

CLASSIFICATION OF EEG DATA FOR A BRAIN COMPUTER INTERFACE.

A Thesis Presented

by

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ABSTRACT

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The goal of this project is to provide impaired people, e.g. *'palsy'* patients or *'locked-in'* patients, with the ability to communicate with the outside world via an EEG machine. Different cognitive tasks are known to cause activity in different brain areas: motor functions lead to activity in the premotor and motor cortex, visual tasks lead to activity in the visual cortex and association areas, other complex functions are located in various different frontal cortex areas, and so on. Previous work in this field seems to concentrate mostly on two to three motor tasks or in some cases on a few non-motor tasks. To further utilize this knowledge we instead choose nine different tasks - three of them motor tasks, the other six higher cognitive tasks - and tested the associated brain areas activated using an electroencephalogram (EEG). The recorded data are filtered first and then classified. The goal of this work is to find the maximum number of distinguishable tasks out of the nine tested for future applications in general and spelling applications in particular. The more tasks we can reliably distinguish, the higher bit rates could possibly be attained.

The results show that choosing a mix of cognitive tasks indeed leads to higher performances than using the same kind of tasks, e.g. only using motor tasks. About the same performance is already achieved using only minimal preprocessing tools. Using those tools optimized for the chosen classes would lead to even higher accuracies in the classification tasks.

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CHAPTER 1

THE PROJECT

1.1 Motivation for this project

This project is aimed toward people with severe diseases that lead to the inability to communicate. This can range from some limited problems in the patients' abilities to control their motor functions, like in patients with spinal cord injuries or brain-stem strokes. Completely disabled patients, like patients with *ALS* or *cerebral palsy*, eventually lose many types of motor control in the final stages of these diseases, like eye movement, muscle movement and speech. Any of these abilities would enable the use of other and easier approaches of communication, like eye tracking, muscle recording devices or voice guided systems. But the total absence of any voluntary muscle movement leads to the only willingly controllable organ, the brain, and thus to the need of a brain-computer interface (BCI or brain-machine interface, BMI).

1.1.1 Amyotrophic Lateral Sclerosis - ALS

Amyotrophic lateral sclerosis is a neurological disease that attacks motor neurons. Motor neurons are situated in the brain, brainstem and spinal cord and are responsible for voluntary motor movement. Upper motor neurons in the brain transmit signals to the lower motor neurons in the spinal cord, which relay the signal to the muscles. Those upper and lower neurons gradually degenerate and eventually die in ALS patients. As a consequence the muscles are not usable anymore, and this leads to total *atrophy*. The brain's ability to control motor movement decreases and is lost eventually. Patients with ALS usually die within three to five years due to respiratory

failure, after gradually losing more and more muscle function. These patients are fully aware of their surroundings and retain their intellectual and sensory abilities.

In the U.S. around 5,600 (100,000 worldwide) new cases of ALS are reported each year, and around 30,000 americans suffer from ALS at any given time ¹ . According to the ALS CARE database 60% of the patients are men and 93% are caucasians. Patients usually live at least three years after diagnosis, up to 10% even over ten years. Mostly 40- to 70-year-old people develop ALS at random without any clear associated risk factor; only about 5-10% of all cases are inherited. No cure has been found yet, but tests of treatment with some drugs, like *Riluzole* seem to increase the lifespan. The technologies suggested in this thesis might be a help to increase the quality of life. Instead of being totally 'locked' into their own bodies patients are able to express themselves and are able to do small, but personally rewarding tasks, such as reading an e-book alone or using the remote control for their television.

1.1.2 Cerebral Palsy

Cerebral palsy [4] is not a single disease but a group of chronic conditions affecting body movement and muscle coordination. It can usually be diagnosed before 18 months of age and does not get worse in general, but some symptoms, like seizures might change and get worse over time. The conditions are caused by errors in development or by suffered damage in motor areas controlling motor movement. So the symptoms can include spasms and seizures as well as problems with fine motor tasks, like writing, difficulties to maintain balance, and hence walking. Treatments vary from drugs to surgery, but no general cure is known. A successful application of a BCI might be able to assist patients in communication with the outside world, just like it could help the ALS patients. Around 764,000 cases of cerebral palsy are recorded in the U.S. alone in one or the other form and around 8,000 babies and

¹Numbers and statistics in this paragraph are taken from [1, 3].

infants and 1,400 preschool age kids in the U.S. are diagnosed each year (numbers taken from [4]).

1.2 Challenge

A brain computer interface provides a solution against the total lack in communication. The user can concentrate on different cognitive tasks while an EEG machine records electrical signals that a brain computer interface can use for the application at hand. She could control her own wheelchair or, more commonly, a spelling-based communication device. Nice and easy as this sounds, we cannot simply read the mind.

Temporal resolution in an EEG is high but the main problem for the application lies in the classification of the recorded EEG signals, because the spatial resolution is very limited. Different cognitive tasks produce electrical signals in different areas of the brain, but the final recorded signal from the scalp is a mixed signal from all surrounding brain areas, due to scattering effects of the electrical signals through bone and other tissue. The tissue acts as a volume conductor for the electrical signals. So we do not actually get signals from a specific cortical area but a summation of all signals originating around an electrode's position. For example, an electrode over the left motor cortex area representing finger movements not only records right-finger activity but also activity from right arm, right leg, and many more.

The knowledge of spatial mapping of cortical activity in the brain seems widely ignored in previous work. But it could be used to choose tasks that are more distant on the cortex to each other, so that the resulting signals and recordings are not mixed together that much and hence are easier to distinguish. For example, a visual imagination should result in more activity near the visual cortex, while motor imaginations are mostly active in the motor and premotor cortex. Another very important point is that different cognitive tasks seem to lead to high value peaks at different times. For example, motor tasks induce high positive peaks at around 300 ms after the cue

presentation, while a calculation leads to a high negative peak at around 400 ms. Thus the choice of the feature vector also leads to a different result, and choosing values around the peaks at 100, 200, 300 and 400 ms could improve the classification result. This neurological knowledge did not seem to get the proper credit in previous work. This thesis tries to implement it to improve the work in this field even further and to combine it with the good results from past research.

Another goal besides the improvement of the classification is the spelling application itself. The standard binary tree requires many user decisions for a single letter, and since every decision bears the risk of misclassification even more decisions are needed to correct the error again, and the fatigue increases. Other approaches try to reduce of the number of decisions to make. Here I propose the possibility of inserting a prediction system for the next letter or even word, which potentially cuts down the necessary decisions to make.

1.3 Previous Work

In the relatively young field of brain-computer interfaces there is no general approach to the subject and many aspects are still to be evaluated, like which data features are to be used. Some prefer to use certain frequency bands [27, 44] and others use the values of specific time frames [17, 35]. Others emphasize the distinction between voluntary and automated approaches in the mental efforts, or they try to grasp the value of synchronous or asynchronous applications [16, 65]. Then, of course, we have the research groups concentrating on the development of better suitable classification algorithms and preprocessing tools [22, 23] or trying to improve the performance with the help of other resources, like the combination of EEG and fMRI data [34] or simply increasing the number of classes that can be used [43, 44].

Research on BCI's can be found as early as 1976 and 1978 with experiments in *Biofeedback*, such as Bauer et al. [10] and Bird et al. [12, 13]. They used μ and β

frequencies (see Figure 1.1) and showed that users are able to learn the control of those in the sensorimotor cortex, when they get feedback of their current performance. μ and β frequency bands can be separated in the EEG recordings and are more active with certain activities; e.g. the β band is more active in an awake state. This frequency approach is still popular [27, 44] although other researchers [26, 34] concentrate on slow cortical potentials (SCP) instead. Some even try to combine the frequency and SCP approaches [45].

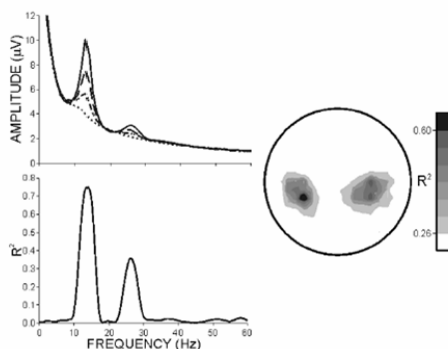


Figure 1.1. Mu/Beta Rhythm Control. Users can learn to control their μ and β frequencies with feedback.

Other researchers use voltage values taken directly at certain time intervals, mostly at the peak called P300. ERP research indicates that at roughly 300 ms after a cue presentation there is a large positive amplitude in the parietal electrodes, which are located over the sensorimotor cortex. For some examples see the research from the BCI competitions [14, 15, 17, 35, 38, 39, 45, 69, 73, 74] and some general research results in [21, 24, 29, 32, 57, 59, 75]. Currently the third international BCI competition is in progress already.

Besides the decision of which feature to use in a functional BCI one must choose between voluntary and adaptive control [9, 30, 32, 56, 66, 67]. In voluntary control of pre-defined classes the user has to make a conscious mental effort to adapt to the

task by controlling his μ and β frequencies (see Figure 1.1). An adaptive algorithm, on the other hand, adapts to the user and thus makes use of more natural control. Other researchers study the advantages of synchronous control versus asynchronous control [16, 65]. The synchronous approach is much simpler and easier to realize, because the data have to be taken only at a cued time frame, while the asynchronous approach has to analyze the incoming EEG data at all times and filter out noise and at times of inactivity.

Additional effort is focused on how many different cognitive tasks can be discriminated confidently. Using both nonmotor and motor tasks together has shown improvement over motor tasks alone [23]. But more classes might lead to higher information transfer rates. McFarland [43, 44] suggests that using four tasks presents the highest rate (Figure 4.1); more tasks lead to a decreasing accuracy in classification and thus the actual information transfer rate. Culpepper [22] evaluated two out of five tasks (a binary classification): multiplication, rotation, visual counting, baseline resting and mental letter composition. With an independent component analysis and a neural network, Culpepper reached 94% accuracy between the multiplication and rotation task. Curran [23] used two out of four tasks: navigation, auditory imagination, left and right hand closing and opening. In particular, spatial navigation versus the auditory task was most promising, with less concentration required by the subject. Other promising approaches incorporate Kalman filters [67]).

Fast processing is needed for real applications, so some researchers try to decrease the number of electrodes [47] or try to find better electrode positions for fewer electrodes [55, 71]. The combination of results attained from fMRI research with the EEG proved helpful for this task [6, 34, 46, 70]. The advantage of fMRI recordings is a high spatial resolution, on the order of millimeters. This complements the high temporal resolution found in EEG recordings. Thus knowledge gained from fMRI and knowledge of the topography of the cortical organization helps overcome the lack of

spatial resolution with EEG usage, which is on the order of centimeters, while fMRI has limitations in temporal resolution. Unfortunately this combination is impractical, because EEG recordings are distorted by the fMRI device, which is too big and too expensive for online and mobile use with patients. Babiloni [8] tried to combine MEG with the EEG data, which is a bit more feasible than use of fMRI.

More recently electrocorticograms (ECoG) have offered some advantages over EEG, such as a higher spatial resolution and higher voltage amplitudes, with some observed improvements in performance [28]. This is because ECoG signals are not scattered by tissue between the cortex and the electrodes, since electrodes are implanted below the bone. Some companies, like Cyberkinetics Inc, are developing commercial applications of ECoG, although the disadvantage is that it is an invasive method. The EEG is easier to apply and also cheaper for now.

Case studies with patients show that the endeavor of developing a working BCI is a worthwhile task improving the quality of life significantly [48, 53]. The BCI 2000 system developed by Schalk, Wolpaw and Mason [41, 64, 72] (see Figure 1.2) serves as a framework allowing developers and researchers to concentrate on their particular field and to provide a basis for comparison between classifiers, preprocessing tools and applications.

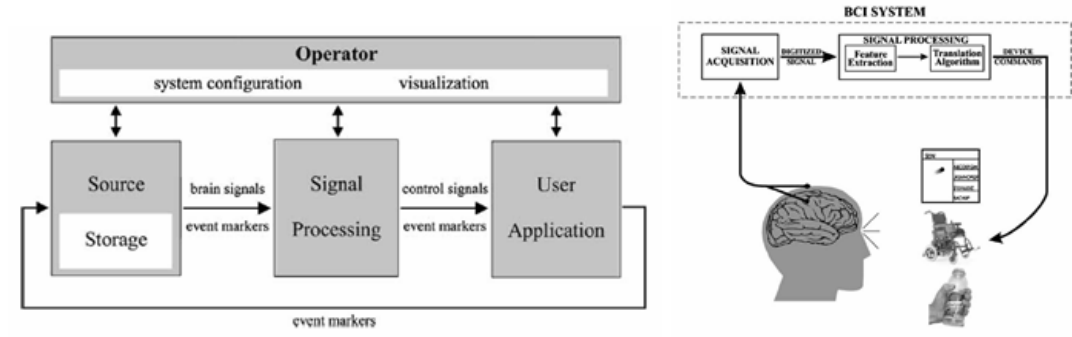


Figure 1.2. BCI 2000. The BCI 2000 System from [44].

CHAPTER 2

ELECTROENCEPHALOGRAPHIC RECORDINGS

2.1 Short Introduction to EEG

The EEG records differences in the surface voltage on the skull in correlation to the reference electrodes. These recorded signals reflect the firing pattern of the thalamo-cortical system and also the accumulated activity of synaptic potentials in the dendrites of the cortical neurons (induced by the flow of ions in and out of the neurons in the cortex layers). The resulting recording represents the net electrical field associated with the sum of neuronal activity of the cortical pyramidal cells. The signals are then scattered through the layers between the actual flow site and the electrodes - the skull bone, hair, skin, blood vessels and other neurons, together acting as a big conductor. Because of this scattering effect the spatial resolution of EEG recordings is very limited, but the temporal resolution is very good, in the range of milliseconds¹.

What you can see in the EEG signal is spontaneous activity and evoked potentials. The amplitudes range from 1-2 mV on the cortex, but only 10-100 μ V on the scalp surface with frequencies between 1-50 Hz. Those frequencies can be broken down into bands. For example, β band activity can be seen at the frequencies over 13 Hz, α activity is seen from 8-13 Hz, θ from 4-7 Hz, and δ under 4 Hz. The activity of each band depends on the task and cortical area. For example, the δ band is active during sleep and the β band in an awake state.

¹This contrasts with fMRI, which has a temporal resolution of minutes but a spatial resolution of millimeters.

Work on event-related potentials (ERP) also indicates that certain cognitive tasks lead to higher amplitudes at certain times after the cue presentation [62]. We are using four out of this collection. The first big negative peak, called '*N1*', is at around 100 ms and shows increased values with auditory tasks. Both auditory and visual tasks increase amplitudes at the second near 200 ms, called '*N2*'. And the third big peak, called '*P300*' is positive around 300 ms, and is involved with motor tasks and context updating. The last significant peak '*N400*' is negative at 400 ms and seems to be increased only when *semantic meaning*, like the meaning in a sentence or potentially in a picture, gets involved [58].

2.2 Hard- and Software

Hardware

For the recording of the data the SynAmps-1 amplifier was used in combination with a 32 channel electro-cap with tin electrodes. The electrodes on the electro-cap were arranged according to the international 10-20 system [2]. Two of the electrodes (channel 31 and 32) were used for easy exclusion of generated artifacts by eye, jaw or facial muscle movement. They were placed next to the left eye and under the right eye respectively to record the *electrooculogram* (EOG). Two more electrodes for reference were placed at both mastoids. The impedances were kept below 5 $k\Omega$ throughout the experiment (see Figure 2.1). Each single trial was arranged into epochs of 600 frames (ranging from -0.2 seconds to 1 second around the cue presentation), with a resulting sampling rate of 500 Hz.

Software

The presentation software used was e-Prime from the company *Psychological Testing PST*. For the recording the NeuroScan software *Scan 4.2*, with some build-in processing functions, was used to produce continuous EEG files.

2.3 Subjects

For this study the results from three healthy male subjects aged 23 to 29 years old were recorded. Subject B is left-handed, A and C are right-handed. All subjects were graduate students of the University of Massachusetts and had some basic knowledge about the physiological and psychological background of the study.

2.4 Organization of Task Presentation

The subjects were seated approximately 100 cm from the presentation monitor. They were asked to sit still, to not move their heads and to minimize blinking. Each trial showed a fixation point for one second, then one of the three tasks randomly for another second, followed by a blank screen for five seconds. No feedback was provided at any time.

The nine tasks² used were divided into three subsets. Every subset took about 30 minutes to record and two sets of every subset were recorded during each of the three sessions. The first subset included the three motor tasks *left hand*, *right hand* and *feet motor imagery*. The second and third set used higher cognitive tasks only. *sound imagination*, *visual counting* and *object rotation* were used in the second set, and *face visualization*, *calculation* and *spatial navigation* in the third subset.

²See Table 2.1 and Figure 2.2 for detailed description.

1. **Left Hand Motor Imagery:** imagine closing the left hand and grip as hard as possible. Activation expected in sensorimotor cortex in the parietal electrodes, right hemisphere at P300.
2. **Right Hand Motor Imagery:** imagine closing right hand and grip. Sensorimotor cortex, left hemisphere, P300.
3. **Feet Motor Imagery:** imagine lifting both feet and pressing against the bottom of the table. Again sensorimotor cortex, both hemispheres and P300.
4. **Sound Imagination:** imagine hearing a song and singing along. Auditory cortex and speech production area (Broca). Additionally increased amplitudes at N1 and N2 are expected.
5. **Visual Counting:** imagine sheep jumping over a fence and counting them. Visual cortex and speech production and frontal reasoning areas. The increase of amplitude should be around N2.
6. **Object Rotation:** imagine the presented object rotating in front of the eyes. Visual cortex, right parietal lobe. Again an increase in amplitude at N2 is to be expected, because of the visual aspect.
7. **Spatial Navigation:** imagine moving around a well known environment and visualizing all the details (e.g. walk in your apartment and see all the floor tiles, the pictures on the wall, the cups arranged on the cupboard). Visual cortex, frontal lobe (orientation). Again N2 and N400 increases are expected, because of the visual and the 'meaning' part.
8. **Face Visualization:** imagine seeing a face in front of you of somebody with high emotional value for you (e.g. mother, girlfriend). Visual cortex, emotional. To the visual amplitude increase at N2, an extra peak might be expected at N400 due to the meaning aspect brought in by the emotional value. Face components more detailed are seen in N170.
9. **Calculation:** try to solve a difficult equation (the equation presented is unsolvable in the given time). Frontal lobe (maybe visual cortex as well). The meaningful task might increase an amplitude in N400.

Table 2.1. Details of cognitive tasks and the expected brain areas activated, according to neurological knowledge. Times of expected activity are taken from [58, 62] and some other articles.

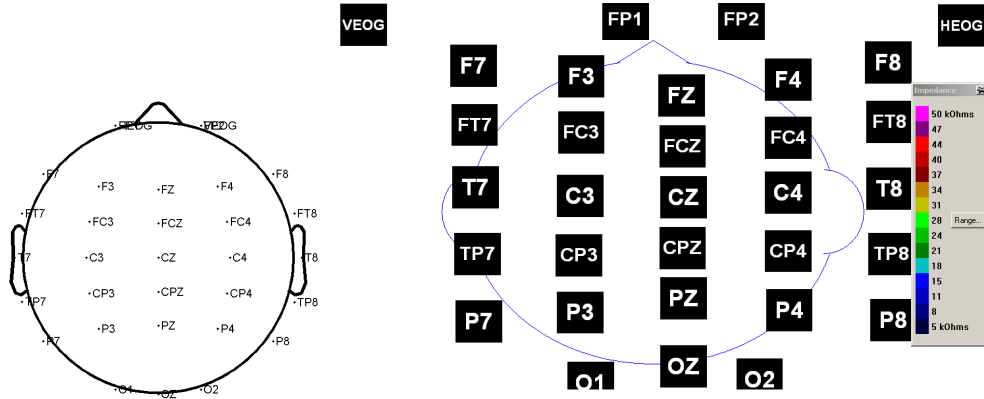


Figure 2.1. Electrode placement according to the international 10-20 System (left). The impedances (right) during the recordings are kept under $5\text{ k}\Omega$.

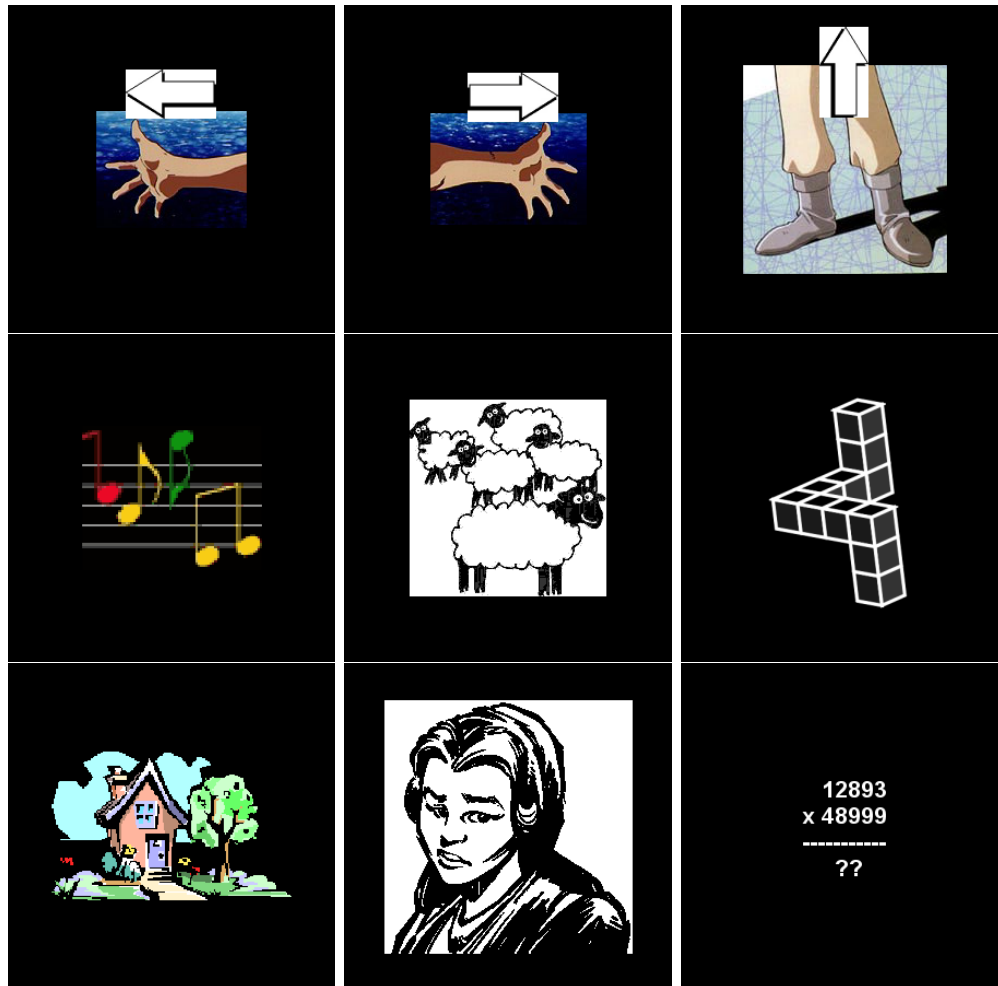


Figure 2.2. Images for the task presentations (in the order of Table 2.1)

CHAPTER 3

CLASSIFICATION

3.1 Data Preparation

3.1.1 Preprocessing

The recordings were baseline corrected, stored in the NeuroScan CNT file format, and then imported into Matlab using the open source toolbox EEGLAB. Custom Matlab functions were developed to import the raw data files and add the electrode locations. The Matlab functions eliminated dead time between trials and filtered out artifacts that were not usable due to eye, jaw or head movement or other noise¹. The different files for each subject were merged into one single file and the features for the classification by the support vector machine (SVM) were extracted. As is typical for an ERP study the data for all three subjects are merged and the ERP average over all the data was computed as well.

	Total	1	2	3	4	5	6	7	8	9
Subject 1	1,472	258	252	259	112	120	111	120	123	117
Subject 2	810	105	107	109	85	84	93	68	68	91
Subject 3	788	113	109	125	42	43	42	98	106	110

Table 3.1. Recorded and Usable ERP Epochs. From initially 140 points (280 for subject 1, tasks 1 to 3) these are the numbers of epochs left after artifact removal due to noise, head, eye or jaw movement for our training and testing. The number of usable epochs are very dependent on the subject and his alertness - subject 3 nearly fell asleep during the recording of the tasks 4 to 6, while subject 1 got a very high percentage of usable data overall.

¹See Figure 3.2 and 3.1 and Table 3.1 for the final number of epochs, that are usable for our training purposes after removing artifacts for each subject and task.

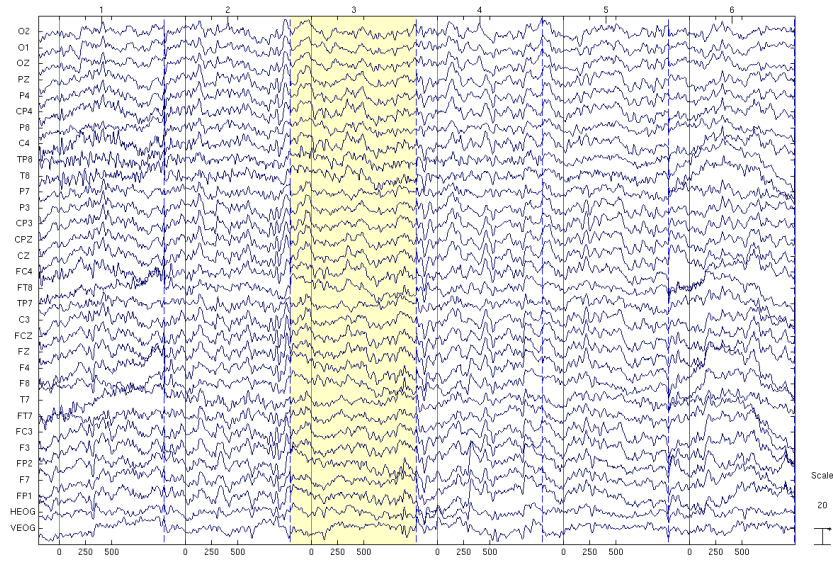


Figure 3.1. EEG Epochs. Each line shows the 32 channels, and each epoch spans from -200 to 998 ms around the cue presentation.

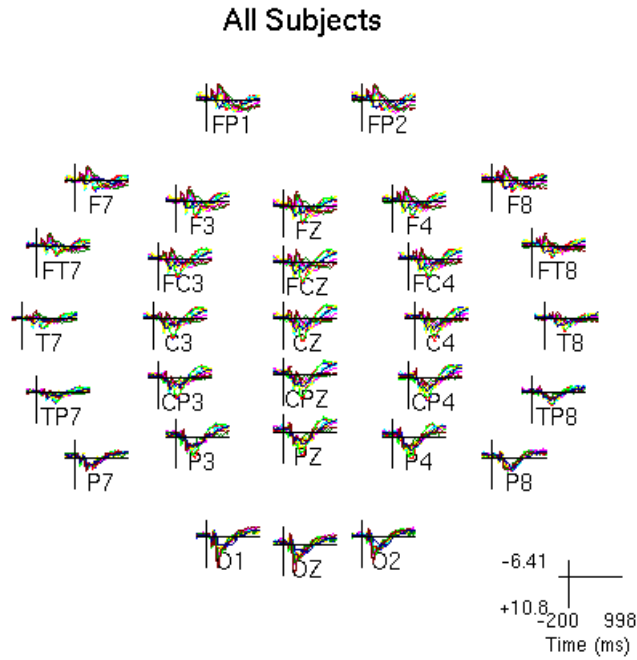


Figure 3.2. Event-related potentials (ERPs) for the average over all three subjects. All nine event types are shown in different colors on each channel as the average over all epochs of this type.

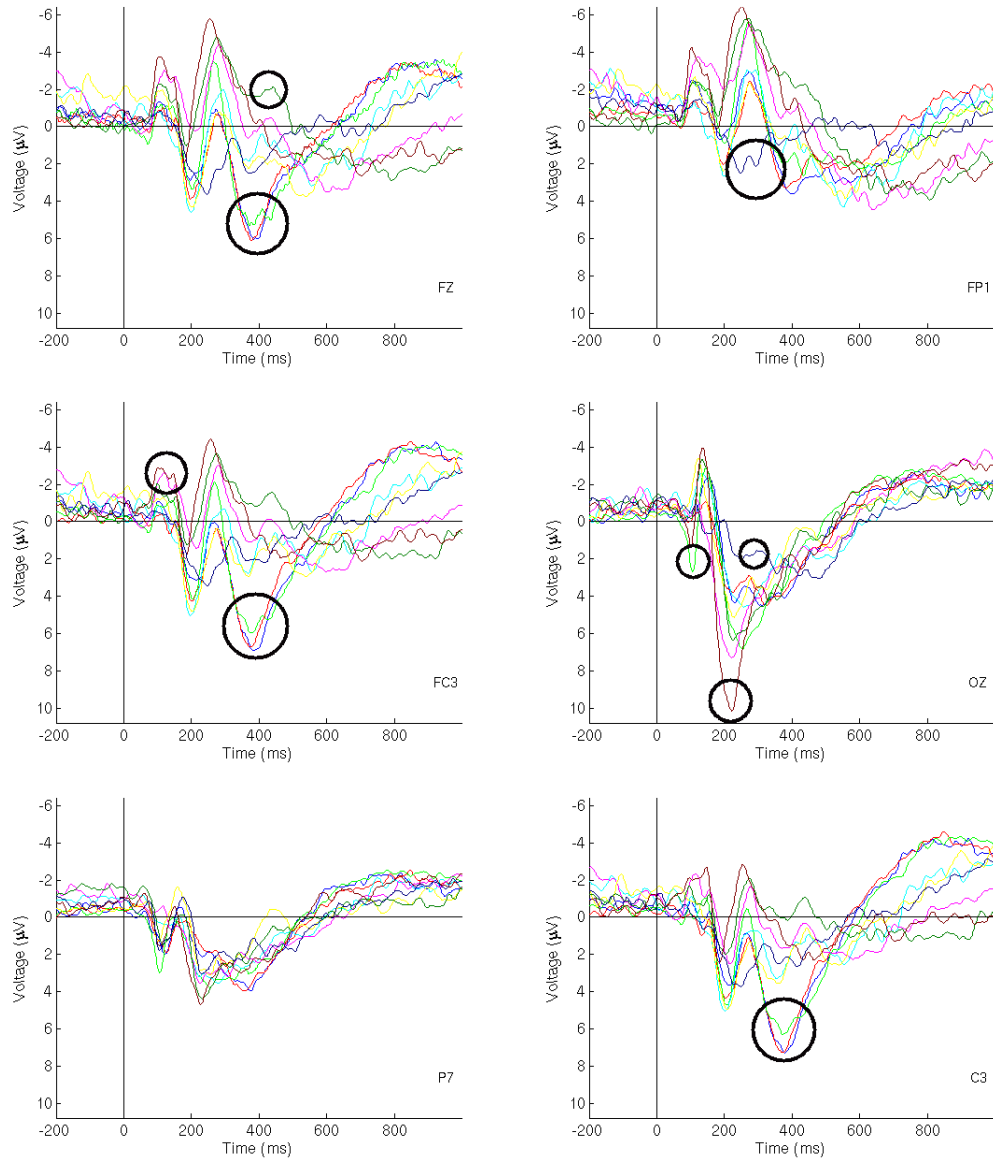


Figure 3.3. Sample ERPs of the average over all three subjects. Channel FZ shows a good distinction between the three motor tasks against the rest at around 400 ms, as well as a pretty good separable spatial navigation. In FP1 we see a very nice separation of calculation to the rest at 300 ms. FC3 again shows the motor and the navigation tasks at 400 ms, but here we also see both counting and face imagination at around 200 ms. In OZ the face task has the biggest peak at 200 ms, calculation can nicely be seen at 300 ms and even feet motor imagery can be seen at 100 ms. P7 is a good example for a channel without any visual recognizable separation, and thus could be left out of the feature extraction without loss in accuracy. C3 shows the motor tasks again at 400 ms with a higher peak.

3.1.2 Feature Selection

The data for the SVM algorithm was in the form

$\langle label/class \rangle : \langle featurenumber1 \rangle : \langle value1 \rangle \langle featurenumber2 \rangle : \langle value2 \rangle \dots$

The recorded EEG data was, therefore, transformed into Matlab readable *set* files and then into *svm* files. The feature selection shows an important difference for the classification result and seven different test series for the features were done with the physiological research results in mind, that certain cognitive tasks are best distinguishable at the peaks N1, N2, P300 and N400². Test series *I* and *II* contained pure P300 features, *III* and *IV* were expanded by adding N1 and N2 features and *V* to *VII* were further expanded with N400 features.

A closer look at the averaged ERP signals suggested, that some channels might contribute less to the classification accuracy, than others³. So in *VI* 10 channels were left out in the feature extraction, namely P7, P8, TP7, TP8, T7, T8, FT7, FT8 and F7, F8. Those channels are all located at the bottom of the cap on both hemispheres.

3.2 Support Vector Machines - The *libsvm* Toolbox

For this work the toolbox *libsvm* version 2.8 was used. The library from Chang et al. [20] supports all the main features of support vector machines and makes it a handy tool for researchers. It contains *C*-Support vector classification and the ν -Support vector classification for the binary case, the distribution estimation (a one class SVM) and the ϵ -Support vector regression, as well as the ν -Support vector regression. For multi-class classification the *one-against-one* approach is used, where

²See Table 2.1 for details.

³Compare Figures 3.2 and 3.3.

Series	Size	N1	N2	P300	N400	Sampling Rate
I	(3) → 96			298 - 302		500 Hz
II	(30) → 960			298 - 326		500 Hz
III	(9) → 864	98 - 106	198 - 206	298 - 306		500 Hz
IV	(6) → 540	96 - 116	196 - 216	296 - 316		250 Hz
V	(5) → 600	96 - 114	196 - 214	296 - 314	396 - 414	250 Hz
VI	(5) → 400	96 - 114	196 - 214	296 - 314	396 - 414	250 Hz
VII	(5) → 440	96 - 114	196 - 214	296 - 314	396 - 414	250 Hz

Table 3.2. Feature Series for Classifications. The size denotes the number of values per feature vector. N1 to N400 show which times are used around the peak values in [ms]. I to III use 32 channels, IV and V only 30 channels (without VEOG and HEOG). VI uses 20 channels (not included are all X7 and X8 channels) and VII uses 22 channels (like VI, but F7 and F8 are included).

for k classes we basically train $k(k - 1)/2$ different classifiers, for two classes each. The model uses the radial basis function (RBF⁴) kernel, with the two parameters C and γ to find hyperplanes between classes that separate them for our classification purpose.

The python script *easy.py* included in the libsvm library simplifies the procedure. It does the data scaling into the range of -1 to 1 , uses cross-validation to find the best values for the parameters C and γ and uses these parameters for the training. For this purpose the cross validation process divides the training set into ν subsets and each subset is then tested against the classifier trained with the remaining $\nu - 1$ subsets, which also prevents the usual over-fitting problem in classification tasks.

The '*libsvm*' program builds a model with the input data, and then revalidates the model with the input vectors. The resulting performance finally shows the percentage of correctly classified feature vectors with this produced model. Overall the classification performances seem usually better for subject 3. This is due to the fewer number of usable epochs and thus the lower number of feature vectors that are used for the classification. The SVM can then find a clearer hyperplane separating the classes.

⁴The general form of the RBF kernel is: $K_{rbf}(x, y) = e^{-\gamma||x-y||^2}$.

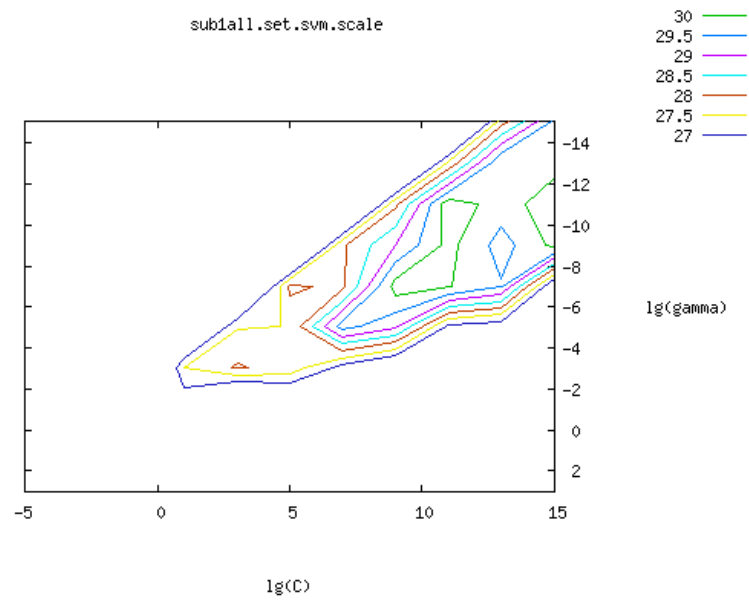


Figure 3.4. SVM Result for Parameter Search. Cross validation of C and γ values produces results like this figure.

CHAPTER 4

RESULTS

4.1 Classification Performance

4.1.1 Results for nine tasks

Classifications for all nine tasks were performed first, to evaluate which feature vectors should be used for the best possible results. As shown in Table 4.1 the performances were rapidly improving with the use of features not only from the widely used P300 peak but also from measurements around 100, 200, 300 and 400 ms. Series *V* in Table 3.2 gave the best performance and was used in all further classifications. Using fewer electrodes in series *VI* and *VII* led to slightly worse performance in subjects 2 and 3, while the results for subject 1 increased, but the average still implied better performance with 30 channels. For online applications the number of channels and the features have to be evaluated individually.

The performance for nine classes is surprisingly high with 45 to 55.5%, because with pure chance we would expect an accuracy of 11.1%.

4.1.2 Results for two to eight tasks

In Table 4.3 you see that the performances for binary classification are very consistent over all three subjects between one of the motor tasks and the face imagination task (1,2,3 versus 8) with 90 to 96.5% accuracy. But also song imagery or calculation against face imagination (4, 9 vs. 8) hold promising results with 95.2 and 94.8% in average. Also feet movement imagery against sound imagination (3 vs. 4) and object

Series	Average	Subject 1	Subject 2	Subject 3
I	33.2%	30.0%	32.0%	37.5%
II	37.8%	37.0%	35.0%	41.5%
III	51.2%	43.5%	55.5%	54.5%
IV	50.7%	45.0%	55.0%	52.0%
V	51.7%	45.0%	55.5%	54.5%
VI	49.2%	46.0%	52.5%	49.0%
VII	49.3%	47.0%	52.0%	49.0%

Table 4.1. Feature Evaluation and SVM Results for nine Classes. Compare Table 3.2 for the detailed definition of the series *I-VII*. The results for series V is the best and taken in all the future classifications.

rotation against face imagination (6 vs. 8) seem possible to be used for a binary decision task. For a real application we would have to find the best classes for each individual (see Table 4.2). For our case here the results would recommend the use of left hand motor imagery and the calculation task for subject 1. Subject 2 and 3 would probably perform best with sound imagination and face imagination or calculation and face imagination. An individual choice of the feature selection (see Table 4.2) for each subject leads to better performance also. For subject 2 series IV leads to the best results, while subject 3 performs with II. For the complete interpretation of the results see Table 4.11 and Figure 4.1. For the individual results see Tables 4.1 to 4.10.

	Average	Subject 1	Subject 2	Subject 3
II	62.0%	58.5%	60.0%	67.5%
III	62.7%	61.0%	68.0%	59.0%
IV	64.5%	61.0%	69.0%	63.5%
V	62.8%	61.0%	65.5%	62.0%

Table 4.2. Feature Vector Evaluation for two Classes. Here on event 1 versus 2. Subject 1: 18, Subject 2 and 3: 48.

$$B = \log_2 N + P \log_2 P + (1 - P) \log_2 \left[\frac{(1 - P)}{(N - 1)} \right] \quad (4.1)$$

SUBJECT 1	2	3	4	5	6	7	8	9
1	61.0	83.5	77.0	82.0	81.0	86.5	96.0	84.5
2	-	76.5	76.5	83.0	78.5	84.5	92.0	85.5
3	-	-	87.5	86.0	84.5	83.5	92.5	88.5
4	-	-	-	76.5	73.5	74.0	92.0	72.0
5	-	-	-	-	69.0	79.5	86.0	83.0
6	-	-	-	-	-	78.0	88.0	76.0
7	-	-	-	-	-	-	85.0	79.5
8	-	-	-	-	-	-	-	93.0
SUBJECT 2	2	3	4	5	6	7	8	9
1	65.5	88.0	81.0	84.0	90.0	84.0	89.5	85.0
2	-	85.0	79.0	82.5	84.0	88.0	92.5	86.5
3	-	-	91.0	87.0	93.0	89.0	92.5	92.0
4	-	-	-	88.0	84.0	86.0	96.5	80.5
5	-	-	-	-	89.5	78.5	84.5	90.5
6	-	-	-	-	-	88.0	90.0	89.0
7	-	-	-	-	-	-	80.0	91.0
8	-	-	-	-	-	-	-	95.5
SUBJECT 3	2	3	4	5	6	7	8	9
1	62.0	68.0	92.0	91.5	92.5	84.0	93.5	82.5
2	-	73.5	94.5	92.0	90.0	83.5	93.0	83.0
3	-	-	94.5	93.0	91.5	87.0	90.0	87.0
4	-	-	-	85.5	83.0	90.0	97.0	88.0
5	-	-	-	-	82.0	85.5	87.5	88.0
6	-	-	-	-	-	88.5	94.5	92.0
7	-	-	-	-	-	-	87.5	88.5
8	-	-	-	-	-	-	-	96.0
AVERAGE	2	3	4	5	6	7	8	9
1	62.8	79.8	83.3	85.8	87.8	84.8	93.0	84.0
2	-	78.3	83.3	85.8	84.2	85.3	92.5	85.0
3	-	-	91.0	88.7	89.7	86.5	91.7	89.2
4	-	-	-	83.3	80.2	83.3	95.2	80.2
5	-	-	-	-	80.2	81.2	86.0	87.2
6	-	-	-	-	-	84.8	90.8	85.7
7	-	-	-	-	-	-	84.2	86.3
8	-	-	-	-	-	-	-	94.8

Table 4.3. SVM Results for two Classes.

	Average						Subject 1					
	4	5	6	7	8	9	4	5	6	7	8	9
1,3	73.0	74.5	75.7	73.2	78.7	73.8	71.0	74.5	72.0	74.0	81.0	74.5
1,4	-	77.2	75.3	72.8	80.0	71.5	-	70.0	66.5	68.5	77.5	67.5
1,5	-	-	77.2	74.7	82.7	78.7	-	-	70.5	75.5	82.0	76.5
1,6	-	-	-	75.2	83.0	75.2	-	-	-	71.5	79.0	67.5
1,7	-	-	-	-	79.2	76.0	-	-	-	-	81.5	75.0
1,8	-	-	-	-	-	83.2	-	-	-	-	-	85.0
2,5	-	-	76.2	74.8	79.5	77.2	-	-	68.5	72.5	77.0	74.0
2,6	-	-	-	74.7	80.8	75.3	-	-	-	69.5	76.0	69.0
2,7	-	-	-	-	79.2	76.0	-	-	-	-	79.5	71.5
2,8	-	-	-	-	-	83.5	-	-	-	-	-	81.5
3,4	-	81.3	79.7	77.7	86.0	78.2	-	74.0	71.5	74.5	84.0	75.0
3,5	-	-	79.8	77.3	81.5	81.5	-	-	72.0	73.0	79.0	78.0
3,6	-	-	-	78.8	84.5	81.0	-	-	-	71.0	79.0	73.5
3,7	-	-	-	-	79.8	79.2	-	-	-	-	80.0	75.5
3,8	-	-	-	-	-	85.5	-	-	-	-	-	83.0
4,5	-	-	70.5	70.7	79.2	72.7	-	-	60.5	60.5	74.0	65.5
4,6	-	-	-	71.7	80.0	70.3	-	-	-	60.5	72.5	58.5
4,7	-	-	-	-	76.7	72.5	-	-	-	-	70.5	63.0
4,8	-	-	-	-	-	80.7	-	-	-	-	-	75.0
5,6	-	-	-	70.5	8	9	-	-	-	59.5	65.5	62.0
5,7	-	-	-	-	8	9	-	-	-	-	72.5	68.5
5,8	-	-	-	-	-	9	-	-	-	-	-	77.0
6,7	-	-	-	-	-	8	9	-	-	-	-	72.5
6,8	-	-	-	-	-	9	-	-	-	-	-	75.5
7,8	-	-	-	-	-	9	-	-	-	-	-	78.5

	Subject 2						Subject 3					
	4	5	6	7	8	9	4	5	6	7	8	9
1,3	78.5	79.0	84.0	77.0	83.5	80.0	69.5	70.0	71.0	68.5	71.5	67.0
1,4	-	76.0	75.5	72.0	75.5	70.5	-	85.5	84.0	78.0	87.0	76.5
1,5	-	-	78.0	71.0	80.0	79.5	-	-	83.0	77.5	86.0	80.0
1,6	-	-	-	77.0	85.0	80.5	-	-	-	77.0	85.0	77.5
1,7	-	-	-	-	76.0	76.5	-	-	-	-	80.0	76.5
1,8	-	-	-	-	-	81.0	-	-	-	-	-	83.5
2,5	-	-	76.0	74.0	77.5	78.5	-	-	84.0	78.0	84.0	79.0
2,6	-	-	-	76.0	80.0	77.5	-	-	-	78.5	86.5	79.5
2,7	-	-	-	-	78.0	79.0	-	-	-	-	80.0	77.5
2,8	-	-	-	-	-	84.5	-	-	-	-	-	84.5
3,4	-	81.5	81.5	79.5	87.0	78.5	-	88.5	86.0	79.0	87.0	81.0
3,5	-	-	86.0	79.5	80.5	83.0	-	-	81.5	79.5	85.0	83.5
3,6	-	-	-	85.0	88.5	85.5	-	-	-	80.5	86.0	84.0
3,7	-	-	-	-	79.0	84.0	-	-	-	-	80.5	78.0
3,8	-	-	-	-	-	87.5	-	-	-	-	-	86.0
4,5	-	-	76.5	75.0	81.5	74.0	-	-	74.5	76.5	82.0	78.5
4,6	-	-	-	73.5	81.0	73.0	-	-	-	81.0	86.5	79.5
4,7	-	-	-	-	75.0	76.5	-	-	-	-	84.5	78.0
4,8	-	-	-	-	-	79.5	-	-	-	-	-	87.5
5,6	-	-	-	76.5	82.0	84.0	-	-	-	75.5	81.0	80.5
5,7	-	-	-	-	71.0	72.5	-	-	-	-	78.5	77.5
5,8	-	-	-	-	-	83.5	-	-	-	-	-	87.5
6,7	-	-	-	-	76.5	80.0	-	-	-	-	82.0	80.0
6,8	-	-	-	-	-	85.0	-	-	-	-	-	91.5
7,8	-	-	-	-	-	80.5	-	-	-	-	-	84.0

Table 4.4. SVM Results for three Classes.

		Avg					Sub 1				
		5	6	7	8	9	5	6	7	8	9
	1,3,4	69.2	68.7	67.5	74.2	67.7	66.0	65.0	65.0	71.5	65.5
77.3	73.5 1,3,5	-	69.7	68.0	72.3	70.0	-	67.5	68.0	73.5	70.5
	1,3,6	-	-	67.8	73.0	70.5	-	-	65.5	73.0	68.0
	1,3,7	-	-	-	66.0	65.8	-	-	-	71.0	69.5
	1,3,8	-	-	-	-	67.0	-	-	-	-	75.0
	1,4,5	-	69.7	67.0	74.0	69.7	-	61.0	64.0	71.0	65.0
	1,4,6	-	-	65.7	70.8	68.2	-	-	59.5	67.5	60.0
	1,4,7	-	-	-	72.2	66.7	-	-	-	71.0	63.5
	1,4,8	-	-	-	-	73.3	-	-	-	-	71.0
	1,5,6	-	-	69.0	74.3	71.0	-	-	66.0	69.0	66.5
	1,5,7	-	-	-	70.8	69.3	-	-	-	72.5	67.5
	1,5,8	-	-	-	-	76.3	-	-	-	-	74.0
	1,6,7	-	-	-	72.5	70.2	-	-	-	70.0	65.0
	1,6,8	-	-	-	-	75.5	-	-	-	-	71.0
	1,7,8	-	-	-	-	72.8	-	-	-	-	74.5
	2,5,6	-	-	68.5	72.2	68.8	-	-	61.5	66.5	62.5
	2,5,7	-	-	-	70.3	68.8	-	-	-	69.5	67.0
	2,5,8	-	-	-	-	75.5	-	-	-	-	71.5
	2,6,7	-	-	-	71.0	70.5	-	-	-	66.5	66.0
	2,6,8	-	-	-	-	74.7	-	-	-	-	67.5
	2,7,8	-	-	-	-	73.7	-	-	-	-	71.5
	3,4,5	-	71.7	69.8	75.8	73.7	-	62.5	65.0	70.0	67.0
	3,4,6	-	-	69.7	78.7	72.7	-	-	62.5	70.0	63.5
	3,4,7	-	-	-	75.2	70.8	-	-	-	72.5	67.0
	3,4,8	-	-	-	-	77.3	-	-	-	-	73.5
	3,5,6	-	-	71.7	71.8	73.8	-	-	64.0	68.0	66.5
	3,5,7	-	-	-	72.0	70.5	-	-	-	68.5	66.5
	3,5,8	-	-	-	-	77.2	-	-	-	-	73.5
	3,6,7	-	-	-	74.5	72.5	-	-	-	69.0	65.5
	3,6,8	-	-	-	-	78.7	-	-	-	-	74.0
	3,7,8	-	-	-	-	75.3	-	-	-	-	73.0
	4,5,6	-	-	63.0	70.0	67.7	-	-	51.5	59.5	55.0
	4,5,7	-	-	-	67.8	64.7	-	-	-	61.5	55.0
	4,5,8	-	-	-	-	73.5	-	-	-	-	65.5
	4,6,7	-	-	-	69.7	66.2	-	-	-	61.0	55.0
	4,6,8	-	-	-	-	72.5	-	-	-	-	62.0
	4,7,8	-	-	-	-	70.5	-	-	-	-	61.5
	5,6,7	-	-	-	67.5	66.3	-	-	-	59.5	55.0
	5,6,8	-	-	-	-	73.2	-	-	-	-	61.0
	5,7,8	-	-	-	-	69.5	-	-	-	-	65.0
	6,7,8	-	-	-	-	72.7	-	-	-	-	65.5

Table 4.5. SVM Results for four Classes - first half.

	Sub 2					Sub 3				
	5	6	7	8	9	5	6	7	8	9
1,3,4	73.0	74.0	72.0	77.5	72.5	68.5	67.0	65.5	73.5	65.0
80.0 83 1,3,5	-	76.0	69.5	75.5	76.5	-	65.5	66.5	68.0	63.0
1,3,6	-	-	75.5	81.5	77.5	-	-	62.5	73.0	66.0
1,3,7	-	-	-	59.5	62.0	-	-	-	67.5	66.0
1,3,8	-	-	-	-	63.0	-	-	-	-	71.0
1,4,5	-	70.5	66.5	71.5	69.0	-	77.5	70.5	79.5	75.0
1,4,6	-	-	68.5	74.0	67.5	-	-	69.0	85.0	77.0
1,4,7	-	-	-	69.5	65.5	-	-	-	76.0	71.0
1,4,8	-	-	-	-	69.5	-	-	-	-	79.5
1,5,6	-	-	71.5	76.0	73.5	-	-	69.5	78.0	73.0
1,5,7	-	-	-	68.0	71.5	-	-	-	72.0	69.0
1,5,8	-	-	-	-	77.0	-	-	-	-	75.5
1,6,7	-	-	-	73.0	74.5	-	-	-	74.5	71.0
1,6,8	-	-	-	-	77.0	-	-	-	-	78.5
1,7,8	-	-	-	-	71.0	-	-	-	-	74.5
2,5,6	-	-	71.5	71.5	71.5	-	-	72.5	78.5	72.5
2,5,7	-	-	-	68.5	68.5	-	-	-	73.0	71.0
2,5,8	-	-	-	-	76.5	-	-	-	-	78.5
2,6,7	-	-	-	70.5	72.0	-	-	-	76.0	73.5
2,6,8	-	-	-	-	76.0	-	-	-	-	80.5
2,7,8	-	-	-	-	74.0	-	-	-	-	75.5
3,4,5	-	74.0	71.5	78.5	76.0	-	78.5	73.0	79.0	78.0
3,4,6	-	-	74.0	80.0	75.5	-	-	72.5	86.0	79.0
3,4,7	-	-	-	76.0	72.5	-	-	-	77.0	73.0
3,4,8	-	-	-	-	78.0	-	-	-	-	80.5
3,5,6	-	-	78.0	80.5	79.0	-	-	73.0	75.5	76.0
3,5,7	-	-	-	73.5	73.0	-	-	-	74.0	72.0
3,5,8	-	-	-	-	80.0	-	-	-	-	78.0
3,6,7	-	-	-	78.5	77.5	-	-	-	76.0	74.5
3,6,8	-	-	-	-	81.0	-	-	-	-	81.0
3,7,8	-	-	-	-	76.5	-	-	-	-	76.5
4,5,6	-	-	67.5	73.0	71.0	-	-	70.0	77.5	77.0
4,5,7	-	-	-	70.0	66.0	-	-	-	72.0	73.0
4,5,8	-	-	-	-	75.0	-	-	-	-	80.0
4,6,7	-	-	-	70.0	67.5	-	-	-	78.0	76.0
4,6,8	-	-	-	-	72.5	-	-	-	-	83.0
4,7,8	-	-	-	-	72.0	-	-	-	-	78.0
5,6,7	-	-	-	69.0	72.5	-	-	-	74.0	71.5
5,6,8	-	-	-	-	79.0	-	-	-	-	79.5
5,7,8	-	-	-	-	68.0	-	-	-	-	75.5
6,7,8	-	-	-	-	74.0	-	-	-	-	78.5

Table 4.6. SVM Results for four Classes - second half.

	Avg				Sub 1				Sub 2				Sub 3			
	6	7	8	9	6	7	8	9	6	7	8	9	6	7	8	9
1,3,4,5	64.2	62.7	67.7	64.7	57.5	59.0	64.0	59.5	68.5	66.5	70.5	68.5	66.5	62.5	68.5	66.0
1,3,4,6	-	61.8	69.0	64.3	-	56.0	62.0	57.5	-	68.5	72.5	70.0	-	61.0	72.5	65.5
1,3,4,7	-	-	66.2	62.5	-	-	63.5	58.0	-	-	69.5	66.5	-	-	65.5	63.0
1,3,4,8	-	-	-	68.0	-	-	-	64.5	-	-	-	71.0	-	-	-	68.5
1,3,5,6	-	64.0	67.3	66.0	-	59.5	63.0	61.5	-	69.0	73.5	73.0	-	63.5	65.5	63.5
1,3,5,7	-	-	64.8	63.7	-	-	65.0	62.0	-	-	66.5	67.5	-	-	63.0	61.5
1,3,5,8	-	-	-	69.7	-	-	-	68.0	-	-	-	75.0	-	-	-	66.0
1,3,6,7	-	-	67.3	64.7	-	-	64.5	59.0	-	-	71.5	72.0	-	-	66.0	63.0
1,3,6,8	-	-	-	69.8	-	-	-	65.5	-	-	-	75.5	-	-	-	68.5
1,3,7,8	-	-	-	67.8	-	-	-	67.0	-	-	-	70.0	-	-	-	66.5
1,4,5,6	-	62.3	67.2	63.2	-	55.0	59.5	55.0	-	64.0	67.0	66.0	-	68.0	75.0	68.5
1,4,5,7	-	-	65.3	63.3	-	-	62.0	58.5	-	-	63.0	64.0	-	-	71.0	67.5
1,4,5,8	-	-	-	67.5	-	-	-	63.0	-	-	-	66.5	-	-	-	73.0
1,4,6,7	-	-	67.2	63.2	-	-	61.0	56.5	-	-	66.0	64.0	-	-	74.5	69.0
1,4,6,8	-	-	-	67.8	-	-	-	61.0	-	-	-	67.5	-	-	-	75.0
1,4,7,8	-	-	-	66.0	-	-	-	63.0	-	-	-	64.5	-	-	-	70.5
1,5,6,7	-	-	66.5	64.5	-	-	62.5	58.5	-	-	67.0	67.5	-	-	70.0	67.5
1,5,6,8	-	-	-	69.0	-	-	-	64.0	-	-	-	71.0	-	-	-	72.0
1,5,7,8	-	-	-	67.5	-	-	-	65.5	-	-	-	68.0	-	-	-	69.0
1,6,7,8	-	-	-	68.2	-	-	-	63.5	-	-	-	70.5	-	-	-	70.5
2,5,6,7	-	-	65.3	62.8	-	-	60.5	57.0	-	-	66.5	67.0	-	-	69.0	64.5
2,5,6,8	-	-	-	68.3	-	-	-	61.0	-	-	-	71.0	-	-	-	73.0
2,5,7,8	-	-	-	66.2	-	-	-	63.0	-	-	-	65.5	-	-	-	70.0
2,6,7,8	-	-	-	67.2	-	-	-	61.5	-	-	-	68.0	-	-	-	72.0
3,4,5,6	-	64.7	70.0	67.3	-	56.0	61.5	58.0	-	69.0	71.5	71.0	-	69.0	77.0	73.0
3,4,5,7	-	-	67.0	66.2	-	-	62.0	58.5	-	-	70.0	70.0	-	-	69.0	70.0
3,4,5,8	-	-	-	72.0	-	-	-	65.5	-	-	-	75.0	-	-	-	75.5
3,4,6,7	-	-	68.8	66.3	-	-	61.5	58.5	-	-	72.0	69.5	-	-	73.0	71.0
3,4,6,8	-	-	-	73.0	-	-	-	65.5	-	-	-	75.0	-	-	-	78.5
3,4,7,8	-	-	-	69.5	-	-	-	67.5	-	-	-	69.0	-	-	-	72.0
3,5,6,7	-	-	68.2	66.8	-	-	62.0	60.0	-	-	73.5	71.0	-	-	69.0	69.5
3,5,6,8	-	-	-	71.7	-	-	-	65.0	-	-	-	76.0	-	-	-	74.0
3,5,7,8	-	-	-	67.8	-	-	-	64.5	-	-	-	68.5	-	-	-	70.5
3,6,7,8	-	-	-	70.0	-	-	-	64.0	-	-	-	73.5	-	-	-	72.5
4,5,6,7	-	-	61.7	59.5	-	-	52.5	47.5	-	-	64.0	65.5	-	-	68.5	65.5
4,5,6,8	-	-	-	66.2	-	-	-	55.0	-	-	-	69.5	-	-	-	74.0
4,5,7,8	-	-	-	63.8	-	-	-	57.0	-	-	-	63.5	-	-	-	71.0
4,6,7,8	-	-	-	64.7	-	-	-	55.5	-	-	-	64.0	-	-	-	74.5
5,6,7,8	-	-	-	66.0	-	-	-	56.5	-	-	-	70.0	-	-	-	71.5

Table 4.7. SVM Results for five Classes

	Avg			Sub 1			Sub 2			Sub 3		
	7	8	9	7	8	9	7	8	9	7	8	9
1,3,4,5,6	59.2	63.0	60.0	53.5	57.0	54.0	65.0	67.5	64.5	59.0	64.5	61.5
1,3,4,5,7	-	61.7	59.7	-	59.0	54.5	-	64.5	63.5	-	61.5	61.0
1,3,4,5,8	-	-	64.3	-	-	61.0	-	-	67.5	-	-	64.5
1,3,4,6,7	-	62.5	59.8	-	56.5	53.0	-	66.5	66.5	-	64.5	60.0
1,3,4,6,8	-	-	64.2	-	-	58.5	-	-	67.5	-	-	66.5
1,3,4,7,8	-	-	62.3	-	-	59.5	-	-	64.0	-	-	63.5
1,3,5,6,7	-	62.2	61.7	-	58.0	56.0	-	66.5	68.5	-	62.0	60.5
1,3,5,6,8	-	-	65.3	-	-	59.0	-	-	72.0	-	-	65.0
1,3,5,7,8	-	-	62.8	-	-	61.5	-	-	65.0	-	-	62.0
1,3,6,7,8	-	-	64.2	-	-	59.5	-	-	69.5	-	-	63.5
1,4,5,6,7	-	61.2	58.2	-	54.5	51.5	-	62.5	61.0	-	66.5	62.0
1,4,5,6,8	-	-	63.3	-	-	55.0	-	-	65.5	-	-	69.5
1,4,5,7,8	-	-	61.8	-	-	58.0	-	-	61.5	-	-	66.0
1,4,6,7,8	-	-	61.2	-	-	55.0	-	-	61.5	-	-	67.0
1,5,6,7,8	-	-	63.0	-	-	57.5	-	-	65.5	-	-	66.0
2,5,6,7,8	-	-	62.8	-	-	57.5	-	-	64.5	-	-	66.5
3,4,5,6,7	-	62.8	61.2	-	56.5	53.0	-	66.0	66.5	-	66.0	64.0
3,4,5,6,8	-	-	66.8	-	-	58.5	-	-	70.0	-	-	72.0
3,4,5,7,8	-	-	64.0	-	-	56.5	-	-	67.5	-	-	68.0
3,4,6,7,8	-	-	65.7	-	-	58.0	-	-	67.0	-	-	72.0
3,5,6,7,8	-	-	65.2	-	-	60.0	-	-	68.0	-	-	67.5
4,5,6,7,8	-	-	60.2	-	-	49.5	-	-	63.0	-	-	68.0

Table 4.8. SVM Results for six Classes

	Average	Subject 1	Subject 2	Subject 3
1,3,4,5,6,7,8	58.3	53.0	63.5	58.5
1,3,4,5,6,7,9	56.5	50.5	61.5	57.5
1,3,4,5,6,8,9	61.2	54.5	64.5	64.5
1,3,4,5,7,8,9	59.8	56.5	63.0	60.0
1,3,4,6,7,8,9	59.7	54.5	63.5	61.0
1,3,5,6,7,8,9	60.5	55.0	66.5	60.0
1,4,5,6,7,8,9	58.5	51.5	60.0	64.0
2,4,5,6,7,8,9	57.7	50.5	58.0	64.5
3,4,5,6,7,8,9	61.0	54.0	65.0	64.0

Table 4.9. SVM Results for seven Classes.

	Average	Subject 1	Subject 2	Subject 3
2,3,4,5,6,7,8,9	54.8%	47.0%	58.0%	59.5%
1,3,4,5,6,7,8,9	56.5%	49.5%	60.0%	60.0%
1,2,4,5,6,7,8,9	51.5%	43.5%	53.5%	57.5%
1,2,3,5,6,7,8,9	53.0%	46.5%	57.5%	55.0%
1,2,3,4,6,7,8,9	52.8%	46.5%	55.5%	56.5%
1,2,3,4,5,7,8,9	51.7%	45.5%	54.0%	55.5%
1,2,3,4,5,6,8,9	53.7%	45.5%	58.0%	57.5%
1,2,3,4,5,6,7,9	50.2%	42.5%	55.5%	52.5%
1,2,3,4,5,6,7,8	51.8%	45.0%	58.0%	52.5%
total avg	52.9%	45.7%	56.7%	56.3%

Table 4.10. SVM Results for eight Classes.

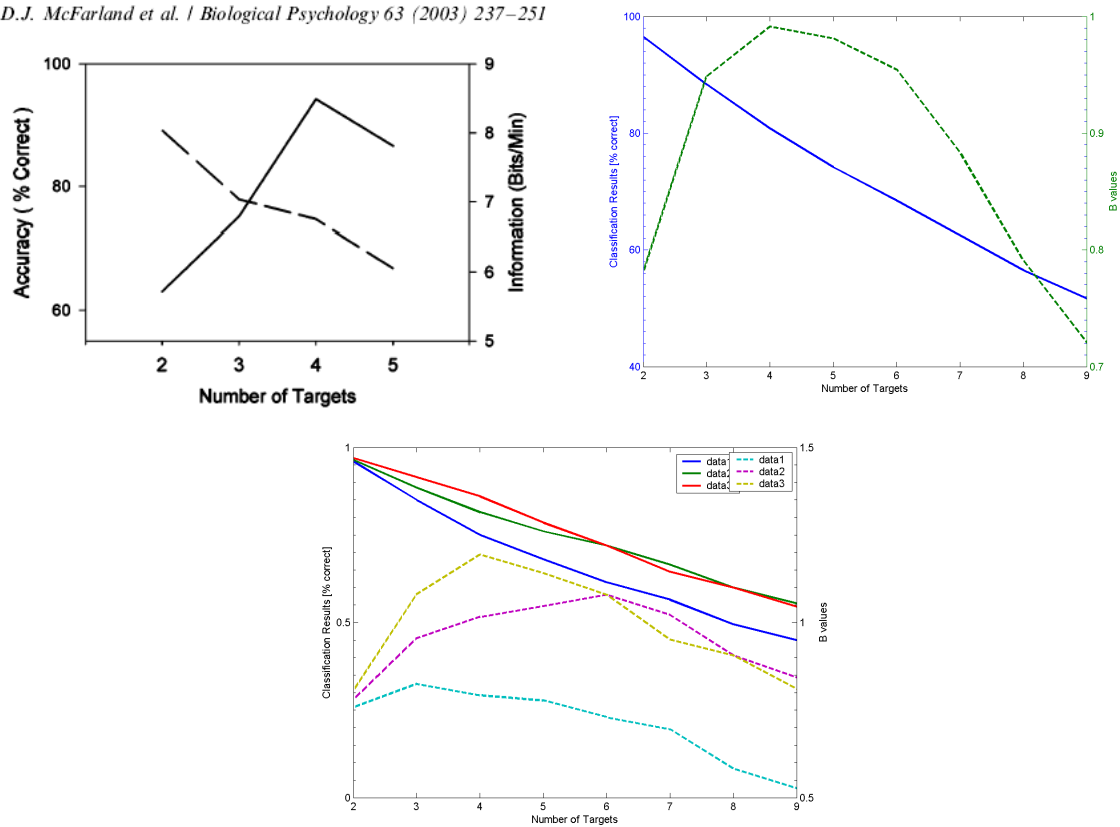


Figure 4.1. Performance of Classification as derived from Table 4.11 (right). Average classification performance (solid line) decrease constantly, while calculated B values (dashed) increase at first and then fall after a peak value at around five classes. For comparison the results from [44] on the left. At the bottom are the results of the individual subjects.

	Number of classes							
Best Classes	2	3	4	5	6	7	8	9
Sub 1	1,8	1,8,9	1,3,8,9	1,3,5,8,9	1,3,5,7,8,9	1,3,4,5,7,8,9	1,3,4,5,6,7,8,9	1-9
Sub 2	4,8	3,6,8	1,3,6,8	3,5,6,8,9	1,3,5,6,8,9	1,3,5,6,7,8,9	1,3,4,5,6,7,8,9	1-9
Sub 3	4,8	6,8,9	3,4,6,8	3,4,6,8,9	3,4,5,6,8,9 3,4,6,7,8,9	1,3,4,5,6,8,9 2,4,5,6,7,8,9	1,3,4,5,6,7,8,9	1-9
Percentage								
Sub 1	96.0	85.0	75.0	68.0	61.5	56.5	49.5	45.0
Sub 2	96.5	88.5	81.5	76.0	72.0	66.5	60.0	55.5
Sub 3	97.0	91.5	86.0	78.5	72.0	64.5	60.0	54.5
Avg	96.5	88.3	80.8	74.2	68.5	62.5	56.5	51.7
B-Values								
Sub 1	0.758	0.825	0.793	0.778	0.730	0.695	0.582	0.527
Sub 2	0.781	0.955	1.016	1.047	1.079	1.021	0.906	0.844
Sub 3	0.806	1.080	1.194	1.141	1.079	0.951	0.906	0.811
Avg	0.781	0.949	0.991	0.981	0.955	0.884	0.791	0.721

Table 4.11. Overall Performance of Classification. The best performances are taken from each subject for 2 to 9 classes (top and middle), and according to Equation 4.1 (from [44]) the B values, or the number of bits transmitted per trial, are calculated as a measure of bitrate (bottom).

4.2 Discussion

We don't need to discuss every individual table here, but a look at the tables shows consistency for an increasing number of classes for each subject. Interestingly, and as expected, every subject has different classes that work best for him. You can see this easily in Table 4.11, where all information from the tables of results are put together for an easy overview.

Another expectation is also confirmed by the results. For every subject different number of classes leads to the highest transfer rate (here shown by the calculated B-Values). Subject 1 performs best with three classes, 1,8 and 9, which stand for 'left motor imagery', 'face visualization' and 'calculation'. Subject 3's performance is best with four classes, 3,4,6,8 ('feet motor imagery', 'sound imagination', 'object rotation' and 'face visualization'). And finally subject 2 does best with six classes, 1,3,5,6,8,9 ('left hand motor imagery', 'feet motor imagery', 'visual counting', 'object rotation', 'face visualization' and 'calculation').

One interesting observation is that for each subject the best results come from different groups of cognitive tasks. We can group the motor tasks together (1,2,3), auditory tasks (4), the visual tasks (5,6,7 and 8), number tasks (5,9) and tasks with meaning involved (8,9). Past research has focused on motor tasks, and the results here show that performance could be improved by using a mix of cognitive tasks. For example, some research groups managed to reach up to 99% of performance accuracy for using only left and right hand motor imagery, while I got for these about 61 to 65.5% only, because I did not use all possibilities of preprocessing the data. But I also got 96 to 97% without using an in-depth preprocessing for two different tasks. Using in-depth preprocessing tools could lead to optimal results for the two classes and thus also for the classifications with a higher number of classes.

4.3 A View in the Future

4.3.1 Spelling Applications

The classic idea for a spelling application is the widely used binary spelling application (compare Figure 4.2). The alphabet is divided into a binary tree of 32 characters of a '*virtual keyboard*', with some submenus of numbers and symbols, that is narrowed down by every choice. The work done in this thesis suggests that the binary tree could be extended to use more branches instead of just two.

Using running letters rather than a presentation of all characters at a given node can improve the bit rate and practicability even more. For example, in the classic binary tree instead of presenting the complete half on each side the whole time, only a small part of the letters is seen at a time, e.g. in the first view of the screen four characters at a time are seen. When one letter drops out of the bottom of the window the next letter appears on the top. Thus the first decision cuts the decision tree already down to four letters instead of thirteen.

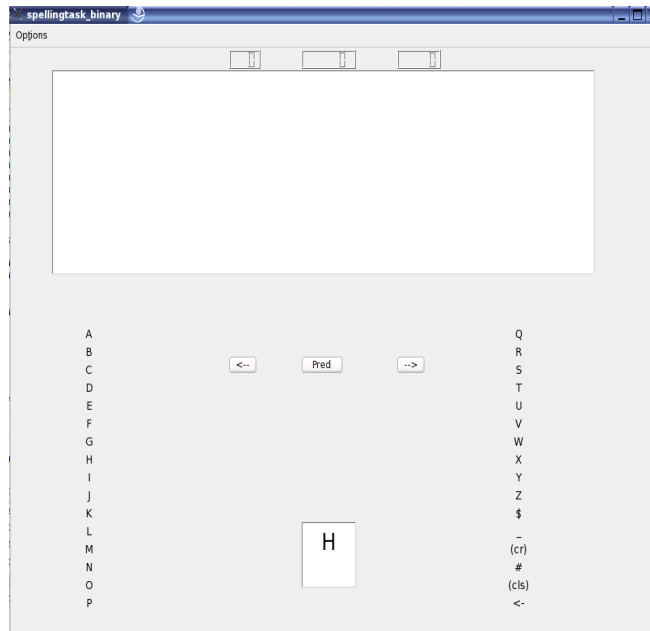


Figure 4.2. Classic Binary Application. On the left you see the first half of the 32 character set and the second half is on the right. On the bottom is the Letter Prediction Box, showing the next most possible letter. With the first decision we choose one of those halves and divide them again in a first and second half to be presented on one side of the screen. Thus we need five decisions to choose a single letter ($32 = 2^5$). The finally chosen letter will then be added to all previous chosen and presented on the top half of the screen, our output of communication.

Adding an efficient prediction of the next letter or even the next word or both could speed up our spelling even more. Similar to David MacKays' Dasher program [40] the same prediction can be used to code the likelihood of the presented letters in the size of a frame around them - the more likely a letter is to be chosen next the larger the frame around it will be.

4.3.2 General Ideas

The *organization of a virtual keyboard* can be extended to include remote control of the wheelchair, home appliances and maybe even a service robot to improve the quality of life even further. And with the development of better artificial intelligence or other classifiers in combination with the always increasing computation performance, more and more classes can be used, until eventually a *real time interpretation of the users will and thoughts* can be done. Advances in technology, e.g. the use of ECoG recording directly on the cortex surface, could also contribute to clearer classification and usage of more classes to an eventual unlimited end. *Direct knowledge of the spatial location*, not only on the cortex surface, but also in depth, gained in neurological research combined with further medical and surgical advances can help place electrodes safely in specific brain areas without affecting other brain functions. This may sound like science fiction, but I imagine that it will be possible to *control a virtual avatar* in cyberspace to communicate and act freely while interacting with other avatars, writing documents and emails, and searching the internet. Eventually *robotic devices* might be developed and controlled like the avatar, and act as extension of one's own body.

APPENDIX

MATLAB CODES

A.1 Conversion from CNT (continuous recorded EEG Data) to SET (EEGLAB format)

```
function cnt2set(fileid)
addpath('/exp/rcf/common/matlab_addons/eeglab4.512');
%eeglab;

EEG = pop_loadcnt(fileid, 'dataformat', 'int16');
filename = [fileid '.set'];
EEG.setname='CNT file';

%% Remove the first trials
EEG = pop_editeventvals(EEG, 'delete',1, 'delete',1, 'delete',1, 'delete',1,
'delete',1, 'delete',1, 'delete',1, 'delete',1, 'delete',1, 'delete',1,
'delete',1, 'delete',1, 'delete',1, 'delete',1, 'delete',1, 'delete',1,
'delete',1, 'delete',1, 'delete',1, 'delete',1, 'delete',1, 'delete',1,
'delete',1, 'delete',1);

%% GET CHANNELLOCATIONS
EEG.chanlocs=pop_chanedit(EEG.chanlocs, 'lookup',[]);
EEG.chanlocs=pop_chanedit(EEG.chanlocs, 'change field',{31, 'X',0.0949},
'change field',{31, 'Y',0.0307}, 'change field',{31, 'Z',-0.0047},
'change field',{31, 'theta',-17.9263}, 'change field',{31, 'radius',0.51499},
'change field',{31, 'sph_theta',17.9263}, 'change field',{31,
'sph_phi',-2.6979}, 'change field',{31, 'sph_radius',0.099853},
'change field',{31, 'Z',-1.0047}, 'change field',{31, 'Z',-0.00147});

EEG.chanlocs=pop_chanedit(EEG.chanlocs, 'change field',{31, 'Z',-0.01047},
'change field',{31, 'Z',-0.10047}, 'change field',{31, 'Z',-0.03047},
'change field',{31, 'X',0.1949}, 'change field',{31, 'X',1.0949},
'change field',{31, 'X',4.0949}, 'change field',{31, 'X',0.0949},
'change field',{31, 'Y',0.1107}, 'change field',{32, 'theta',17.9263},
'change field',{32, 'radius',0.51499}, 'change field',{32, 'X',0.0949},
'change field',{32, 'Y',-0.0307}, 'change field',{32, 'Z',-0.0047},
'change field',{32, 'sph_theta',-17.9263}, 'change field',{32,
'sph_phi',-2.6979}, 'change field',{32, 'sph_radius',0.099853},
'change field',{32, 'Y',-0.1107}, 'change field',{32, 'Z',-0.03047});

%% Epoch files, baseline removal
EEG = pop_epoch( EEG, { }, [-.2 1], 'newname', 'CNT file epochs',
'epochinfo', 'yes');
EEG.setname='CNT file epochs';
EEG = pop_rmbase( EEG, [200 0]);

%% Reject Artifacts in all channels
EEG = eeg_checkset( EEG );
EEG = pop_eegthresh(EEG,1,[1:32] , -80,80,-0.2,0.998,2,0);
EEG = eeg_checkset( EEG );
EEG = pop_rejtrend(EEG,1,[1:32] ,600,50,0.3,2,0);
EEG = eeg_checkset( EEG );
```

```

EEG = pop_jointprob(EEG,1,[1:32] ,5,5,0,0);
EEG = pop_rejkurt(EEG,1,[1:32] ,5,5,0,0);
EEG = eeg_rejsuperpose( EEG, 1, 1, 1, 1, 1, 1, 1, 1);
EEG = pop_rejepoch( EEG, find(EEG.reject.rejglobal), 0);
%% Reject EOG Artifacts
EEG = pop_eegthresh(EEG,1,[31 32] ,-50,50,-0.2,0.998,2,0);
EEG = eeg_rejsuperpose( EEG, 1, 1, 1, 1, 1, 1, 1, 1);
EEG = pop_rejepoch( EEG, find(EEG.reject.rejglobal), 0);

EEG = pop_saveset( EEG, filename);
%eeglab redraw;
%pop_eegplot(EEG,1,1,1);

```

A.2 Conversion from SET files to SVM readable format

```

% load combined set files and work on them
function set2svm(fileid)

addpath('/exp/rcf/common/matlab_addons/eeglab4.512');
[ALLEEG EEG CURRENTSET ALLCOM] = eeglab;
EEG = pop_loadset(fileid);
[ALLEEG EEG CURRENTSET] = eeg_store(ALLEEG, EEG);

nvMax = 30; %% number of vectors used for SVM,
            also used as trial identificator (3), (30) or (9)
fileid2 = [fileid '-' int2str(nvMax) 'new'];
filename = [fileid '-' int2str(nvMax) '.svm'];

%% Filter highpass
%EEG = pop_eegfilt( EEG, 1, 0, [], [0]);

%% ICA
EEG = pop_runica(EEG, 'runica');

EEG = pop_saveset( EEG, fileid2);%'sub2-1-1.set');%, 'C:\MATLAB6p5\work\');
eeglab redraw;
pop_eegplot(EEG,1,1,1);

%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%% Write files in SVM format

% open file
fid = fopen(filename,'wt');% 'wt' means "write text"
if (fid < 0)
    error('could not open file');
end;

%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%% VERSION FOR CONTINUOUS TRIALS
sz = size(ALLEEG.event,2);
for i=1:1:sz % loop over all events
    fprintf(fid,'%3d: ',ALLEEG.event(1,i).type);
    for nv=1:1:nvMax % loop over number of used vectors
        for nc=1:1:32 % loop over number of channels
            fprintf(fid,'%3d:%6d ',nc*nv,ALLEEG.data(nc,249+nv,i));
            %% 249+nv starts at 298ms and ends at 298 + (nvMax-1)*2ms
            %% 252+nv starts at 304ms
        end
    end
    fprintf(fid,'\n');
end
end

```

```

% close the file
fclose(fid);

%% VERSION FOR COMBINED TRIALS (like in (9), N1, N2, P300)

sz = size(ALLEEG.event,2);
for i=1:1:sz % loop over all events
    fprintf(fid,'%3d: ',ALLEEG.event(1,i).type);
    for nv=1:1:nvMax % loop over number of used vectors
        for nc=1:1:32
            fprintf(fid,'%3d:%6d ',nc*nv,ALLEEG.data(nc,149+nv,i));
        end
        for nc=1:1:32 % loop over number of channels
            fprintf(fid,'%3d:%6d ',nc*nv+32*nvMax,ALLEEG.data(nc,199+nv,i));
        end
        for nc=1:1:32 % loop over number of channels
            fprintf(fid,'%3d:%6d ',nc*nv+2*32*nvMax,ALLEEG.data(nc,249+nv,i));
        end
    end
    fprintf(fid,'\n');
end
% close the file
fclose(fid);

%% VERSION FOR DOWNSAMPLED TRIALS

sz = size(ALLEEG.event,2);
for i=1:1:sz % loop over all events
    fprintf(fid,'%3d: ',ALLEEG.event(1,i).type);
    for nv=1:1:nvMax % loop over number of used vectors
        for nc=1:1:30
            fprintf(fid,'%3d:%6d ',nc*nv,ALLEEG.data(nc,75+nv,i));
        end
        for nc=1:1:30 % loop over number of channels
            fprintf(fid,'%3d:%6d ',nc*nv+30*nvMax,ALLEEG.data(nc,100+nv,i));
        end
        for nc=1:1:30 % loop over number of channels
            fprintf(fid,'%3d:%6d ',nc*nv+2*30*nvMax,ALLEEG.data(nc,126+nv,i));
        end
    end
    fprintf(fid,'\n');
end
% close the file
fclose(fid);

% with SVM file
sz = size(ALLEEG.event,2);
% SVM = zeros(sz,nvMax*32+1);
% for i=1:1:sz % loop over all events
%     SVM(i,1) = ALLEEG.event(1,i).type;
%     for nv=1:1:nvMax % loop over number of used vectors
%         for nc=1:1:32 % loop over number of channels
%             SVM(i, nc*nv+1) = ALLEEG.data(nc,249+nv,i);
%         end
%     end
% end
%
% save 'sub131.m' SVM;

```

A.3 Derivatives

```

[ALLEEG EEG CURRENTSET ALLCOM] = eeglab;
FQ = 15;

% ***** 1 *****
EEG = pop_loadset( 'allev1.set');%; '/nfs/fen/scratch1/bernier/old/');
[ALLEEG EEG CURRENTSET] = eeg_store(ALLEEG, EEG);
EEG = pop_resample( EEG, FQ);
[ALLEEG EEG CURRENTSET] = pop_newset(ALLEEG, EEG, CURRENTSET, 'setname', 'All Subjects Event 1 resampled',
'save', 'allev1x');

pop_comperp( ALLEEG, 1, 2,[], 'addavg', 'off', 'addstd', 'off', 'addall', 'on', 'subavg', 'on', 'diffavg',
'on', 'diffstd', 'off', 'chans',[1:30] , 'tplotopt',{ 'ydir',-1, 'title', 'EVENT 1'});
%ans(1,1);
Blubb1 = ans((1:30),:);
SZ = EEG.pnts
X = EEG.times(1:(SZ-2))
%figure(1), plottopo(Blubb1);
% compute Derivative *****
Blubb1a = diff(Blubb1,1,2);
%figure(11), plottopo(Blubb1a);
Blubb1b = diff(Blubb1,2,2);
%figure(12), plottopo(Blubb1b);

ALLEEG = pop_delset( ALLEEG, [1:2] );
EEG = eeg_retrieve(ALLEEG,1); CURRENTSET = 1;

% ***** 2 *****
EEG = pop_loadset( 'allev2.set');%; '/nfs/fen/scratch1/bernier/old/');
[ALLEEG EEG CURRENTSET] = eeg_store(ALLEEG, EEG);
EEG = pop_resample( EEG, FQ);
[ALLEEG EEG CURRENTSET] = pop_newset(ALLEEG, EEG, CURRENTSET, 'setname', 'All Subjects Event 2 resampled',
'save', 'allev2x');

pop_comperp( ALLEEG, 1, 2,[], 'addavg', 'off', 'addstd', 'off', 'addall', 'on', 'subavg', 'on', 'diffavg',
'on', 'diffstd', 'off', 'chans',[1:30] , 'tplotopt',{ 'ydir',-1, 'title', 'EVENT 2'});
%ans(1,1);
Blubb2 = ans((1:30),:);
%figure(2), plottopo(Blubb2);
% compute Derivative *****
Blubb2a = diff(Blubb2,1,2);
%figure(21), plottopo(Blubb2a);
Blubb2b = diff(Blubb2,2,2);
%figure(22), plottopo(Blubb2b);

ALLEEG = pop_delset( ALLEEG, [1:2] );
EEG = eeg_retrieve(ALLEEG,1); CURRENTSET = 1;

% ***** 3 *****
EEG = pop_loadset( 'allev3.set');%;%; '/nfs/fen/scratch1/bernier/old/');
[ALLEEG EEG CURRENTSET] = eeg_store(ALLEEG, EEG);
EEG = pop_resample( EEG, FQ);
[ALLEEG EEG CURRENTSET] = pop_newset(ALLEEG, EEG, CURRENTSET, 'setname', 'All Subjects Event 3 resampled',
'save', 'allev3x');

pop_comperp( ALLEEG, 1, 2,[], 'addavg', 'off', 'addstd', 'off', 'addall', 'on', 'subavg', 'on', 'diffavg',
'on', 'diffstd', 'off', 'chans',[1:30] , 'tplotopt',{ 'ydir',-1, 'title', 'EVENT 3'});
%ans(1,1);
Blubb3 = ans((1:30),:);
%figure(3), plottopo(Blubb3);
% compute Derivative *****
Blubb3a = diff(Blubb3,1,2);
%figure(31), plottopo(Blubb3a);
Blubb3b = diff(Blubb3,2,2);
%figure(32), plottopo(Blubb3b);

```

```

ALLEEG = pop_delset( ALLEEG, [1:2] );
EEG = eeg_retrieve(ALLEEG,1); CURRENTSET = 1;

% ***** 4 *****
EEG = pop_loadset( 'allev4.set' ); %; %; '/nfs/fen/scratch1/bernier/old/');
[ALLEEG EEG CURRENTSET] = eeg_store(ALLEEG, EEG);
EEG = pop_resample( EEG, FQ);
[ALLEEG EEG CURRENTSET] = pop_newset(ALLEEG, EEG, CURRENTSET, 'setname', 'All Subjects Event 4 resampled',
'save', 'allev4x');

pop_comperp( ALLEEG, 1, 2, [], 'addavg', 'off', 'addstd', 'off', 'addall', 'on', 'subavg', 'on', 'diffavg',
'on', 'diffstd', 'off', 'chans', [1:30], 'tplotopt', { 'ydir', -1, 'title', 'EVENT 4' });
%ans(1,1);
Blubb4 = ans((1:30),:);
%figure(4), plottopo(Blubb4);
% compute Derivative *****
Blubb4a = diff(Blubb4,1,2);
%figure(41), plottopo(Blubb4a);
Blubb4b = diff(Blubb4,2,2);
%figure(42), plottopo(Blubb4b);

ALLEEG = pop_delset( ALLEEG, [1:2] );
EEG = eeg_retrieve(ALLEEG,1); CURRENTSET = 1;

% ***** 5 *****
EEG = pop_loadset( 'allev5.set' ); %; %; '/nfs/fen/scratch1/bernier/old/');
[ALLEEG EEG CURRENTSET] = eeg_store(ALLEEG, EEG);
EEG = pop_resample( EEG, FQ);
[ALLEEG EEG CURRENTSET] = pop_newset(ALLEEG, EEG, CURRENTSET, 'setname', 'All Subjects Event 5 resampled',
'save', 'allev5x');

pop_comperp( ALLEEG, 1, 2, [], 'addavg', 'off', 'addstd', 'off', 'addall', 'on', 'subavg', 'on', 'diffavg',
'on', 'diffstd', 'off', 'chans', [1:30], 'tplotopt', { 'ydir', -1, 'title', 'EVENT 5' });
%ans(1,1);
Blubb5 = ans((1:30),:);
%figure(5), plottopo(Blubb5);
% compute Derivative *****
Blubb5a = diff(Blubb5,1,2);
%figure(51), plottopo(Blubb5a);
Blubb5b = diff(Blubb5,2,2);
%figure(52), plottopo(Blubb5b);

ALLEEG = pop_delset( ALLEEG, [1:2] );
EEG = eeg_retrieve(ALLEEG,1); CURRENTSET = 1;

% ***** 6 *****
EEG = pop_loadset( 'allev6.set' ); %; %; '/nfs/fen/scratch1/bernier/old/');
[ALLEEG EEG CURRENTSET] = eeg_store(ALLEEG, EEG);
EEG = pop_resample( EEG, FQ);
[ALLEEG EEG CURRENTSET] = pop_newset(ALLEEG, EEG, CURRENTSET, 'setname', 'All Subjects Event 6 resampled',
'save', 'allev6x');

pop_comperp( ALLEEG, 1, 2, [], 'addavg', 'off', 'addstd', 'off', 'addall', 'on', 'subavg', 'on', 'diffavg',
'on', 'diffstd', 'off', 'chans', [1:30], 'tplotopt', { 'ydir', -1, 'title', 'EVENT 6' });
%ans(1,1);
Blubb6 = ans((1:30),:);
%figure(6), plottopo(Blubb6);
% compute Derivative *****
Blubb6a = diff(Blubb6,1,2);
%figure(61), plottopo(Blubb6a);
Blubb6b = diff(Blubb6,2,2);
%figure(62), plottopo(Blubb6b);

```

```

ALLEEG = pop_delset( ALLEEG, [1:2] );
EEG = eeg_retrieve(ALLEEG,1); CURRENTSET = 1;

% ***** 7 *****
EEG = pop_loadset( 'allev7.set');%;%, '/nfs/fen/scratch1/bernier/old/');
[ALLEEG EEG CURRENTSET] = eeg_store(ALLEEG, EEG);
EEG = pop_resample( EEG, FQ);
[ALLEEG EEG CURRENTSET] = pop_newset(ALLEEG, EEG, CURRENTSET, 'setname', 'All Subjects Event 7 resampled',
'save', 'allev7x');

pop_comperp( ALLEEG, 1, 2,[], 'addavg', 'off', 'addstd', 'off', 'addall', 'on', 'subavg', 'on', 'diffavg',
'on', 'diffstd', 'off', 'chans',[1:30] , 'tplotopt',{ 'ydir',-1, 'title', 'EVENT 7'});
%ans(1,1);
Blubb7 = ans((1:30),:);
%figure(9) = plot3(X, Blubb7(:,1), Blubb7(1,:));
%figure(7), plottopo(Blubb7);
% compute Derivative *****
Blubb7a = diff(Blubb7,1,2);
% %figure(71), plottopo(Blubb7a);
Blubb7b = diff(Blubb7,2,2);
% %figure(72), plottopo(Blubb7b);

ALLEEG = pop_delset( ALLEEG, [1:2] );
EEG = eeg_retrieve(ALLEEG,1); CURRENTSET = 1;

% ***** 8 *****
EEG = pop_loadset( 'allev8.set');%;%, '/nfs/fen/scratch1/bernier/old/');
[ALLEEG EEG CURRENTSET] = eeg_store(ALLEEG, EEG);
EEG = pop_resample( EEG, FQ);
[ALLEEG EEG CURRENTSET] = pop_newset(ALLEEG, EEG, CURRENTSET, 'setname', 'All Subjects Event 8 resampled',
'save', 'allev8x');

pop_comperp( ALLEEG, 1, 2,[], 'addavg', 'off', 'addstd', 'off', 'addall', 'on', 'subavg', 'on', 'diffavg',
'on', 'diffstd', 'off', 'chans',[1:30] , 'tplotopt',{ 'ydir',-1, 'title', 'EVENT 8'});
%ans(1,1);
Blubb8 = ans((1:30),:);
%figure(8), plottopo(Blubb8);
% compute Derivative *****
Blubb8a = diff(Blubb8,1,2);
%figure(81), plottopo(Blubb8a);
Blubb8b = diff(Blubb8,2,2);
%figure(82), plottopo(Blubb8b);

ALLEEG = pop_delset( ALLEEG, [1:2] );
EEG = eeg_retrieve(ALLEEG,1); CURRENTSET = 1;

% ***** 9 *****
EEG = pop_loadset( 'allev9.set');%;%;%, '/nfs/fen/scratch1/bernier/old/');
[ALLEEG EEG CURRENTSET] = eeg_store(ALLEEG, EEG);
EEG = pop_resample( EEG, FQ);
[ALLEEG EEG CURRENTSET] = pop_newset(ALLEEG, EEG, CURRENTSET, 'setname', 'All Subjects Event 9 resampled',
'save', 'allev9x');

pop_comperp( ALLEEG, 1, 2,[], 'addavg', 'off', 'addstd', 'off', 'addall', 'on', 'subavg', 'on', 'diffavg',
'on', 'diffstd', 'off', 'chans',[1:30] , 'tplotopt',{ 'ydir',-1, 'title', 'EVENT 9'});
%ans(1,1);
Blubb9 = ans((1:30),:);
%figure(9), plottopo(Blubb9);
% compute Derivative *****
Blubb9a = diff(Blubb9,1,2);
%figure(91), plottopo(Blubb9a);
Blubb9b = diff(Blubb9,2,2);
%figure(92), plottopo(Blubb9b);

ALLEEG = pop_delset( ALLEEG, [1:2] );
EEG = eeg_retrieve(ALLEEG,1); CURRENTSET = 1;

```

```

%% PLOT COMPARE FIGURES
for xx=1:30
    channelNr = xx;
    CNX = ['Channel ' int2str(channelNr)];
    CNXstore = ['channel' int2str(channelNr) '.png'];

    %X = 1:1:34;
    figure(xx+30),
    subplot(3,1,1); plot(X,Blubb1(channelNr,(1:(SZ-2))),X,Blubb2(channelNr,(1:(SZ-2))),X,
    Blubb3(channelNr,(1:(SZ-2))),X,Blubb4(channelNr,(1:(SZ-2))),X,Blubb5(channelNr,(1:(SZ-2))),X,
    Blubb6(channelNr,(1:(SZ-2))),X,Blubb7(channelNr,(1:(SZ-2))),X,Blubb8(channelNr,(1:(SZ-2))),X,
    Blubb9(channelNr,(1:(SZ-2))) );%, 'ydir','-1', 'title', 'normal');
    %figure(41),
    subplot(3,1,2); plot(X,Blubb1a(channelNr,(1:(SZ-2))),X,Blubb2a(channelNr,(1:(SZ-2))),X,
    Blubb3a(channelNr,(1:(SZ-2))),X,Blubb4a(channelNr,(1:(SZ-2))),X,Blubb5a(channelNr,(1:(SZ-2))),X,
    Blubb6a(channelNr,(1:(SZ-2))),X,Blubb7a(channelNr,(1:(SZ-2))),X,Blubb8a(channelNr,(1:(SZ-2))),X,
    Blubb9a(channelNr,(1:(SZ-2))) );%, 'ydir','-1', 'title', 'normal');
    %figure(42),
    subplot(3,1,3); plot(X,Blubb1b(channelNr,(1:(SZ-2))),X,Blubb2b(channelNr,(1:(SZ-2))),X,
    Blubb3b(channelNr,(1:(SZ-2))),X,Blubb4b(channelNr,(1:(SZ-2))),X,Blubb5b(channelNr,(1:(SZ-2))),X,
    Blubb6b(channelNr,(1:(SZ-2))),X,Blubb7b(channelNr,(1:(SZ-2))),X,Blubb8b(channelNr,(1:(SZ-2))),X,
    Blubb9b(channelNr,(1:(SZ-2))) );%, 'ydir','-1', 'title', 'normal');
    I = getframe(gcf);
    imwrite(I.cdata, CNXstore);
    %print -dpng CNXstore;
end

```

A.4 Performance Measurement

```

Perf = [0.960 0.850 0.750 0.680 0.615 0.565 0.495 0.450;
        0.965 0.885 0.815 0.760 0.720 0.665 0.600 0.555;
        0.970 0.915 0.860 0.785 0.720 0.645 0.600 0.545;
        0 0 0 0 0 0 0 0;

        0 0 0 0 0 0 0 0;
        0 0 0 0 0 0 0 0;
        0 0 0 0 0 0 0 0;
        0 0 0 0 0 0 0 0;

        0 0 0 0 0 0 0 0;
        0 0 0 0 0 0 0 0;
        0 0 0 0 0 0 0 0;
        0 0 0 0 0 0 0 0];%

for n=1:8
    Perf(4,n) = (Perf(1,n)+Perf(2,n)+Perf(3,n)) /3;
end

Rep = [32 81 64 64 125 36 49 64];
Rep = Rep/32;

for i=1:4
    for j=1:8
        Perf(i+4,j) = log2(j+1) + Perf(i,j)*log2(Perf(i,j)) + (1-Perf(i,j))*log2((1-Perf(i,j))/(j+1-1));
    end
end
Perf

```

```

x = 2:1:9;
y1 = Perf(1:3,1:8);
y2 = Perf(5:7,1:8);
y3 = Perf(4,1:8)*100;
y4 = Perf(8,1:8);

figure(1),
[AX,H1,H2] = plotyy(x,y3,x,y4, 'plot');%bval
set(get(AX(1),'Ylabel'),'String','Classification Results [% correct]');
set(AX(1),'YMinorTick','on');
set(get(AX(2),'Ylabel'),'String','B values');

xlabel('Number of Targets');
set(H1,'LineStyle','-', 'LineWidth',2);
set(H2,'LineStyle','--','LineWidth',2);

figure(2),
[AX,H3,H4] = plotyy(x,y1,x,y2, 'plot');%bval
set(get(AX(1),'Ylabel'),'String','Classification Results [% correct]');
set(AX(1),'YMinorTick','on');
set(get(AX(2),'Ylabel'),'String','B values');

xlabel('Number of Targets');
set(H3,'LineStyle','-', 'LineWidth',2);
set(H4,'LineStyle','--','LineWidth',2);

```

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