely 40 trials) that had a marginally better performance. The number of hits is also roughly the same. The user’s performance during the hand task has a slightly higher hit rate than during the foot task (71 vs. 67). Because both measures do not agree on which physical task gave a better performance, we cannot draw any conclusions.

The other research question was about comparing control dimensions. As shown in table 7, the condition in which the BCI controlled the vertical dimension performed a bit better (380 vs. 400). This could be due to the fact that in the horizontal condition, the physical task was responsible for movement in the vertical direction. Specifically in the conditions where the physical task was the foot task, the subject reported some confusion about the discrepancy between left/right feet and up/down movement. This was not a problem in the hand condition, because that condition uses a

joystick which would be moved forward/backward instead of left/right. The horizontal conditions did have a slightly higher hit rate again (70 vs. 68).

Looking at the results for each block of 40 trials (table 4 and table 5), we can see that there is an interaction between the two dimensions and the two physical tasks. In the vertical condition, the user performs better during the foot task than during the hand task, but in the horizontal condition it is the other way around. This was already mentioned in the previous paragraph, the subject reported some confusion.

6.2 Future Research

This project is by no means perfect. There are many problems we encountered during the course of this project.

Firstly, the number of subjects is really low. In order to gain results that have any significance, we would need a lot more subjects and preferably more trials as well. Overall performance was still quite low (performance of 400 in most cases and less than 50% hit), so spending more time training the subjects could be a great starting point as well.

Secondly, the size of the target converged a bit too fast to the maximal size. The convergence parameter in Kaernbach's formula was set to 0.8, which might have been too high. The target would grow in size until 80% of the trials would be a hit. Because of the maximum size of 400, it would not grow any larger even with multiple misses. This means that the final size of 400 would not necessarily mean the same performance every time. A possible fix for this is to set the convergence parameter to a lower value, or to remove the upper bound on the target size.

Thirdly, while training the classifier we noticed that during some sessions, the auditory imagery task had little to no effect on the classifier performance (the AUC graph did not show any blue lines). Possible future work could investigate the possibility of removing one mental task and achieving 2D control with only one mental task (e.g. spatial navigation vs. baseline).

6.3 Conclusion

The first results look promising, the subject reported a feeling of control. There is no clear difference yet between flight performance in the different tasks. The same holds for flight performance when the physical tasks control the vertical dimension instead of the horizontal dimension. Based on the results reported in this study, the first answers to the research questions would be: *Users with 2D BCI control perform equally well with both physical tasks* and *There are no clear differences when the control dimensions are switched*. Further studies need to be performed in order to get significant results and a final answer to the research questions.

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