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Bachelor Thesis for Artificial Intelligence

Faculty of Social Sciences

UAV BCI

Comparison of Mental Task Combinations for a Two Dimensional BCI-Based UAV Control

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1 Abstract

In this study, the effectiveness of mental tasks in their use of achieving 2D control is investigated along with the effects of the transfer of mental tasks from 1D control to 2D control. This is done by taking mental tasks that have proven effective in achieving 1D control and then combine them for usable 2D control. A subject is chosen from a selection of four candidates based on the classifier accuracies when performing the selected mental tasks. The subject is then first trained in 1D control followed by training in 2D control. The training consists of hitting a target with a dot that can move in 1D or 2D depending on the training. After the training the subject is asked to perform the training task again with two different sets of tasks for 2D control. The performances of this system is measured using the hit-rate and the Weighted Up-Down method. The main results are that 1D task pairs that result in a high classifier accuracy are not neccessarily better tasks for control than task pairs that have a lower classifier accuracy. Simultaneous 2D control is harder, has a lower hit-rate, than 1D control. The different 2D control task sets seem equally hard to use. This study can serve as an example of the problems that occur when training 1D to 2D control.

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 send 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 [18].

Early research into BCIs has mainly focused on developing and improving means of communication for patients suffering from neuromuscular disorders (e.g. *Amyotropic Lateral Sclerosis* – ALS) [2, 23, 20, 21, 15]. More recently, applications have been targeted at enabling patients with neuromuscular disorders to move again [11], as well as applying BCIs to healthy people to aid them in their daily lives. [7].

2.1 BCI Hardware

Several types of hardware can be used in BCIs. The most common being *electroencephalography* (EEG), *mangnetoencephalography* (MEG), *functional Magnetic Resonance Imaging* (fMRI), *electrocorticography* ECoG and *functional Near-Infrared Spectroscopy* fNIRS.[18]
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 [20]. 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 [7]. A BCI will be constructed, using various combinations of mental tasks to operate a Parrot AR.Drone 2 quadcopter (hereafter referred to as UAV or Drone). EEG will be used for mental tasks. Linear Logistic Regression will be used to classify brain data into continuous command to change the drones direction while it flies forward with a constant velocity. [12]

2.4 Research Question

This thesis will extend on the idea of comparing mental task as done by [14]. Whereas they focused solely on task pairs for 1D control, this thesis will focus on the effects of combining pairs of tasks for 2D control, while also focusing on comparing a small set of mental tasks for 2D control. The main question of this thesis will be: "Which set of mental tasks lets the user perform better with a 2D control BCI after equal amount of training?" It will also discuss the effects of the transfer of tasks from 1D control to 2D control.

3 Theory

3.1 Mental tasks

Mental tasks are the tasks a user can perform to generate a desired brain signal (an induced signal), rather than the desired brain signal being triggered by external stimuli (an evoked signal). For this research induced signals will be used since relying on external stimuli for the control of an UAV is, although possible, not the most convenient method. The user will then be severely dependent on controlling the UAV in a setting where those external stimuli are present. With the use of mental tasks all the methods of generating a signal needed for the control of the UAV are present in the user themselves and is thus only limited by himself and the equipment required to measure the signal and control the drone. All of which in theory can be very portable, but for this research the user and all equipment remained in the same environment.

The controls for the UAV can each be mapped to a generated signal corresponding to a mental task. For instance one task for flying to the left, one task for flying upwards and so on. In order for this mapping to be efficient you need mental tasks that are independent of each other. This means among other things that the user can easily switch from executing one task to executing another task. It also means that the signal, which is generated from executing the task, must not cause conflict (e.g. overlapping) with the other signals, or else it will be very hard during classification to distinguish those signals. Preferably a signal that stands out in both spatial origin and frequency range should be used. However it is also possible to use signals that fall in the same frequency range but originate from different brain regions or signals that originate from the same brain region but fall in different frequency ranges.

Based on previous research [14] [13][1] [7],which studied a range of mental tasks to establish their performance and signal characteristics, we made a small selection of tasks. These specific tasks are selected because aforementioned research showed that high accuracy is achievable. Some tasks are commonly used (Imagined Movement), some are task you perform in daily life (Auditory Recall), and some are uncommon (Sensorimotor Attention). A description is provided by [14]

- Auditory Recall: 'Select a familiar tune, listen to this in your mind. Do not mouth the lyrics or make movements related to the tune.'
- Mental Navigation: 'Select a place, this should be somewhere familiar to you. Imagine yourself in this location and try to visualize the objects around yourself and move slowly within the enviroment.'
- Imagined Movement: Left hand (Wrist extension); 'Imagine extending your left wrist. Rather than visualizing the hand moving, try to concentrate on the perceptions associated without actually performing the movements.'

- Imagined Movement: Right hand (Wrist extension); 'See above.'
- Sensorimotor Attention: Left hand; 'Focus your attention on your left hand. Attempt to concentrate on the physical feelings you receive from it without actually attempting to move it.'
- Sensorimotor Attention: Right hand; 'See above.'

Each task has a certain spatial origin and frequency range. Although exact location and frequency may vary slightly between subjects, an investigation in previous research has been done to establish an expectation for the test results. Studies like [3], where the subject of the experiment had to walk a route and later imagine the same route reproducing the sequence of turns, show that during an imagined mental navigation task hippocampal regions and the left middle occipital gyri are used most prominently, among other areas. With the active frequencies ranging around the theta (4-7 Hz) and alpha (8-15 Hz) frequencies. Other studies like Janata et al. [5], where the subject was asked to imagine part of tone sequences, show that for auditory imagery the more prominent activity is located around the centro-parietal cortex. The frequencies are in the alpha range. The active brain regions of motor imagery are the motor cortical areas with a peak at roughly the 12Hz frequency, as investigated by laFleur et al.[7]. [14] used the sensorimotor attention task. The active brain regions are similar to those of a motor imagery task, namely the motor and/or sensory cortical areas with also a peak at roughly the 12Hz frequency. The active areas can be seen in Figures 1, 2 and 3

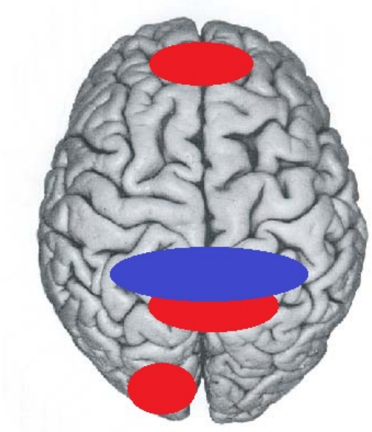

Figure 1: The active brain regions for Auditory Recall (Blue) and Mental Navigation (Red).

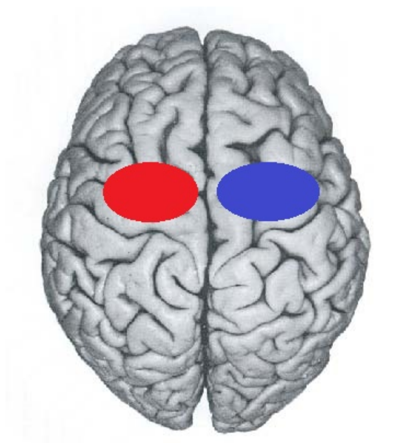

Figure 2: The active brain regions for Imagined Movement: Left Hand (Blue) and Imagined Movement: Right Hand (Red)

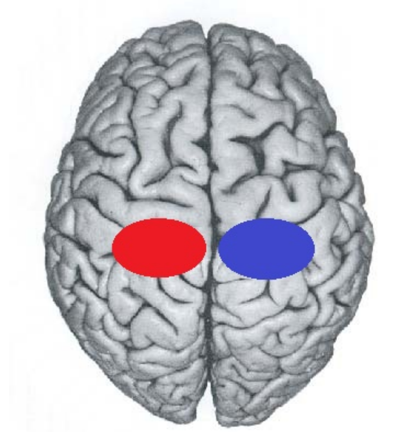

Figure 3: The active brain regions for Sensorimotor Attention: Left Hand (Blue) and Sensorimotor Attention: Right Hand (Red)

3.2 performance measure

In order to get a good estimate of how the subjects are performing a method to measure their performance must be established. Note that measuring the subject's performance can be as simple as just counting the times the subject succeeds versus the times the subject fails. However, using this method when the control is good it can reach the maximum score very easily. The same holds when the control is very bad, then this method can reach the minimum score very easily. The problem is then that differences between sessions are hard to find. Using a measure that adapts to the subject's performance level will be more useful. One of such measures is the Weighted Up-Down Method [6], which is the one that will be used in this thesis. In the context of this experiment the method works as follows: A successful hit will decrease the target size, a miss will increase the target size. However the increase is larger than the decrease. This ratio follows the formula:

$$S_{decrease} * p = S_{increase} * (1 - p) \tag{1}$$

Where $S_{decrease}$ is the amount the target decreases in size, $S_{increase}$ the amount the target increases in size and p is the target hit rate which can be set to a desired number (In this case $p = 0.8$ is used). Let's say the target size must decrease with 20 pixels, and $p = 0.8$ means a decrease to increase ratio of 1 to 4, the target will increase with 80 pixels. Another aspect of this method is that you are not indifferent to the order of hits and misses (which you are in the basic example given above) but actually adjust the amount the target increases ($S_{increase}$) based on the current amount of hits. To describe it in the same terms as Hill et al.[4], where they adjust a difficulty level based on the Weighted Up-Down Method, the difficulty level was increased when the user was successful and the difficulty level decreased when the user was unsuccessful. However the amount the difficulty level decreased when the user was unsuccessful got smaller the more the user was successful. When applied to this thesis's experiment the $S_{increase}$ ends up being determined by a factor $1 - \frac{hits}{totalpossiblehits}$, where $\frac{hits}{totalpossiblehits}$ will converge to p (wddddhere p = 0.8). The final size of the target after the user completes the experiment is the measure of performance used in this thesis.

4 Methods

4.1 subjects

Out of a selection of four subjects, all male, right handed and of age 21-24, the best subject was chosen for further training. The chosen subject was male, of age 21 and right handed. All subjects had some experience with BCI, but not with the particular tasks of this study. Each subject was asked for a short training session to determine their capabilities for performing the mental tasks. The best subject was contacted after the initial phase to participate in the final experiment and its corresponding training sessions, to which the subject consented. The results of the selection phase can be found in the result section.

4.2 Equipment

All of the experimental designs were made in the programming environment of Eclipse (Version: Luna Service Release 2 (4.4.2)) with the Java language. All the systems needed for the BCI were supplied by the 'Buffer BCI' platform based on the FieldTrip Buffer [9]. This includes the classification of the signals which was done in Matlab (Version: R2013b (8.2.0.701)).

A 64-channel Biosemi EEG system was used and a cap was fitted according to the 10-10 system (see Figure: 4), the electrodes placed with a conductive gel. The signals were processed by a Matlab script. First the signal was sliced in pieces of 3 seconds starting from each cue event. The data is then Detrended, bad channels are identified and removed, a spatial filter is applied, the specified range of frequencies are selected, the data is visualized and then a regularised linear logistic regressor classifier is trained with reg-parameter tuning by 10-fold cross validation. All the sessions were held in the BCI-lab of the Radboud University.

4.3 Task Pairing

The six possible mental tasks are each assigned a direction and paired accordingly. There are a total of three pairs, one for the vertical dimension and two for the horizontal dimension. These are then further combined into two sets to enable 2D control. The first set is a combination of pair 1 and 2, the second set combination of pair 1 and 3. This can be seen in Table 1.

4.4 Calibration

During the Calibration sessions the subject has to perform two mental tasks during the corresponding cues, which were abbreviations of the task written on the screen for the Sensorimotor Attention and Imagined

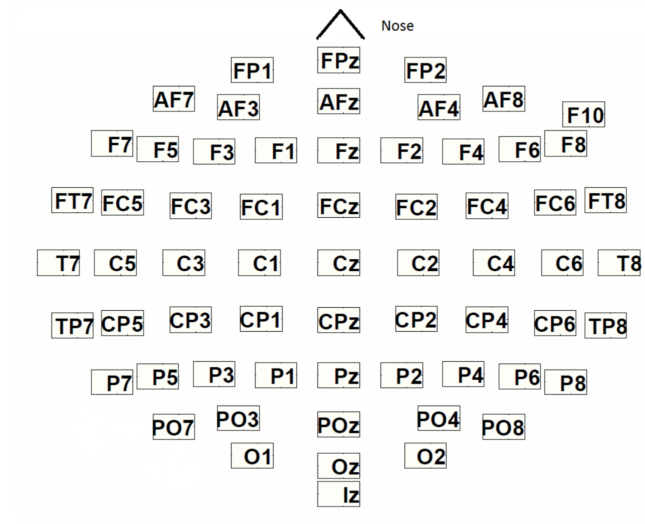

Figure 4: The 10-10 layout system

	Up	Down	Left	Right
Pair 1	Mental Navigation	Auditory Recall		
Pair 2			Imagined Movement	Imagined Movement
Pair 3			Sensorimotor Attention	Sensorimotor Attention
Set 1	Mental Navigation	Auditory Recall	Imagined Movement	Imagined Movement
Set 2	Mental Navigation	Auditory Recall	Sensorimotor Attention	Sensorimotor Attention

Table 1: Task Pairing

Movement tasks and pictures for the Auditory Recall and Mental Navigation tasks. The whole session consists of 60 trials with a 30 second break after 30 trials, and a 10 second break after 5 trials. A trial starts out with a one second display of a fixation cross to draw the subject's attention, followed by a cue of one of the two mental tasks that lasts for 5 seconds. In order to improve signal quality the first two seconds of the cue were not used because of the possible delay from the reaction time of the subject.

4.5 User Training Design

During the User Training sessions the subject has to control the movement of a dot with the mental tasks corresponding to a direction. For instance, motor imagery of the left hand should result in the dot going left on the screen, auditory recall should result in the dot going down. The goal was to steer the dot onto a target and remain on the target until the trial ended. The dot then resets to a random location on a fixed distance from the center of the screen. If the subject is successful in keeping the dot on the target, the target would become smaller the next try to increase difficulty. If the subject was unsuccessful the target would become larger to decrease the difficulty. The subject is first presented with the situation itself to allow for some planning, this is cued by the target being red. After two seconds the target becomes green signaling the subject that the dot is starting to move. The subject than has 3 seconds, corresponding to about 6 moves from the dot, to get the dot onto the target, which should take 2 moves on average depending on the target size. This is done 5 times in quick succession, after which the subjects gets a 10 second break. After 25 trials the user gets a 30 second break. The score is measured after every 50 trials, this is done 3 times resulting in a total of 150 trials worth of training for each session.

The design is the same for both the 1D training and the 2D training, the only differences is that for the 1D training the spawning position for the dot is locked in one axis depending on which dimension you train. To clarify: If you want to train the subject on the horizontal dimension with the Imagined Movement tasks, the dot will always spawn on the same spot on the Y-axis (the center) so you cannot miss the target on the vertical dimension.

The subject has to be trained five times on different settings. These settings can be found in Table 1.

4.6 Experiment

After the subject is trained for 150 trials on each 1D and 2D setting we run the final experiment. The subject will do a 100 trial version of the 2D training for both sets of tasks. The performance will be measured by the method discussed earlier.

5 Results

5.1 Subject Selection Results

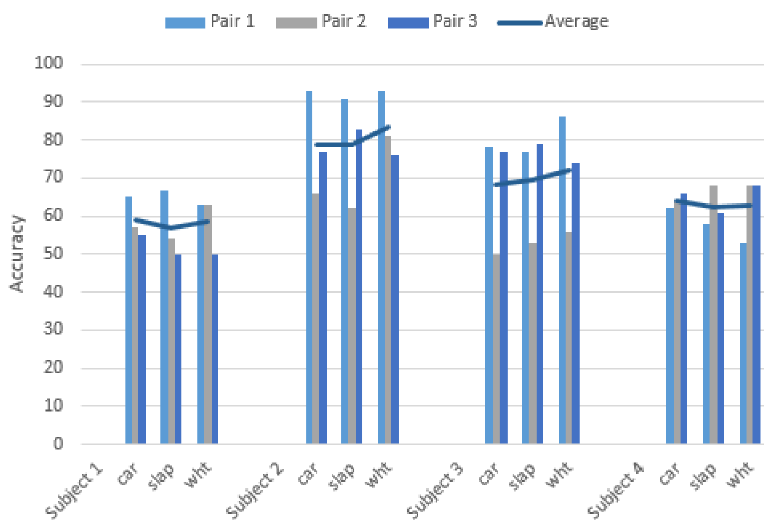

Figure 5: A diagram of the classifier accuracy during the subject selection phase

The subjects were all able to perform the required mental tasks without much difficulty. However, most subjects stated that they had concerns whether they were actually thinking about the task since they also had other thoughts. The results of the calibration are displayed in Figure 5. Based on these results subject 2 was selected for further training, as the average accuracy of subject 2 is higher than the average accuracy of the other subjects. Since the Whitening filter on average results in a higher accuracy for the classifier for this subject than other filters, only this filter was used for further calibration.

Other interesting results are that for Subject 4 the classifier accuracy with the Imagined Movement tasks is on average higher than the other tasks. Subject 2 and 3 have the highest classifier accuracy with the Auditory Recall and Mental Navigation tasks, followed by the Sensorimotor Attention tasks and then the Imagined Movement tasks. Subject 1 has a low classifier accuracy for the Sensorimotor Attention tasks.

	Pair 1	Pair 2	Pair 3	Set 1	Set 2
1D	85	81	77		
2D	84	83	81	85	73
				81	83
				87	87
				87	87
Exp	86	72	72	77	71
				82	79
				86	88
				92	88

Table 2: A summary of all the classifier accuracies for each system calibration, where 1D stands for the accuracies during the 1D training, 2D stand for the accuracies during 2D training and Exp stands for the accuracies during the final experiment

	Pair1	Pair 2	Pair 3	Set 1	Set 2
#Trials	150	150	150	150	150
#Hits	48/150	55/150	63/150	13/150	20/150
Final Size	380/400	400/400	400/400	400/400	400/400
Performance score	9.33/10	10/10	10/10	10/10	10/10

Table 3: A summary of the subject performance over the different training sessions. Included are the number of trials, number of hits, size of the final target and the performance score according to the Weighted Up-Down method.

5.2 Subject Training Results

The subject was in general able to control the direction of the dot in 1D space. The subject also had some, albeit little, form of control of the direction of the dot in 2D space. The result can be seen in Table 3.

Notable is that the hit-rate with 1D control from the Sensorimotor Attention tasks is the highest, followed by 1D control from the Imagined Movement tasks and slightly lower the 1D control from the Auditory Recall and Mental Navigation tasks. 2D control sets had a lower hit-rate than the 1D control sets.

The performance measure in Table 3 is expressed by the final size of the target and the performance score, which is a converted scale from the size by the function:

$$\frac{\left(\frac{Finalsize-Minimumsize}{Maximumsize-Minimumsize}\right)}{10}$$

The numbers show almost no deviation.

5.3 Experiment Results

	Set 1	Set 2
#Trials	100	100
#Hits	12/100	9/100
Final Size	400/400	400/400
Performance	10/10	10/10

Table 4: A summary of the subject performance for the experimental session. Included are the number of trials, number of hits, size of the final target and the performance score according to the Weighted Up-Down method.

The subject had little form of control of the direction of the dot in 2D space. The results can be seen in Table 4. Notable is the number of hits is almost equal.

5.4 Brain Signals

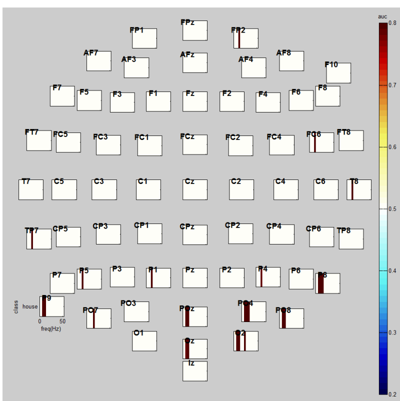

Figure 6: The subject's AUC diagram for Auditory Recall (Blue) and Mental Navigation (Red).

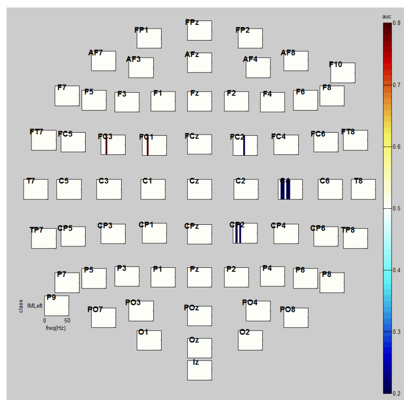

Figure 7: The subject's AUC diagram for Imagined Movement Left (Red) and Imagined Movement Right (Blue).

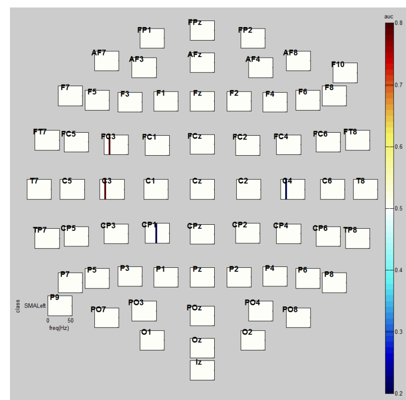

Figure 8: The subject's AUC diagram for Sensorimotor Attention Left (Red) And Sensorimotor Attention Right (Blue).

The subjects most distinctly active brain regions for each task pairing can be seen in Figures 6, 7 and 8. Notable is that the frequencies of Auditory Recall does not appear at all in it's AUC diagram. Also the Imagined Movement and Sensorimotor Attention tasks appear to have the left hand activity on the left hemisphere and the right hand activity on the right hemisphere. Mental Navigation triggers high activity in the occipital cortex.

6 Discussion

The results were not very conclusive, however this inconclusiveness can be attributed to several factors. These factors are the subject experience, performance measure, calibration performance, simulation difficulty and going from a 2-class discrimination problem to a 4-class discrimination problem.

6.1 Subject Experience

During the subject selection phase several factors were observed that could influence the accuracy of the classifier. However, these factors are present in any BCI setup with a subject. Most notable is the difference in signal strength between subjects. Not every subject is able to produce a clear signal because for instance the subject's skull reduces the signal strength or the electrodes and gel do not make clear contact with the surface of the skull because of subject's hair. Other factors are that the subjects had a hard time concentrating on the trials, making a lot of eye movement resulting in artefacts, which sometimes was also caused by eye spasms. Another cause of artefacts is that the subject concentrates too much and tenses his neck muscles, which result in spikes around the occipital cortex. Factors that are more related to the mental tasks are that the subjects reported doubts about their ability to perform the tasks. They were uncertain about performing the task in a correct way, mostly concerning the mental navigation task as subjects reported that they both name the objects in the environment and visualize the objects in their head. Another reported problem was that the subjects had trouble to drown out the song they recalled once done with recalling. The signals of this tasks are thus also present during other tasks.

During the subject training phase with subject 2, the subject reported to have some form of control of the direction of the dot, and that he felt more capable of doing so after more trials had passed. When his concentration faltered the subject had the feeling that it went worse. The subject stated that it was difficult to perform the tasks in quick succession and to keep a hold of the thought that controlled a certain direction. It was also difficult to visualize an environment with Mental Navigation while also keeping the eyes fixed on the screen. When the subject started training on 2D control, he immediately stated that it was a lot harder to control twice as many directions in the same time.

It is important to note that the experience of the subject tends to be biased towards feeling in control even if that is not the case. Although interesting to mention, this subject experience does not hold much value when making a conclusion. However, the experience of the subject can be used to improve the system for a better user experience (e.g. make a better simulation).

6.2 Performance Measure

In Tables 3 and 4 the performance measure scores can be found. And as previously said, almost no deviation can be found between the performance scores. The scores are all located around the upper limit, which is the worst possible score. This can be explained by the fact that the there is a limit to the maximum size of the target, which is the spawning range of the dot. This means that when the target is at it's largest the dot would only have to take one step in the right direction. However since the dot can also take steps in a wrong direction, the rescaling of the target will not improve the hit rate if the dot takes a step in the wrong direction every trial. This is conflict with the purpose of the Weighted Up-Down method which is to avoid those limits. It adapts the difficulty to the performance of the user. However, in this case the easiest difficulty setting is still harder than the performance of the subjects, resulting in the same problem it tried to avoid which is a floor effect. Almost every score is the worst possible. The number of the performance measure can therefore not be used to draw a conclusion.

6.3 Calibration Performance

The classifier accuracies achieved during the training sessions are quite good as can be seen in Table 2. This is remarkable since studies have shown that for Imagined Movement of the hands it can take a great amount of sessions before a subject achieves a higher classifier accuracy. [10] It is plausible that the subject in the study had a hard time performing the task and that the subject of this thesis does it with ease. Interesting is that even though the accurcies are high, the training results are quite low. This is most likely due to the difficulty of the simulation.

6.4 Simulation Difficulty

In order to get a significant amount of data a great number of trials had to be run. However, letting the subject perform more trials costs more time and eventually the subject gets tired. To train a subject properly you need at least 100 minutes of training per task to really increase the performance. With the quantity of tasks and a limited amount of sessions with the subject the duration of the training phase had to be made fitting within the time span. This resulted in significantly less training per task than needed, around 25 minutes instead of 100 minutes. As a necessity the duration of control in one simulation trial was about 3 seconds. With a prediction sent every half second the subject had 6 steps before the trials was over. This made the simulation incredibly difficult where the switching between tasks was required every half second which is hard for an inexperienced BCI user with little training. As stated before, the limit in target size unintentionally limited the difficulty. All these factors influence the possible hit-rates causing the hit-rates to be very low.

However, since all condition are influenced by this difficulty and the aforementioned factors, any difference between the tasks can still be attributed to the tasks themselves to some degree.

6.5 1D control to 2D control

In Table 3 you can see the hit-rates for the 1D pairs and the 2D sets. With 1D control tasks the user performs better than with 2D control tasks. This can be attributed to the fact that 2D control is simultaneous horizontal and vertical control. This requires the subject to perform two tasks at once to control the direction.

The difference between 1D and 2D is clear, but the differences between Set 1 and Set 2 is not. When you look at Table 3 you can see that with set 2 the user has a higher hit-rate than with set 1, but when looking at Table 4 the hit-rate is roughly the same.

The differences between the 1D control tasks are more distinct. Table 3 shows that the Sensorimotor Attention tasks were better than the Imagined Movement Tasks and the Imagined Movement tasks were better than the Auditory Recall and Mental Navigation tasks. This is interesting since the results from Figure 5 show that Auditory Recall and Mental Navigation had the highest classification accuracy. The signals from Auditory Recall and Mental Navigation are easily distinguishable but harder to switch between than Sensorimotor Attention, according to the subject, even though Sensorimotor Attention had lower classification accuracy. This indicates that even though with some task the user achieves high classifier accuracy, it is hard to perform the task in a more engaging environment (e.g. the simulation) as a lot more is happening that draws the user's attention (e.g the moving of the dot).

6.6 Brain Signals

The subject's brain signals were expected to be in the areas shown in Figures 1, 2 and 3. The resulting activity can be seen in Figures 6, 7 and 8. Fortunatly most of the activity occured in the areas where it was expected, with the exception of activity caused by Auditory Recall. Although the activity of Auditory Recall was certainly present in the data, it did not show up in the diagram. The most likely scenario is that the subject had great difficulty to stop recalling the song. This causes the activity to be present throughout the data, even in the activity of Mental Navigation, which means that it disappears in the background signals. Although expected to show up in more regions, the resulting activity of Mental Navigation appears mostly in the occipital cortex, which includes the occipital gyri where the signal was expected. It's strongest frequencies are around the 10 Hz. The activity caused by Imagined Movement shows some clear left and right sided motor cortex signals. The frequencies are around the expected 12 Hz. The activity cause by Sensorimotor Attention also shows some clear left and right sided somatomotor and somatosensory cortex signals, which frequencies also are around the expected 12 Hz. The oddity with these signals is that they do not appear to be contralateral to their imagined physical origin. Even though the frequencies match with the expectations, the locations appear to be swapped in contrast to the expectations. Possible scenarios are that the subject switches up the tasks or that some aspect of the system switched up the signals while plotting the diagrams.

7 Conclusion

In this study an experiment was performed to investigate the possible effects of the transfer of mental tasks from 1D control to 2D control, with a small selection of mental tasks as example. These mental tasks were arranged in one dimensional and two dimensional control sets. These sets were then compared based on the performance of the subject with these control sets. With the use of the BCI system the subjects were able to direct a dot towards a target to some degree. The performance was bad for 1D control and even worse for 2D control. Several factors influenced the results, namely the difficulty of the simulation task, the limiting of the performance measure, and the little amount of training per task. The results are therefore lower than expected. However, since all conditions are exposed to the same influences a comparison can still be made, albeit with less credibility. 1D task pairs that are more distinguishable in the brain and thus result in a higher classifier accuracy are not necessarily better control tasks than task pairs that are harder to classify (e.g. pair 1 versus pair 2 and 3). Based on the results pair 3 (Sensorimotor Attention) is easier to control than pair 2 (Imagined Movement), which in turn is easier to control than pair 1 (Auditory Recall and Mental Navigation).

2D task sets where the dimensions are controlled simultaneously are harder to control than 1D task sets. There seems to be no difference between the two 2D task sets. This indifference is most likely caused by the other factors than the two task sets being equally hard to control.

8 Further Research

Recommendations for further research are to expand the selection of mental tasks and subjects to improve the significance of this kind of research. Furthermore gathering more types of performance indicators would greatly improve the comparisons. Ideas are to measure the direction of the first step to indicate if the user has the right intention, to measure the amount of time the dot is hovering over the target to compensate for last second misses, which were frequently observed.

Another concept to research is the difference between simultaneous 2D control and a 'One versus All' control situation where only one direction is applied at a time. For any future 1D control research there should be no need to have two tasks to control one dimension, you can take the strongest of the two tasks and work with an active versus non-active state. This does not apply if you want to have more than two types of movement in that setting, for instance going left, right and standing still, or when you want to implement this control dimension into a more complex dimension (e.g. this research).

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