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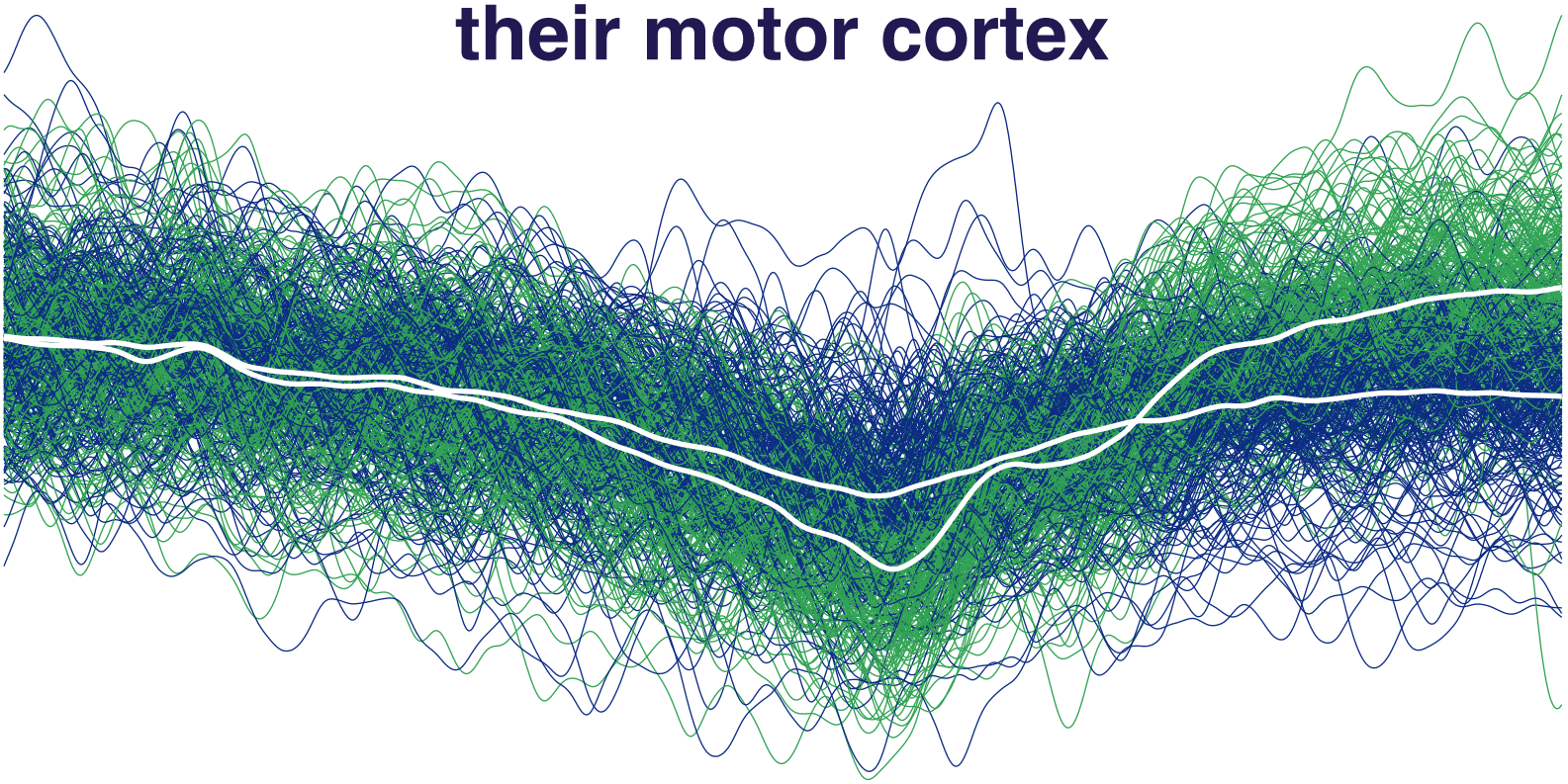
Online detection and classification of movement-related cortical potentials on healthy volunteers and patients with a stroke affecting their motor cortex



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"Online detection and classification of movement-related cortical potentials on healthy volunteers and patients with a stroke affecting their motor cortex"

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Preface

This project was made by Rasmus Wiberg Nedergaard as a master thesis on the 10th semester of Biomedical Engineering and Informatics at Aalborg University.
The report is based on the theme "Applied biomedical engineering and informatics" and written in the period from Feburary 1^{st} 2014 until June 3^{rd} 2014. The content of this report is aimed at fellow students and researchers with interest in the field of brain-computer interface, neural plasticity and rehabilitation.

Reading guide

References to literature are made using the Harvard method, in which the authors last name and the year of publishing are placed in brackets, [Last name, Year] or when directly referenced, Last name [Year]. When an in-text reference is given, the reference can subsequently be found in the References, listed in alphabetical order.

Figures and tables are numbered sequentially according to their appearance in the text and the chapter in which they are placed. For example, a figure numbered as 3.2, is the second figure in chapter 3. A description of the figure or table contents is located below the object along with a reference to the source. If no reference is given, the figure or table belongs to the authors of this report.

Abstract

Stroke is the the third most common cause of death and the main cause of disabilities acquired in adults in high-income countries. While recovering from a stroke early mobilisation is an important factor in recovery as well as continuous maintenance of physical conditions for the rest of the patients life. To overcome the disability, several rehabilitation techniques have been proposed, among these is a relatively novel technique: brain computer interface (BCI) this technique either translates brain features into actions or translates features to activate a device. BCI systems have been designed to detect movement related cortical potentials (MRCP) in real time, and other systems have detected not only the onset of movements, but also detected the intended movement speed and force. None of these systems however has investigated how fast BCI control can be learned, they have also not investigated the robustness of the BCI systems over time using MRCP as a control signal.

The aim of this project was to investigate changes in performance over time of a BCI systems designed to detect MRCPs and the intended speed of the movement. It was believed that MRCP could be used as a control signal from the first session, and that the performance of the system would not change significantly during a longitudinal experimental design due to the simplicity of the movements performed.
7 healthy volunteers were used to test what the effect of training of a BCI system over time was and if the MRCP of healthy subjects for non complex dorsiflexions changed over time. The BCI was also tested for one session on 6 patients suffering a stroke affecting their motor cortex to see how the BCI system performed detecting differences in speed based on MRCPs for stroke patients. This was done to test if the BCI could be used for rehabilitation from the first session. A BCI designed to detect MRCPs and classify them based on movement speed, either fast movements 0.5 seconds or slow movements 3 seconds was tested during two sessions for four weeks and a for week break followed by a control session. Three different training scenarios were tested to investigate if using data from more than one session would increase the performance of the BCI. The first test focused on the effects of only using previously recorded data, no training of the subject that session prior to the test. The second test only used training data recorded during that session for a more current detector and classifier, but with a smaller amount of data. The third test used all available data and trained the subject in the different types of movements prior to testing, this was believed to have the highest accuracies, but also the most time consuming.
The mean detection, classification, and system performance for the three different test were 79 ± 1 %, 56 ± 1 %, and 45 ± 1 % respectively. A single session was performed with 6 patients to test how well the BCI system worked for patients. The mean detection, classification, and system performance for the three different test were 88 ± 12 %, 57 ± 6 %, and 50 ± 9 % respectively.
These findings suggest it is possible to use a BCI with very little training and increase performance by using all available data. The findings also show no increase or decrease in performance of the system over time, the control session showed that it was not necessary to train the subject after a four week break if enough prior training data was available. The session with the patients showed detection accuracies that can most likely be used help patients rehabilitate by combining the online system with e.g. functional electrical stiulation.

Resumè

Slagtilfælde er den tredje hyppigste dødsårsag og den største årsag til handicap erhvervet af voksne i højindkomstlande. Under genoptræningen fra et slagtilfælde er tidlig mobilisering en vigtig faktor i bedringen samt løbende vedligeholdelse af fysisk form resten af patientens liv. For at komme over handicap erhvervet som følge af et slagtilfælde er flere rehabilitering teknikker blevet foreslået, blandt disse er en forholdsvis ny teknik: brain computer interface (BCI) denne teknik kan enten oversætte hjernesignaler til handlinger eller oversætter signaler til aktivering en ekstern enhed. BCI systemer er blevet designet til at genkende movement relaterede cortical potentials (MRCP) i realtid, andre systemer har registreret ikke kun begyndelsen af en bevægelse, men også den ønskede bevægelses hastighed og kraft. Ingen af disse systemer har dog undersøgt, hvor hurtigt BCI kontrol kan læres, og de har heller ikke undersøgt hvor robuste BCI systemer, som bruger MRCP som et styresignal er over tid.

Formålet med dette projekt var at undersøge ændringer i ydeevne over tid for et BCI system designet til at detektere MRCPer og den ønskede hastighed af bevægelsen. Det påtænkes, at MRCP kan anvendes som et styresignal fra den første træningsgang, og at ydeevnen ikke vil ændre sig væsentligt i løbet af et longitudinelt studie på grund af enkelheden af de bevægelser, der udføres.
7 raske frivillige blev brugt til at teste, hvad effekten af træning af et BCI-system over tid var, og om MRCPer fra raske forsøgspersoner for ikke komplekse dorsiflexioner ændre sig over tid. BCI systemet blev også testet en træningsgang på 6 patienter, som har haft et slagtilfælde der påvirker deres motorcortex for at se hvordan BCI-systemet kunne detektere forskelle i hastighed baseret på MRCPer for patienter med slagtilfælde. Dette blev gjort for at undersøge, om BCI kan anvendes til genoptræning fra den første træningsgang.
Et BCI designet til at detektere MRCPer og klassificere dem baseret på bevægelses hastigheder, enten hurtige bevægelser på 0,5 sekunder eller langsomme bevægelser på tre sekunder blev undersøgt i løbet af to træningsgange pr. uge i fire uger og en fire ugers pause efterfulgt af en kontrol træning. Tre forskellige træningsscenarier blev testede for at undersøge om brug af data fra mere end én session vil øge ydeevnen af BCI systemet. Den første test fokuserede på kun at bruge tidligere optaget data og ingen træning af forsøgspersonen inden testen. Den anden test brugt kun træningsdata optaget i løbet af den session for en mere aktuel detektion og klassificeringen, men med en mindre mængde data. Den tredje test, som anvender al tilgængelig data og træner forsøgspersonen i de forskellige typer af bevægelser inden testen blev udført. Dette menes at have den højeste nøjagtighed, men også den mest tidskrævende.
Den gennemsnitlige detektion, klassifikation, og systemets ydeevne til de tre forskellige træningsscenarier var hhv. 79 ± 1 % , 56 ± 1 % og 45 ± 1 %. En enkelt træningsgang blev udført med 6 patienter til at undersøge hvor godt BCI fungerede for patienter. Den gennemsnitlige detektion, klassifikation, og systemets ydeevne til de tre forskellige test var hhv. 88 ± 12 % , 57 ± 6 % , og 50 ± 9 %.
Disse resultater tyder på, det er muligt at bruge et BCI med meget lidt træning og øge ydeevnen af systemet ved at bruge al tilgængelige data. Resultaterne viser også at der ikke er var nogen stigning eller et fald i systemets ydeevne over tid, kontrolsessionen viste, at det ikke var nødvendigt at træne forsøgspersonen efter en fire ugers pause, hvis tilstrækkelig forudgående træningsdata var tilstede. Sessionen med patienter viste detektionsnøjagtigheder, som sandsynligvis kan bruges til hjælpe patienter med rehabilitering ved at kombinere et online BCI system med fx funktionel elektrisk stimulation.

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Part I

Problem Analysis

1

Introduction

The third most common cause of death and the main cause of disabilities acquired in adult humans in high-income countries is stroke. The disabilities acquired after stroke can affect the patients in various areas and to different degrees [Langhorne et al., 2009]. The incidence of stroke was in 2009 9 million, and the prevalence was 30.7 million [Fischer and Norrving, 2011]. Stroke can bring with it many limitations and restrictions in mobility, communicating, and self care. These limitations and restrictions are a strain on the patient and next of kin. Because of this they should be sought to be lowered as much as possible. This can be done with therapy and rehabilitation.

1.1 Treatment strategies of stroke

Depending which areas of the brain and subsequently which areas of the body gets affected by a stroke different rehabilitation methods might have different results. Common for the rehabilitation methods for motor recovery is that it is important to start early mobilisation, studies have shown that delayed result in poor outcomes in rats [Nudo, 2006b]. Brust [2007] report that the major recoveries occur between three and six months after a stroke. Different treatment strategies target different affected areas and mechanisms of recovery. Some of these treatment strategies are: Biofeedback, constraint induced movement therapy, electrostimulation, and physiotherapy [Langhorne et al., 2009].
Biofeedback and constraint induced movement therapy both focus on helping the patient increase control of their affected limbs. This is done by either adding a new kind of feedback to help control limb or postural control using for example EMG as a feedback [Langhorne et al., 2009]. Constraining the less affected or healthy side of the body can force the affected side to compensate, this has been shown to improve motor function and quality of life [Rabadi, 2011]. Electrostimulation can be used to either gain sensory feedback, much like biofeedback, the difference here is that electrostimulation can also be used through the bodies own nervous system and electrostimulation can help patients reuse under-stimulated muscles more efficiently [Pomeroy et al., 2006]. Physiotherapy as a whole deals with rehabilitation of injuries, physiotherapy as a tool can also be used in recovery of motor function due to stroke. Pollock et al. [2006] has researched different trials of physiotherapeutical interventions, they found no significant differences between different kinds of intervention, meaning no single kind of physiotherapy is better than others, they are however all significantly better than no treatment.
Common for these treatment strategies are the fact that it is important for the patient to keep exercising possibly for the rest of their lives. Figure 1.1 shows an illustration of a hypothetical rehabilitation scenario, the dotted line at the end shows the importance of the patient continuously training years after the stroke.

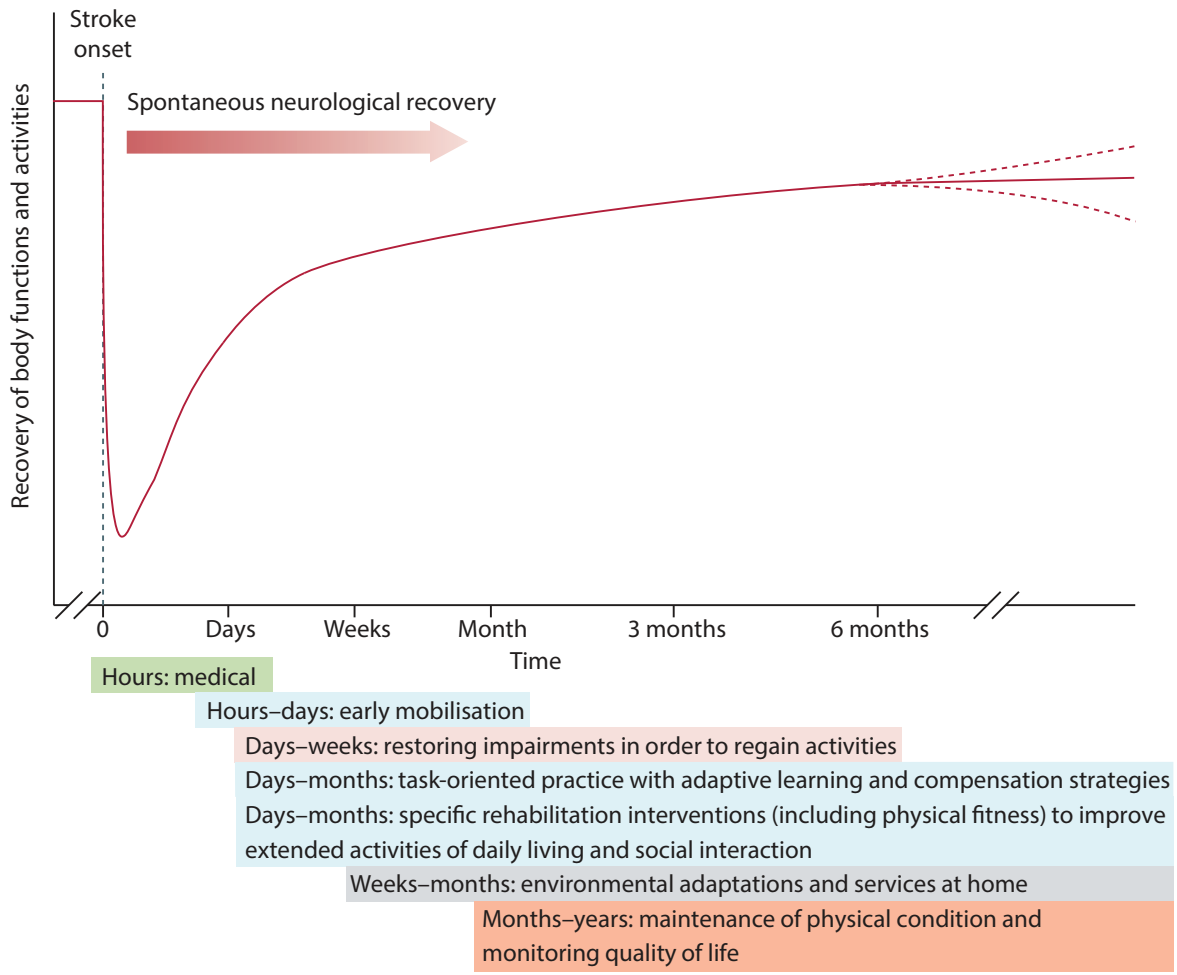

Figure 1.1: A illustration of the different steps and the time it takes to recover from a stroke. The fast recovery of functions in the beginng is a result of natural neurological recovery and early mobilisation. After a period of six months and further the level of motor function and recovery depends on the patients efford level. The illustration is from Langhorne et al. [2011]

As Figure 1.1 suggests rehabilitation can go both ways, depending on the effort level of the subject. Some of the important factors of motor recovery is sticking to the training potentially for the rest of the persons life. An other important factor is regaining the lost link between the brain and the body this is done using adaptation mechanisms in the recovery of motor function. One of the key mechanisms is the plasticity of the brain [Bliss and Cooke, 2011]. This is the brains way to respond to environmental demands or changes. Plasticity occurs by changing the synaptic connections by either strengthening, weakening or adding synaptic connections [Nudo, 2006a]. One of the methods of changing plasticity using a stroke rehabilitation method is using a brain computer interface (BCI). By giving the patient a different feedback dependant of their brain signals it is possible to try and normalise the patients brain signals again, or use the BCI to assist motor function increasing plasticity of the central nervous system [Daly and Wolpaw, 2008]. Another way of increasing plasticity of the brain and thereby improve movement, this can be achieved by extracting movement intent and providing a matching sensory feedback using haptic feedback [Grosse-Wentrup et al., 2011].

2

Brain computer interface

In 2000 Wolpaw et al. [2000] defined the term BCI to be: *"A communication system that does not depend on the brain's normal output pathways of peripheral nerves and muscles."* In 2002 Wolpaw et al. [2002] defined a brain computer interface (BCI) to be a system that:

"Changes electrophysiological signals from mere reflections of central nervous system (CNS) activity into the intended products of that activity: messages and commands that act on the world. It changes a signal such as an EEG rhythm or a neuronal firing rate from a reflection of brain function into the end product of that function: an output that, like output in conventional neuromuscular channels, accomplishes the persons intent."

BCI's can furthermore be divided into two subcategories synchronous or asynchronous systems. An asynchronous BCI identifies brain patterns without any time constraints to the user. A synchronous system only looks for brain patterns in specific time slots, in these systems the computer controls the pace of the user. Asynchronous systems are more suitable for real-world applications, they are however much more complicated to control since the BCI needs to not only classify intents to control the device, it also needs to detect non-control state in which the user might perform other actions or perhaps daydreaming [Leeb et al., 2007].
Both synchronous or asynchronous systems can be used in an online or offline capacity. The online or offline part of BCI systems relate to the design of the system, online system are predominantly designed for real world situations in which a patient is intended to use the system [Hwang et al., 2013].

2.1 Outlines of a BCI system

A BCI system will generally consist of a set of steps to end up being able to output demands to specific device, these steps are:

- Signal acquisition and preprocessing
- Feature extraction
- Classification
- Device commands

An illustration of a general BCI with the steps needed to produce an output are shown in Figure 2.1

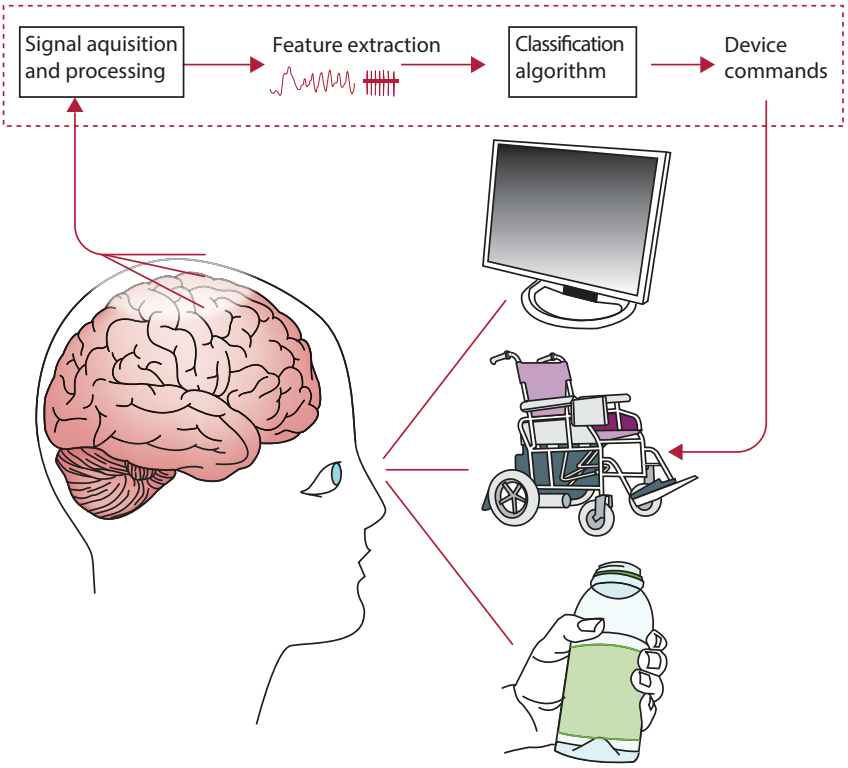

Figure 2.1: An illustration of a general BCI showing the three steps signal acquisition and preprocessing, feature extraction, and classification needed to produce device commands to different devices. The figure is adapted from Daly and Wolpaw [2008].

2.1.1 Signal acquisition

Acquiring signals from the brain can be obtained from a number of different signal modalities. Signals can be recorded either non-invasively or invasively, and the signals recorded can be either evoked or spontaneous [Wolpaw et al., 2002]. Some of the imaging modalities that can be used to record signals from the brain today are functional magnetic resonance imaging (fMRI), positron emission tomography (PET), and functional near-infrared spectroscopy (fNIR). These work using magnetical field- , radioactive isotope-, and near-infrared imaging respectively. These imaging techniques have very complex technical requirements, are expensive, and have limited real-time capabilities [Daly and Wolpaw, 2008]. A different way of recording brain signals is using electrical signals, these can be recorded invasively and non-invasively with different advantages and disadvantages. EEG is non-invasive and has a high temporal resolution, but a low spatial resolution. ECoG electrodes are invasive, and placed on top of the cortex under the scull, they have a high spatial resolution as well, the location of the different EEG electrodes can be seen in Figure 2.2.
Between 2007 and 2011 the most used modality was EEG, it was used in 50% of the published BCI articles. This was done for its low cost, non-invasiveness, and high temporal resolution Hwang et al. [2013].

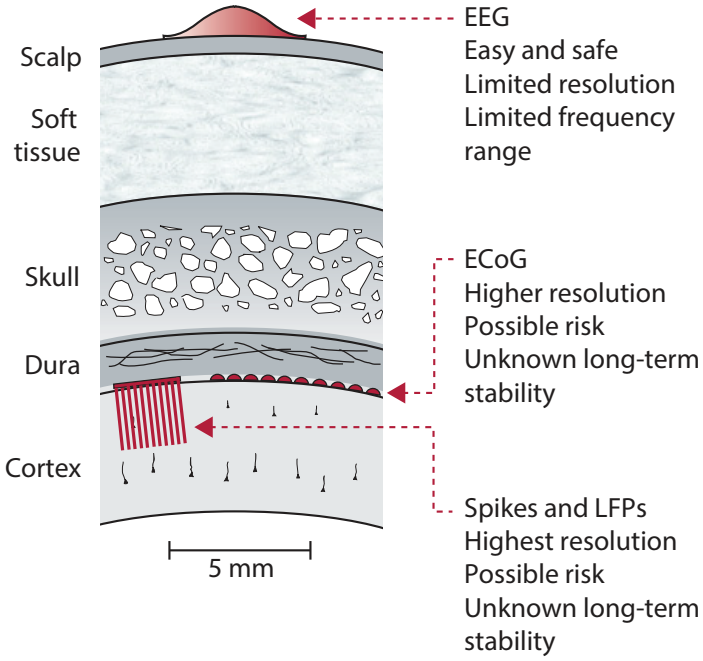

Figure 2.2: Location of three different EEG recording electrodes. The figure is from Daly and Wolpaw [2008]

2.1.2 Preprocessing

Preprocessing the signals is done to increase the signal to noise ratio (SNR), the noises introduced to the signal intended to control the BCI are often other biological signals like muscle or eye movements, EEG signals not involved in performing movements, and 50 or 60 Hz noise. Muscle signals (EMG) occurs above 30 Hz and eye movements (EOG) are maximum below 5 Hz. To improve the SNR different methods have been applied, some of these are applying low, high, or bandpass filters [Fatourechi et al., 2007]. These might be able to remove EMG, EEG, and 50 or 60 Hz noise. Spatial filters may help compensating for the poor spatial resolution from the distortion from volume conduction. Some of the spatial filters used are ear referencing, common average reference (CAR), small Laplacian filters, and large Laplacian filters. Ear referencing and CAR work by selecting a common reference, either the ear or an average of all electrodes and subtracting them form the recorded signal. Small and large Laplacian filters work by averaging an area of electrodes, emphasising the centre electrode in a cross grid. This type of filter accentuates local activity to the selected electrode and reduces diffuse activity [McFarland et al., 1997].

2.1.3 Feature extraction

Feature extraction is extracting features from the desired control signal seeking to minimise the amount of data needed to be processed. Features used for BCI control can be in either the time or frequency domain [Wolpaw et al., 2002]. Examples of time domain features can be amplitudes of evoked potentials or spontaneous potentials, or firing rate of individual cortical neurones [Daly and Wolpaw, 2008]. Features in the frequency domain could be amplitudes of the different frequency bands of the EEG [Wolpaw et al., 2002].
In order to get good features the features need to be distinguishable between classes and invariant over time. Adding more features creates a feature space containing multiple descriptions of the control signal in tern aiding the description of the signal [Duda et al., 2001]. It is important to keep the feature space as low as possible, but still able to define differences between the classes to avoid the "curse of dimensionality", this states that increasing dimensionality decreases the predictive power of the system [Hughes, 1968].

2.1.4 Classification

Finding the correct classifiers and features to run the classification algorithm is of great importance. The features used often have a set of critical properties [Lotte et al., 2007]:

- Noise and outliers
- Features often have high dimensionality
- Non-stationarity
- Small training sets

Lotte et al. [2007] also describes a number of different classification algorithms designed for EEG and their usefulness in terms of performance for specific BCI. A classifier should not only be adapted to the features, but also the user Wolpaw et al. [2002] describes three different levels in which the classification algorithm should adapt to the subject.

- The classifier must adapt to the users signal features
- It must also adjust itself periodically to reduce the impact of spontaneous variation like fatigue
- The system needs to learn the users signals, but the user also needs to learn the outputs of the BCI. The user needs to adapt to a new way of using brain signals like any other new kind of movement.

Another important aspect of a classifier is its ability to generalise data. Creating too complicated decision boundaries for a set of features will tune the classifier to the specific data samples and possible hide the underlying characteristics of a model [Duda et al., 2001]. Complicated decision boundaries might separate the training data well, but fail to properly classify new data obtained from the control signal.

Some of the classifiers used today in BCI systems are: Linear discrimination analysis (LDA), support vector machines (SVM), neural networks (NN) and k nearest neighbours (kNN). LDA and SVM both seek to create a hyperplane to separate data into different classes. NN have a input layer, a hidden layer with a number of nodes that can be strengthened or weakened and then in tern approximate non-linear functions based on training, the classified data the reaches the output layer. KNN classifies a new object based on a majority vote by its neighbouring objects, the new object is then classified based on the objects around it.

2.1.5 BCI performance

Based on the type of BCI different measures of performance can be applied. Thompson et al. [2013] has performed a review of the performance measures used in BCI communication, some of these are: Accuracy, information transfer rate, true and false positives, and accuracy and speed. In BCI systems designed to detect movement intent some of the performance measures have been: Detection or true positive rate, detection latency, classification, and system performance [Niazi et al., 2011], [Niazi et al., 2012] and [Jochumsen et al., 2013]. System performance was defined as correct detection and classification, and correct detection and incorrect classification [Jochumsen et al., 2013]. As described in Section 2.1.4 the classifier and the user needs to adapt to each other. This signifies that performance might change over time as the user gets more used to the system and the the system is able to use more data to classify from.

2.2 BCI in rehabilitation

Using BCI systems for motor adaptation, utilises mechanism that occur to rehabilitate the brain as a result of damage during a stroke, the mechanisms can be aided using different training strategies. Daly and Wolpaw [2008] describes two different strategies. Strategy 1 translates

brain features into actions, like cursor movement, using this action as feedback to over time train subjects to produce more normal brain signals. Strategy 2 uses features to activate a device, that assists in movements, the aim of this strategy is to gain a sensory feedback and then increase plasticity and achieve more normalised neuromuscular control. An illustration of the two strategies can be seen in Figure 2.3.

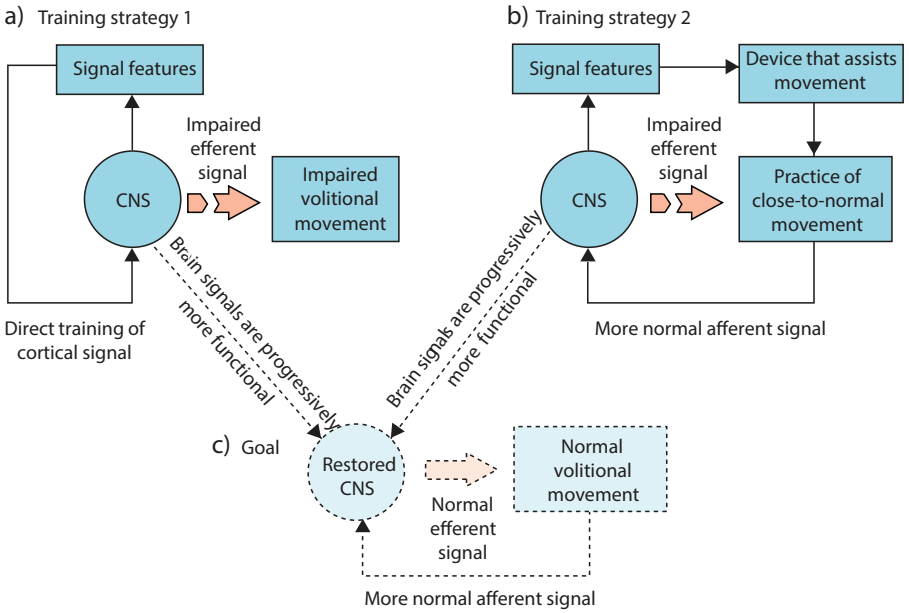

Figure 2.3: A description of two different training strategies. a) aims to prodice more normal brain signals over time by using recorded features to produce actions on a computer. b) aims to increase sensory feedback wich is believet to increase plasticity and achieving more normalised neuromuscular control, this is done by using recorded features to control a device, that in tern moves a body limb. The wished outcome of both training strategies is a resoration of the CNS (central nervous system) c). The figure is from [Daly and Wolpaw, 2008]

2.2.1 Inducing plasticity using BCI

One of the rehabilitation methods BCI can aid is using BCI's to induce neural plasticity, this has previously been suggested as a form of rehabilitation. The difficulties in doing so are finding neural mechanisms that can be used to increase plasticity [Grosse-Wentrup et al., 2011].
Mrachacz-Kersting et al. [2012] has shown an increase in plasticity when motor imagination was paired with precise electrical stimulations. These stimulations were timed to occur at the onset of motor execution to achieve maximum effect. The same effect has been achieved by Niazi et al. [2012] using an an asynchronous BCI system based on online motor imagination that triggered peripheral electrical stimulation. The mechanisms underlying these rehabilitation methods are associative or Hebbian, synaptic plasticity. Synaptic plasticity deals with the strengthening and weakening of synaptic connections in the brain, Hebbian plasticity might be used to treat diseases in the central nervous system [Bliss and Cooke, 2011]. Hebbian plasticity is believed to be the underlying mechanism in experience-dependent changes in the brain, it is associated with motor learning or relearning, this is important in neurorehabilitation [Buonomano and Merzenich, 1998]. Increases in plasticity occur when an intend to move is paired with a feedback from the sensory system of the body. The relation between feedback accuracy and neural plasticity has not yet been fully explored, but can be assumed high degree of feedback accuracy is crucial for inducing plasticity using BCI [Grosse-Wentrup et al., 2011]. Aiding this assumption Shaikhouni et al. [2013] reported the importance of improvement of control of a BCI system in sensory feedback matching the desired movement.
The type of tasks trained is also important, task variability in training sessions can help improve

performance in later sessions even though performances might be worse than compared to a set of repeated tasks. Contextual interference with random orders of trials and tasks also lead to better performance in later sessions and later on. These principals aid in the generalisation of new learned skills, this leads to improved performance not only in clinical settings, but also once the patient gets home improvements in activities of daily living [Krakauer, 2006].

3

Movement related cortical potentials

The movement related cortical potential (MRCP) is a low frequency negative potential that can be used as a control signal for BCI rehabilitation [Niazi et al., 2012] and [Xu et al., 2014b]. It is generated while planning and executing cued or self-paced voluntary movements, and is measurable by EEG. The MRCP can be measured in both real movements and imagined movements [do Nascimento et al., 2006].
The initial negative slope of the MRCP can be observed up to two seconds before a movement is executed, starting with a low frequency negative drop in EEG potential before a peak of maximum negativity occurring between the movement onset and 100 ms before [do Nascimento et al., 2006]. Self-paced movements and externally cued movements can be associated with partially different neural networks of the brain [Lu et al., 2012]. Because of this the mechanisms underlying the two different forms of movement are slightly different as well.

3.1 Elements and morphology of the MRCP

In self-paced movement the MRCP from its initial phase to the peak of maximum negativity is made up of two parts the bereitschaftspotential (BP) or readiness potential and the motor potential (MP) [Slobounov and Ray, 1998]. The BP is the initial part of the cortical potential, it is a slow negative change in amplitude. The magnitude and length of the BP can be influenced by speed and precision of the movement, force exerted during the movement, pace of movements, and wether or not it is a skilled movement [Shibasaki and Hallett, 2006].
The MP of a self-paced movement is defined by a increase if the gradient of the negative slope starting about 400 ms before movement onset till the onset of movement[Shibasaki et al., 1980]. The MP is affected by the complexity, precision, and discreteness of the movement [Shibasaki and Hallett, 2006].
In externally cued movements the MRCP from beginning to peak of maximum negativity is divided into the early and late contingent negative variation (CNV). Since the CNV gets triggered by external cues it starts from the initial cue and ends at the cue to move. The early CNV represents sensory information from a warning or initial stimulus, the late CNV part of the potential represents motor readiness and preparatory activity [Lu et al., 2012]. When the timing between the cues are known and predictable the early CNV lasts 1-1.5 seconds after the initial cue, and the late CNV starts to develop about 1 second before the cue to move [Hamano et al., 1997].
After both an externally cued and self-paced movement a movement-monitoring potential occurs. This is a potential that starts after the onset of a movement, it occurs from the peak of maximum negativity and one second after. The movement-monitoring potential is affected by the force and speed asserted in a movement [Slobounov and Ray, 1998]. A temporal representation of a MRCP can be seen in Figure 3.1

Looking at changes over time very few longitudinal studies which investigate amplitude changes over time have been performed [Wright et al., 2011]. A couple of the ones that do suggest that the amplitudes of the MRCP increase as long as the performance of a given movement improves, this could be decrease in reaction time, when the performance of the movement plateaus the amplitudes of the MRCP decrease or remain the same [Taylor, 1978]. Lang et al. [1992] concludes

that changes in cortical activity reflect changes in motor control, meaning that the MRCP may reflect the amount of effort needed to plan and perform the task.

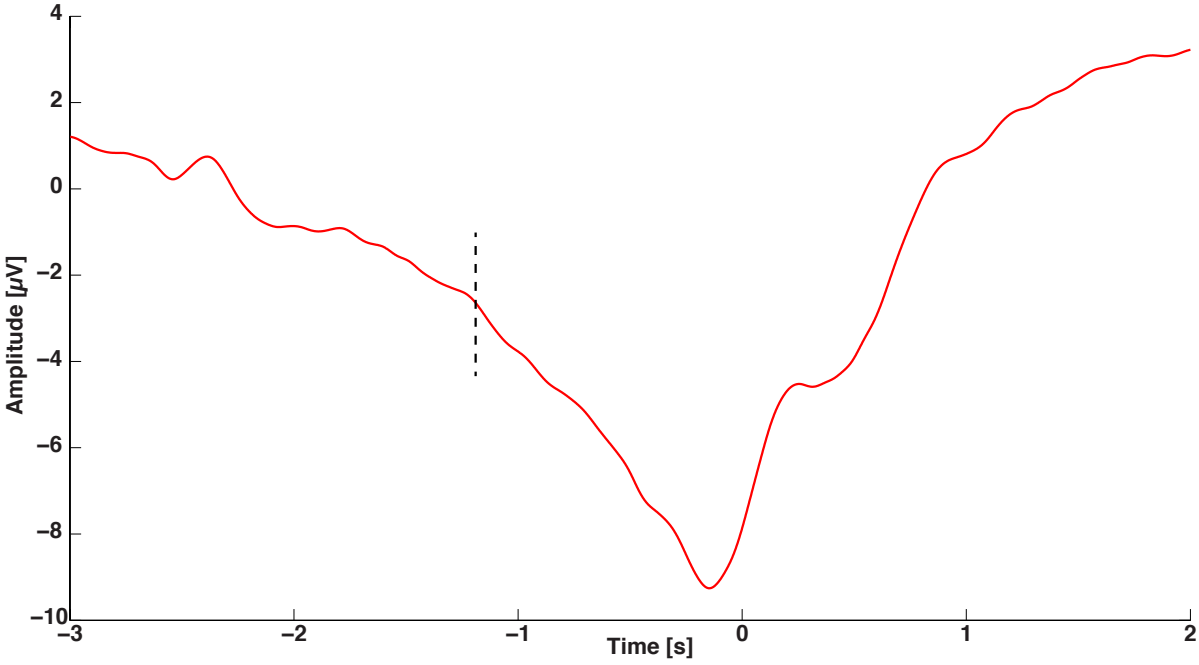

Figure 3.1: An example of a MRCP. The movement onset is at 0, the two phases before the peak of maximum negativity is shown by the dotted line and the movement-monitoring potential occurs after the peak of maximum negativity. The movement is an externally cued movement, it was initiated at time(-3) and the cue to move was given at time(0).

3.2 Neural generators of MRCP

If externally triggered movements are triggered by temporally predictable cues the early and late CNV, and BP and MP are mediated by largely common networks of cortical and subcortical regions [Nachev et al., 2008]. The cortical regions involved in early and late CNV at temporally predictable cues, and BP and MP consist of motor regions of the mesial frontal cortex including supplementary motor area (SMA), the dorsal premotor cortex and cingulate motor areas. The primary motor cortex, pre-SMA, dorsolateral prefrontal cortex and basal ganglia are are also likely to contribute to the generation of MRCPs [Cui and MacKinnon, 2009]. The BP and early CNV are both initiated in the SMA. The SMA participation is bilateral but contralaterally predominant meaning the BP and early CNV can both be detected on either hemisphere of the SMA but will be strongest on the side contralateral to the side that performs the movement [Shibasaki and Hallett, 2006]. The MP and late CNV are initiated in the M1 and premotor cortex contralatterally about 400 ms prior to the movement onset [Shibasaki and Hallett, 2006]. The location of the MP and late CNV potentials in M1 and the premotor cortex are somatotopically distributed according to the areas of the body intended to move [Neshige et al., 1988]. In addition to the M1 and premotor cortex the late CNV also has components related to the frontal cortex [Hultin et al., 1996].

The low frequency drop in cortical activity is believed to be a preparation of motor plans, the preparation consists of: adjustments of reflex excitability, synergist and antagonist muscle activity timed to occur at the same time, and postural adjustments. These preparations occur to minimise unintended deviations from the intended movement. The involvement of the premotor cortex and SMA is believed to occur because these areas of the brain mediate postural control and reflex, because of this these regions are well suited to mediate interactions between intended movements and preparational requirements [Cui and MacKinnon, 2009]. The CNV and BP are generated in the same areas of the brain but are not the same type of cortical potentials. The

CNV depends on sensory perception, attention, expectancy, and other factors where as the BP is dependant of motivation, self initiation, planning, preparation, and other factors [Cui et al., 2000].

3.3 Kinetics encoded in MRCPs

Looking at the kinetics of the MRCP do Nascimento et al. [2005] have looked at the temporal relationship between self-paced MRCPs and force in imagined and actual movements of the foot using EEG. They found statistically significant amplitude differences between low and high torque amplitudes for fast movements, they could also differentiate the BP, MP and MMP between different speeds of movement and torques, lastly they found that the differentiation of MRCPs had a ipsilateral nature in relation to the limb involved in the task. The complexity of the movement also affects the MRCP. Prior to complex movements the MRCP amplitudes are larger compared to simple movements[Cui et al., 2000].
Factors such as force or torque amplitude also affect the MRCP, increases in force yields increases in amplitude of the MRCP [Ray et al., 2000]. do Nascimento et al. [2005] found an increase in the readiness potential, and Slobounov and Ray [1998] found an increase in the MMP at higher forces.
Using wavelets and SVM for feature extraction and classification Gu et al. [2009a] investigated the possibility of differentiating movements using the MRCP during different speeds and torque. They found that it was easier to classify force for ballistic movement speeds than moderate movement speeds.

4

Aim

Patients suffering a stroke affecting their motor cortex will need to recover motor function by performing task specific training. Early mobilisation is an important factor in recovery as well as continuous maintenance of physical conditions for the rest of the patients life. One way of facilitating the recovery is using training strategies as described by Daly and Wolpaw [2008] these training strategies uses BCI systems to either translate brain features into actions or translating features to activate a device. Both of these training strategies aim to restore the CNS by gaining progressively more functional brain signals. BCI based recovery relies on changes in plasticity, an intended signal from the brain yields a feedback of either an action on a computer or activation of a device. Over time correct brain patterns will be potentiated and incorrect patterns resulting in incorrect movements will be depressed.
Using precise electrical stimulations timed to occur at the onset of motor execution has also been proven to increase plasticity of healthy subjects [Mrachacz-Kersting et al., 2012]. The cortical onset of motor execution can be extracted from the MRCP; using a BCI system designed to detect the features of the MRCP and time an electrical stimulation to occur at the onset of motor execution might also be used to increase plasticity. The MRCP is a potential generated during motor planning and motor execution, because of this training may not be needed by the subject to generate the potential. The morphology of the MRCP is affected by the complexity of the movement, so performing simple movements should not affect the MRCP in experiments over time.
BCI systems have been designed to detect MRCPs in real time Niazi et al. [2011], and other systems have detected not only the onset of movements, but also detected the intended movement speed and force Jochumsen et al. [2013]. None of these studies however have investigated the robustness of the BCI systems over time using MRCP as a control signal, they have also not investigated how fast BCI control can be learned.

The aim of this project is to investigate changes in performance over time of a BCI systems designed to detect MRCPs and the intended speed of the movement. It is believed that MRCP can be used as a control signal already from the first session, and that the performance of the system will not change significantly during a longitudinal experimental design due to the simplicity of the movement. The experiments will be performed on healthy subjects doing non complex fast and slow foot movements. It will also be investigated if it is possible to use MRCP as a control signal for BCI for patients in a single session with no prior training performing the same foot movements. The experiments will have the following goals:

- Healthy subjects:
  - What is the effect of training of a BCI system over time
  - Does the MRCP of healthy subjects for non complex movements change over time
- Patients with motor impairments due to a stroke
  - How does a BCI system perform detecting differences in speed based on MRCPs for stroke patients

Part II

Method

5

Subjects

5.1 Healthy subjects

seven healthy volunteers one female and six males age 25.7 ± 1.11 with no neurological disorders and no known disorders of their right foot or ankle were recruited. All the subjects gave their informed consent before participation.

5.2 Patients with motor impairments due to a stroke

Six patients suffering from a stroke two females and four males age 56 ± 12.7 attended a recording session. All the subjects gave their informed consent before participation.

Patient	Diagnosis	Affected side	Gender	Age	Days since event
1	Infarction	Right	Male	51	62
2	Infarction	Left	Male	38	36
3	Infarction	Right	Female	58	46
4	Infarction	Left	Female	59	35
5	Hemorrhage	Right	Male	54	58
6	Infarction	Right	Male	77	46

Table 5.1: A description of the six patients, their diagnosis which side is affected, gender, age, and days since their stroke

6

Recordings

Three kinds of recordings were made, EEG, EOG and force. The EEG and EOG recordings were to measure the MRCP. The force measurement was used to measure the maximum voluntary contraction during dorsiflexion of the foot, display and force exerted during training of the subject, and record force during testing.

6.1 EEG and EOG recording

The EEG recordings were performed using a EEG amplifier (Nuamps Express, Neuroscan) continuously from the scalp using a 32 channel Quick-Cap, Neuroscan. The sampling rate was 500 Hz, and the data was digitally converted with 32 bits accuracy. The electrodes were located at FP1, F3, F4, C3, C4, Cz, P3, P4 and Pz according to the 10-20 system, see Figure 6.1, a reference was placed on the right mastoid bone and the ground electrode was positioned at the nasion. EOG recordings were recorded from the FP1 electrode. The impedance of the electrodes were continually tested and was kept below 5 $k\Omega$. A trigger was send from the software at the beginning of each trial to be able to split the continuous recording into epochs.

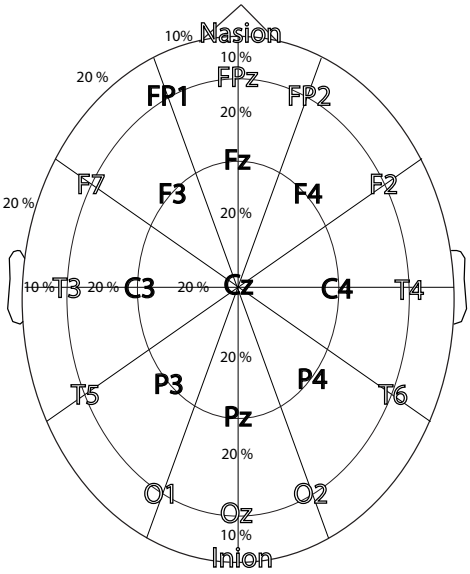

Figure 6.1: The location of the recording sites are marked in bold. The electrodes are placed according to the 10 20 EEG system.

6.2 Force recordings

The force was recorded from a force transducer mounted on a foot pedal and used as input to the BCI system. The recordings were displayed by "Mr. Kick software" (Knud Larsen, SMI, Aalborg University). The signal was sampled at 2000 Hz. The subject was instructed to perform three maximum voluntary contraction (MVC), the highest of the three MVC recordings was used to

tailor the forces needed to be exerted to each individual, that way 100 % of MVC was set to the highest output the subject could perform that day.

7

Experiment design

7.1 Healthy subjects

Each subject was seated in a chair, in an electrically shielded room. The subjects right foot was fixed in a pedal with a force transducer. Each session started with three recordings of the MVC force of the tibialis anterior muscle, which performs the dorsiflexion of the ankle. The subjects were instructed to perform two different kinds of dorsiflexions, a fast movement (reaching the target force in 0.5 seconds) and a slow movement (reaching the target force in 3 seconds), both at low force of 20 % of the MVC, the two kinds of movement can be seen in Figure 7.1. Each session consisted of two different exercises: training and testing.

7.2 Patients with motor impairments due to a stroke

The patients were seated in a comfortable chair and supported to help them best perform the desired foot movements. The patients affected foot was fixed in a pedal with a force transducer. The session started with a recording of the MVC of the subject performing a dorsiflexion to tailor the forces to that specific subjects level of motor control. The subjects were instructed to perform four different kinds of dorsiflexions a fast movement (reaching the target force in 0.5 seconds) and a slow movement (reaching the target force in 3 seconds), both at low and high forces of 20 % and 60 % of MVC respectively. During testing the EEG recordings of the four different kinds of movements were compared to find a combination of fast and slow movements with the biggest amplitude differences.

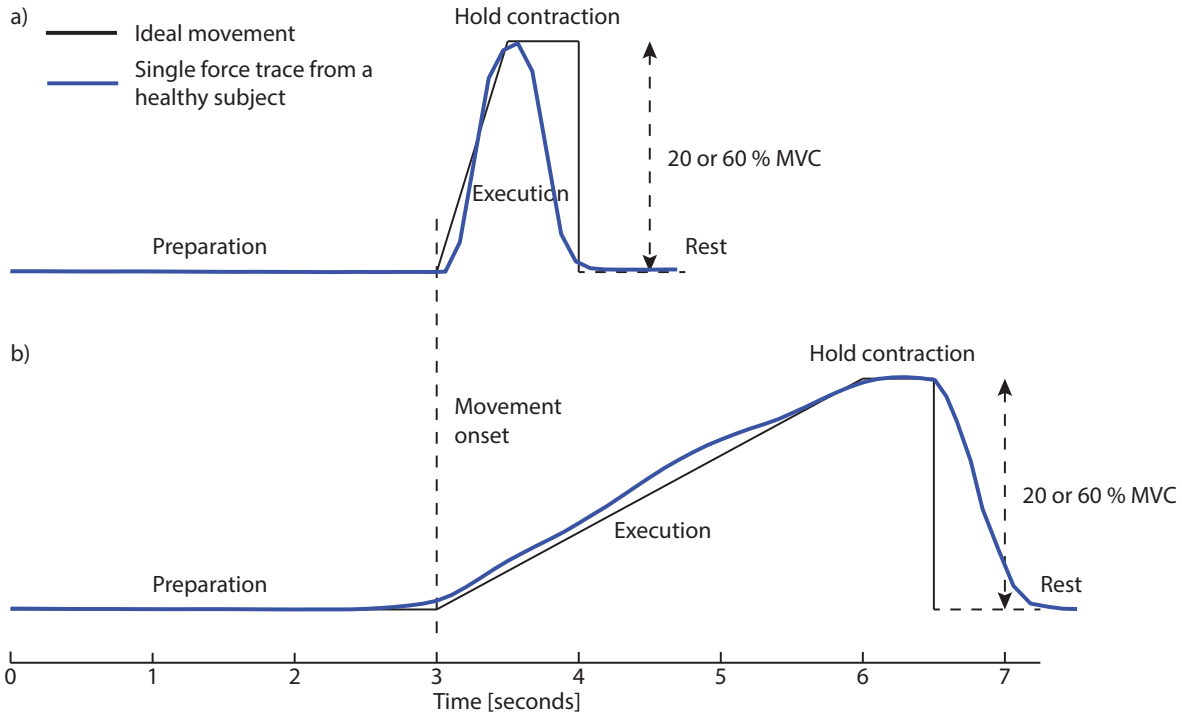

Figure 7.1: The two different kinds of movements performed in the experiment. a) a fast movement with a preparation phase of 3 s, an execution phase of 0.5 s, hold phase of 0.5 s, and a rest phase of 3.5 to 4.5 seconds b) a slow movement with a preparation phase of 3 s, a execution phase of 3 s, hold phase of 0.5 s, and a rest phase of 3.5 to 4.5 seconds Both movements are performed at 20% of MVC for the healthy subjects and at both 20 and 60 % MVC for the patients.

7.3 Training

The training was done to both train the subject in the movements that needed to be performed, and calibrate the BCI systems detector and classifier. The subject was instructed to perform 2 $\times$ 30 movements for healthy subjects and 4 $\times$ 50 movements for patients of the fast and slow dorsiflexions block randomised while looking at a screen displaying their force exertion. The movement type was chosen since controlled dorsiflexions were thought to be simple movements that acquired no learning by the healthy subjects, and these movements were a part of the patients rehabilitation exercises.
EEG was recorded during the movements, and this data was later used to train the detector and classifier. The subjects were instructed to pay very close attention to the timing, speed and force of their movement. The subjects were given visual cues, the first cue was a preparation cue three seconds before the intended movement onset. From the preparation cue the subject was shown an animation with a target seen in Figure 7.1 and a visual representation of their force output over time displayed over the target animation. Between each animation the subject was given a rest period between 7.5 and 8.5 seconds before the next cue to move started.

7.4 Testing

The testing was used to test the performance of the detector and classifier. The subject was asked to perform 20 movements of both the fast and slow dorsiflexions in random order for healthy subjects and 50 movements of fast and slow dorsiflexions for patients. The subject was asked to after each movement say out loud which movement was performed. The movements and whether they were detected and classified correctly and if there were false positives and

false negatives were noted for later analysis, to compare with the with the output of the BCI system.

7.5 Progression of the experiment

The healthy subjects were taking part in a longitudinal study spanning eight weeks. The experiments ran two times per. week for four weeks with a four week break and a final week to test retention. The experiments had at least two days in between and never more than seven days between each session. The four week break and final session of testing was done as a control of the BCI systems ability to detect and classify based on old data. The setup can be seen in Figure 7.2.
The patients were only tested once in a session spanning no longer than two an a half hour.

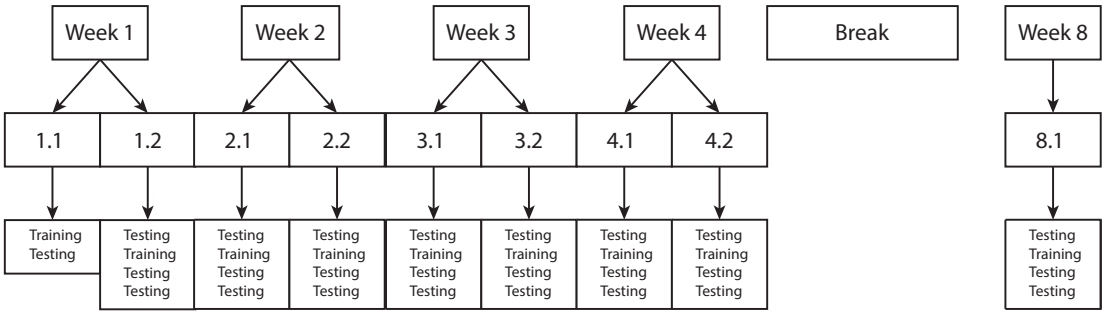

Figure 7.2: The progression of the experiment and the scheule for each individual session. The first four weeks were designed to see if any training effects were apparent and the 8th week was included as a control session.

The setup of the sessions following the first for healthy volunteers was chosen to test the performance of different scenarios of BCI training.
Test I investigates the performance using only previous data and no training prior to testing. This is to see the effect of larger amounts of data without previous subject training that session, this is the fastest of the tree sessions.
Test II investigates the performance using only data recorded that day, for a more current detector and classifier, but with a smaller amount of data.
Test III investigates the performance using all available data and training of the subject prior to testing. This is believed to be a optimal scenario, a lot of available data and training that day prior to test, it is also by far the most time consuming.

8

System design

To be able to perform online analysis of the continuously recorded EEG signal in order to extract MRCPs certain steps had to be performed. These were detection of movements and classification of detected movements. A description of the steps the BCI system needs to perform are shown in Figure 8.1.

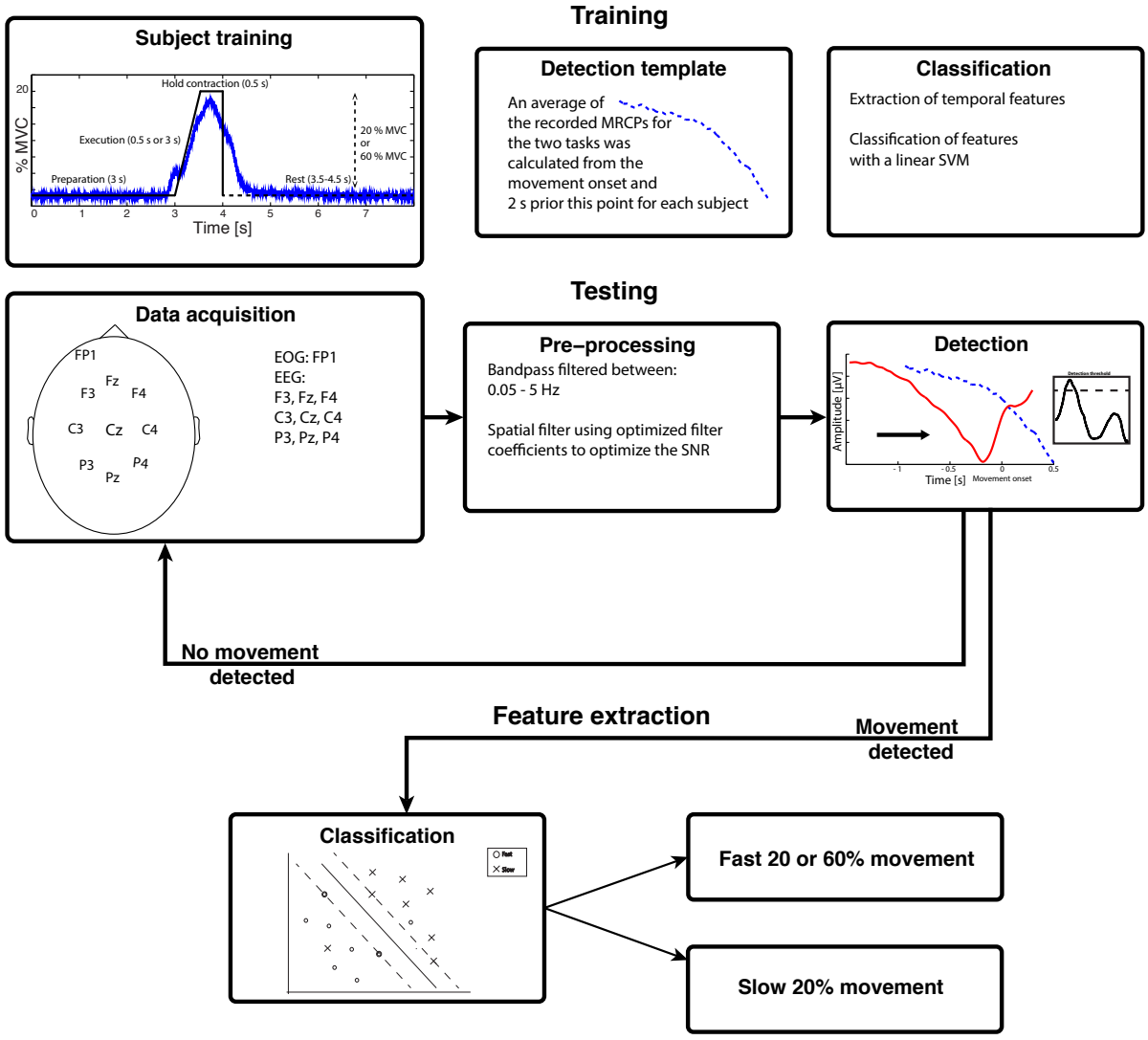

Figure 8.1: The subject training is described in Chapter 7, the detection template is based on a method developed by Niazi et al. [2011], and the temporal features used for the classification is based on Jochumsen et al. [2013] and described in Section 8.3. During testing data was acquired as described in Section 6.1 prior to movement detection the continious EEG data was bandpass filtered and spatially filtered using optimized filter coefficients described by Niazi et al. [2011]. The detection template was applied to the processed EEG signal and if a movement was detected feature extraction was performed to classify the type of movement. Only two types of movement were classified for each session.

8.1 Processing the raw EEG data

The EEG data used for training was also used to visualise changes in the MRCP over time for all the healthy subjects both for fast and slow movements. Filtration and analysis of the EEG recordings used during testing is described in Figure 8.1.

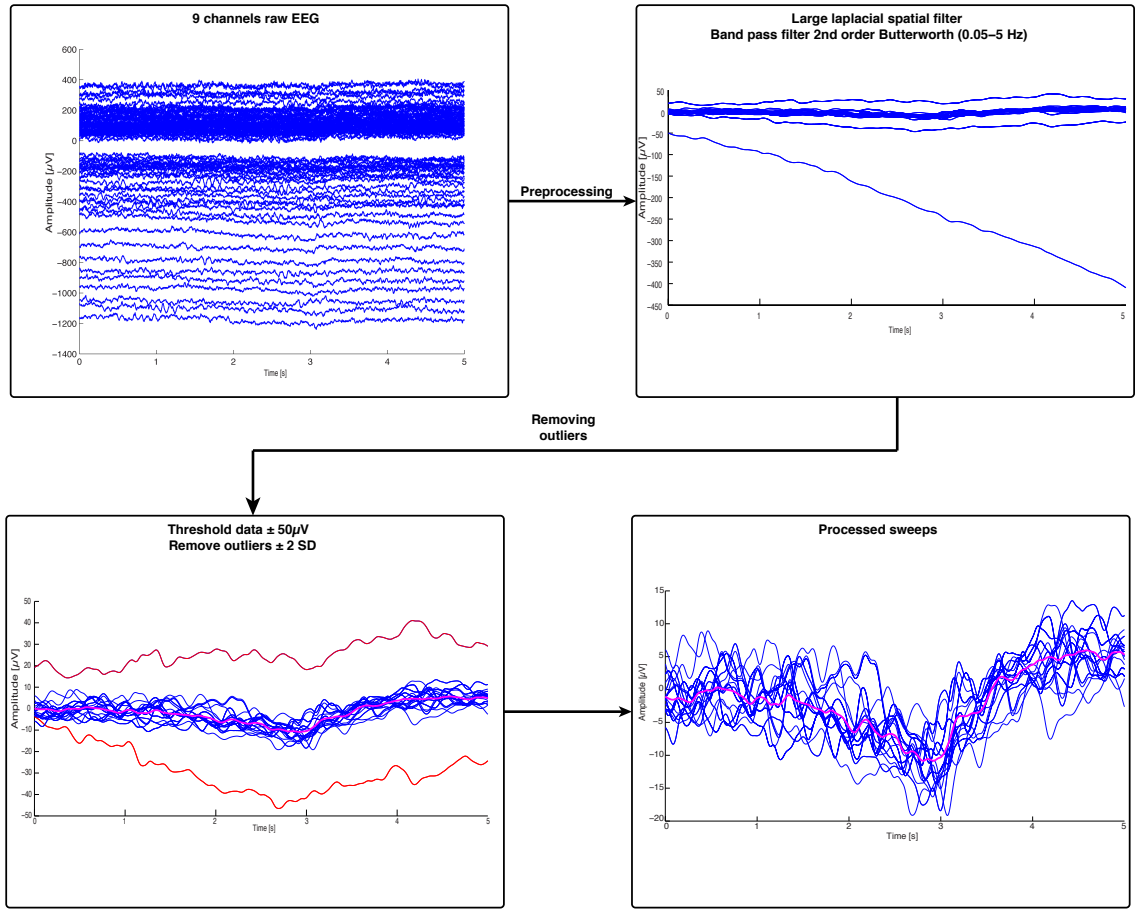

Figure 8.2: The continous nine channel EEG recording was epoched into sweeps five seconds in length starting at the initial cue. A large laplacian spatial filter and after that a bandpass filter was applied to each sweep, before the next step all EEG signals with amplitides exceeding the set threshold were removed. The mean and standarddeviation of the thresholded sweeps was calculate and all sweeps exceeding two std were removed. The mean value is shown as a magenta line and the sweeps that will be removed are marked as read. In this case three sweeps were removed.

8.2 Detection

Previously recorded EEG signals were bandpass filtered between 0.05 and 5 Hz with a second order Butterworth filter. A large laplacian spatial filter was applied, the filter was applied over Cz like this:

$$Cz - \frac{F3 + F4 + Fz + C3 + C4 + P3 + P4 + Pz}{8}$$

The method used to extract a template and detect movements was based on a method developed by Niazi et al. [2011] this method has demonstrated detection of movement intention with a latency limited to less than 200 ms. The method however does have a trade off between true positive rate and false positive rate, to be able to detect movements it is necessary to allow a certain amount of false positives as well. This was visualised using a reciever operating

characteristic (ROC) curve, this curve visualises the tradeoff between true positives and false positives, an illustration can be seen in Figure 8.3.

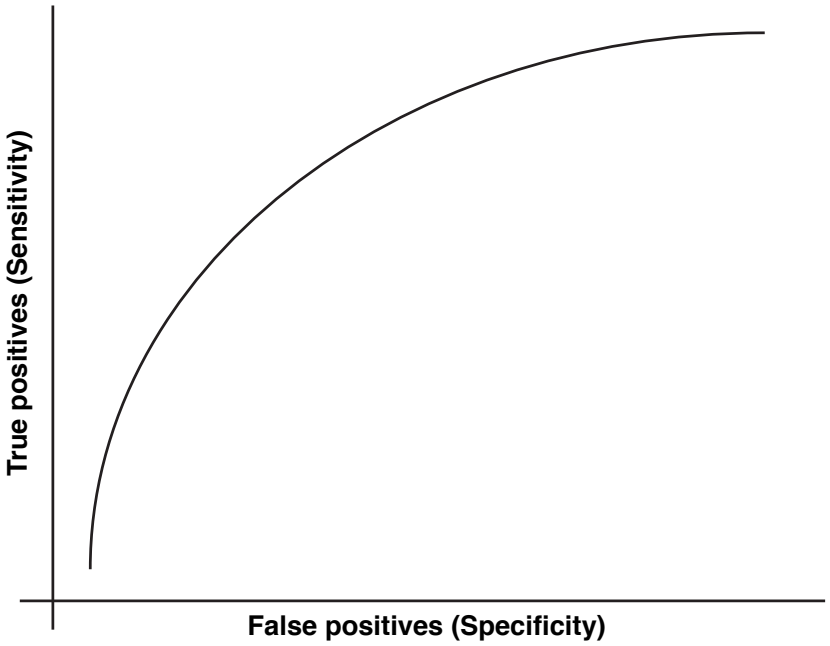

Figure 8.3: An illustration of the tradeoff between true positives and false positives, to have a higher true positive rate one has to allow more false poitives as well.

8.3 Classification

Six temporal features were used to classify the movements, these features were based on Jochumsen et al. [2013]. The features are:

- Point of maximum negativity
- Mean amplitude
- Slope, and intersection of a linear regression of a time interval between detection and two seconds prior
- Slope, and intersection of a linear regression of a time interval between detection and half a second prior

The features described above have been shown to be feasible to use when implementing a BCI system, with two or four classes, that detects movement intentions and decodes levels of force and speed [Jochumsen et al., 2013]. These features are classified with a support vector machine (SVM) where the parameters were extracted using 3-fold cross-validation by optimising the parameters on the training data, this was done to increase the generalisation of the classifier.

8.4 Online perfornance

The online performance of the system described in Figure 8.1 was noted separately, the measures noted were:

- Detection
- Correct and incorrect classification
- False positives
- False negatives

The detection was defined as the true positive rate, meaning all properly detected movements. The correct and incorrect classifications are the after detection classification accuracy. False positives are falsely detected movements, and the false negatives are the number of movements that were not detected even though the subjects moved their foot. The system performance was extracted from the noted data, it was defined as the number of correctly classified and detected movements.

Part III

Results

9

Detection

9.1 Healthy volunteers

The three different detection results for test 1-3 in weekly data are presented in Table 9.1, 9.2, and 9.3. A detailed visualisation of all the sessions is available in Figure 9.1. The overall mean detection for the four weeks for all the subjects for test 1 were 81 ± 1 %, test 2 is 78 ± 3 %, and test 3 is 80 ± 2 %. The results of the control was 85 ± 15 %, 76 ± 9 %, and 80 ± 10 % for test 1-3 respectively. There are no apparent trends for the performance of the detector, other than the fact that it is very stable. The detection accuracy fluctuates around 80 % through the four weeks and the control session. When the accuracy increases so does the standard deviation as well. The overall lowest detection accuracies are during test two and test one and three are very similar.

Detection test 1						
	TPR [%]					
Week	1	2	3	4	Break	8
mean value	83	81	80	79		84
std.	11	10	4	12		15

Table 9.1: Test 1 focuses on testing using previous data, but no prior training that session. The overall mean value for the healthy volunteers is 80.58 ± 1.41

Detection test 2						
	TPR [%]					
Week	1	2	3	4	Break	8
mean value	77	81	79	75		76
std.	12	6	6	17		9

Table 9.2: Test 2 focuses on testing using only data recording during that session. The overall mean value for the healthy volunteers is 77.96 ± 2.59

Detection test 3						
	TPR [%]					
Week	1	2	3	4	Break	8
mean value	82	78	80	80		80
std.	14	11	7	9		10

Table 9.3: Test 3 focuses on testing using all previous data and training just prior to the test. The overall mean value for the healthy volunteers is 79.8 ± 1.74

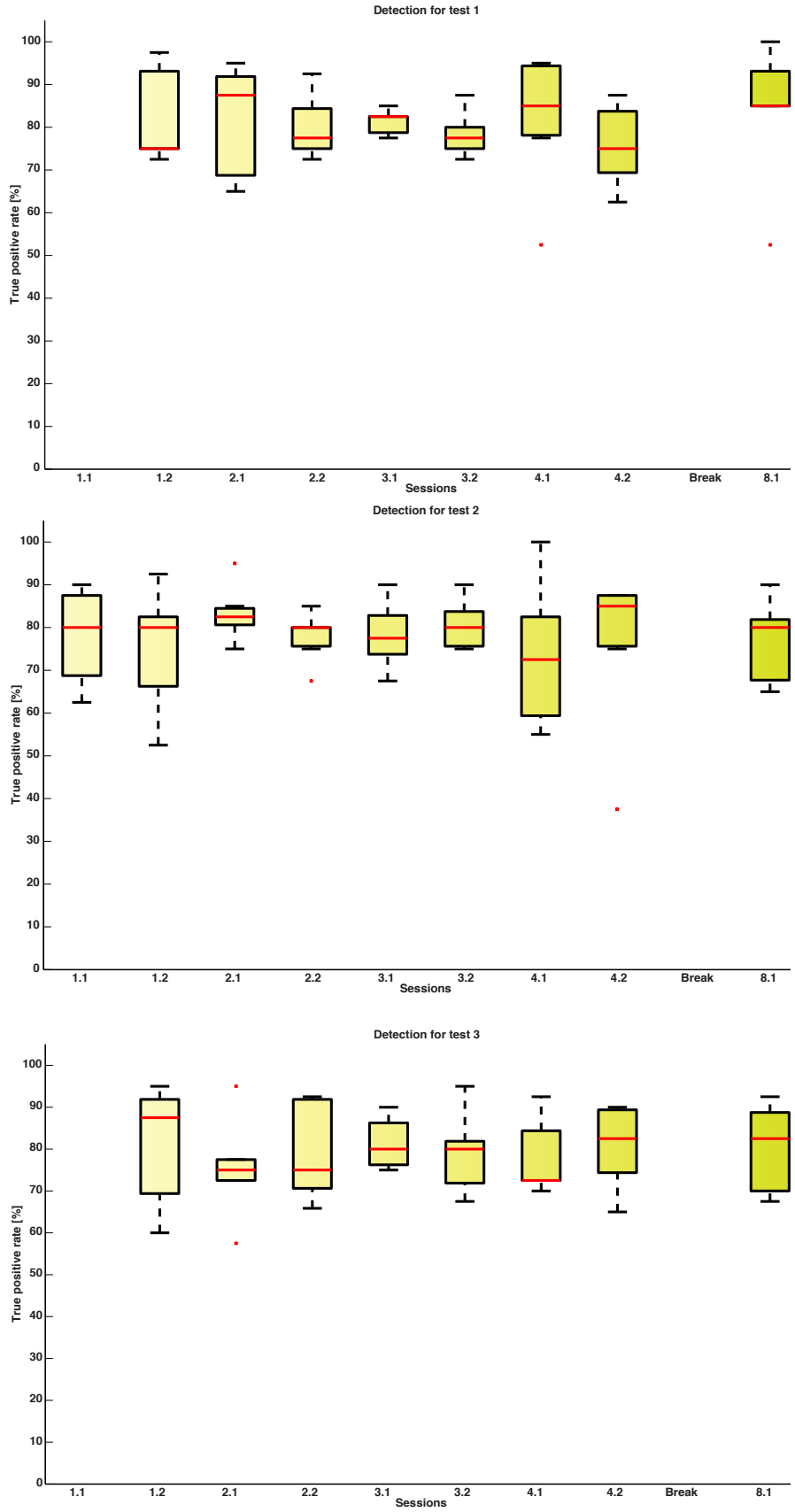

Figure 9.1: The boxplots are divided into 25 % and 75 % quartiles showing the median value in a red line and whiskers depicting the extreme datapoints not considering outliers shown by red dots. Detection for the three different tests. Session 1.1 for test one and three are not present since these were not recorded during the first session.

9.2 Patients

The mean detection values for the six patients was 88 ± 12 % each patients detection can be seen in Figure 9.2. The detection accuracy varies for the patients, this is very likely due to the nature of strokes and how they affect each person differently.

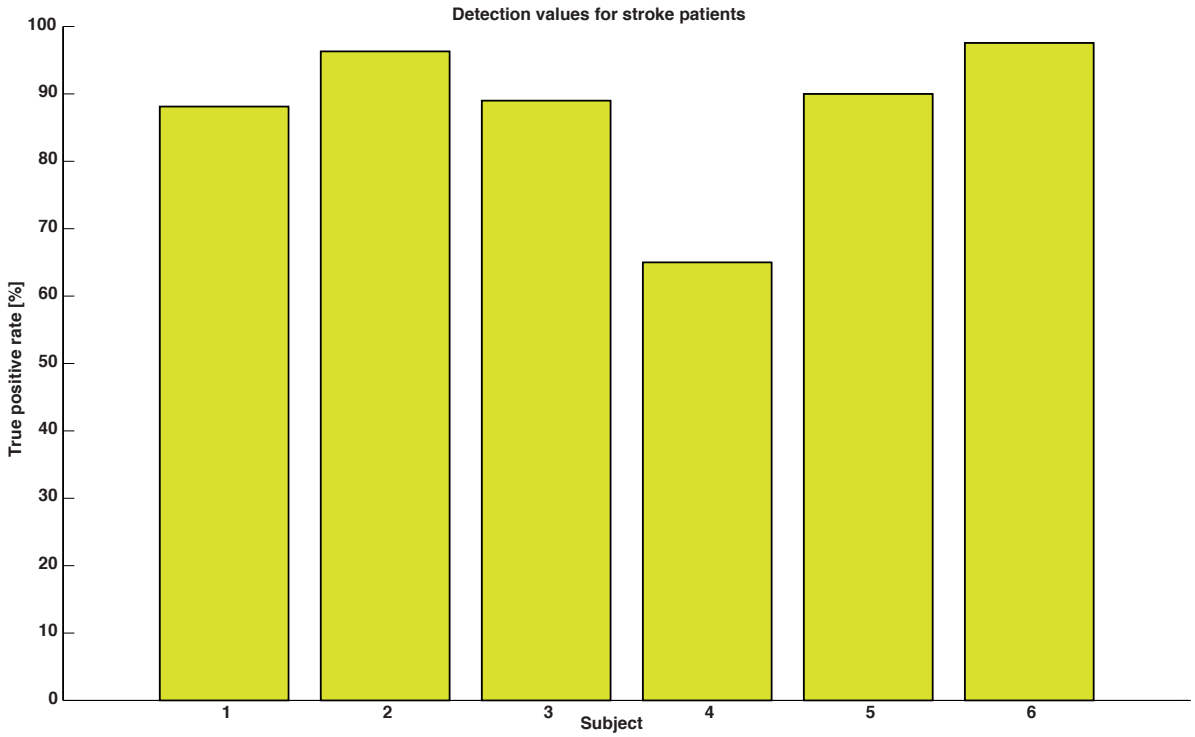

Figure 9.2: Patient detection

10

Classification

10.1 Healthy volunteers

The three different classification results for test 1-3 in weekly data are presented in Table 10.1, 10.2, and 10.3. A detailed visualisation of all the sessions is available in Figure 10.1. The overall mean classification for the four weeks for all the subjects for test 1 was 56 ± 3 %, test 2 is 55 ± 2 %, and test 3 is 57 ± 2 %. The results of the control was 53 ± 10 %, 56 ± 5 %, and 53 ± 9 % for test 1-3 respectively. There are no large changes in accuracy during the four weeks or the control session for the classification. The classification accuracy fluctuates around 54 %, the standard deviations for test two are falling throughout the sessions from 9 % to 5 % indicating more consistent movements for all subjects. Test one and three have the highest classification accuracies.

Classification test 1						
	Correct [%]					
Week	1	2	3	4	Break	8
mean value	56	57	59	53		53
std.	11	8	7	11		10

Table 10.1: Test 1 focuses on testing using previous data, but no prior training that session. The overall mean value for the healthy volunteers is 56.14 ± 2.61

Classification test 2						
	Correct [%]					
Week	1	2	3	4	Break	8
mean value	55	56	55	53		56
std.	9	7	6	6		5

Table 10.2: Test 2 focuses on testing using only data recording during that session. The overall mean value for the healthy volunteers is 54.59 ± 1.54

Classification test 3						
	Correct [%]					
Week	1	2	3	4	Break	8
mean value	60	56	56	56		53
std.	7	10	11	10		9

Table 10.3: Test 3 focuses on testing using all previous data and training just prior to the test. The overall mean value for the healthy volunteers is 56.75 ± 2.17

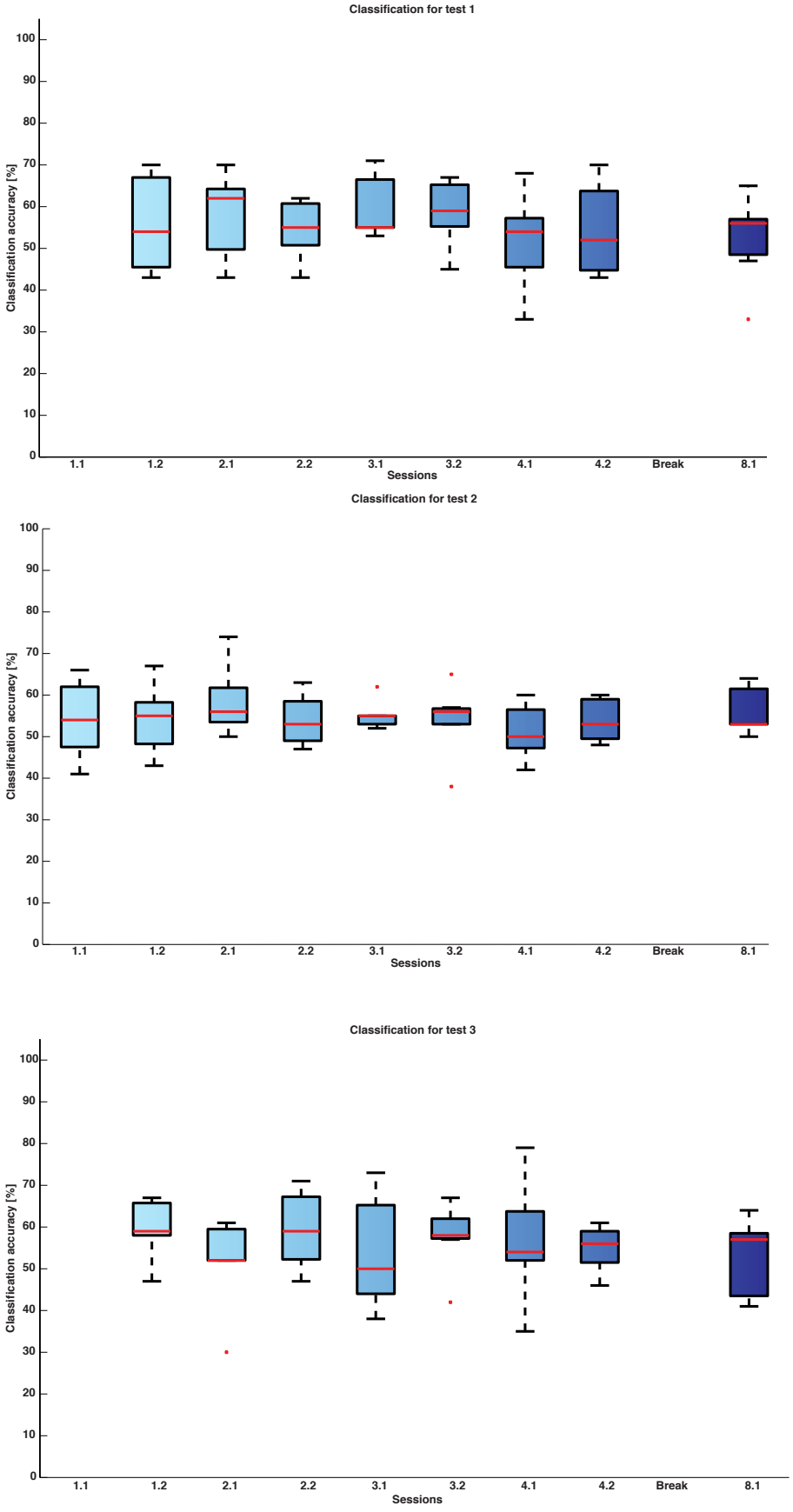

Figure 10.1: The boxplots are divided into 25 % and 75 % quartiles showing the median value in a red line and whiskers depicting the extreme datapoints not considering outliers shown by red dots. Classification for the three different tests. Session 1.1 for test one and three are not present since these were not recorded during the first session.

10.2 Patients

The mean classification values for the six subjects is 57.2 ± 5.76 each patients classifications can be seen in Figure 9.2. The detection accuracy for the patients are very stable, this is most likely because the two movements with the largest differences were chosen among the four different movements recorded.

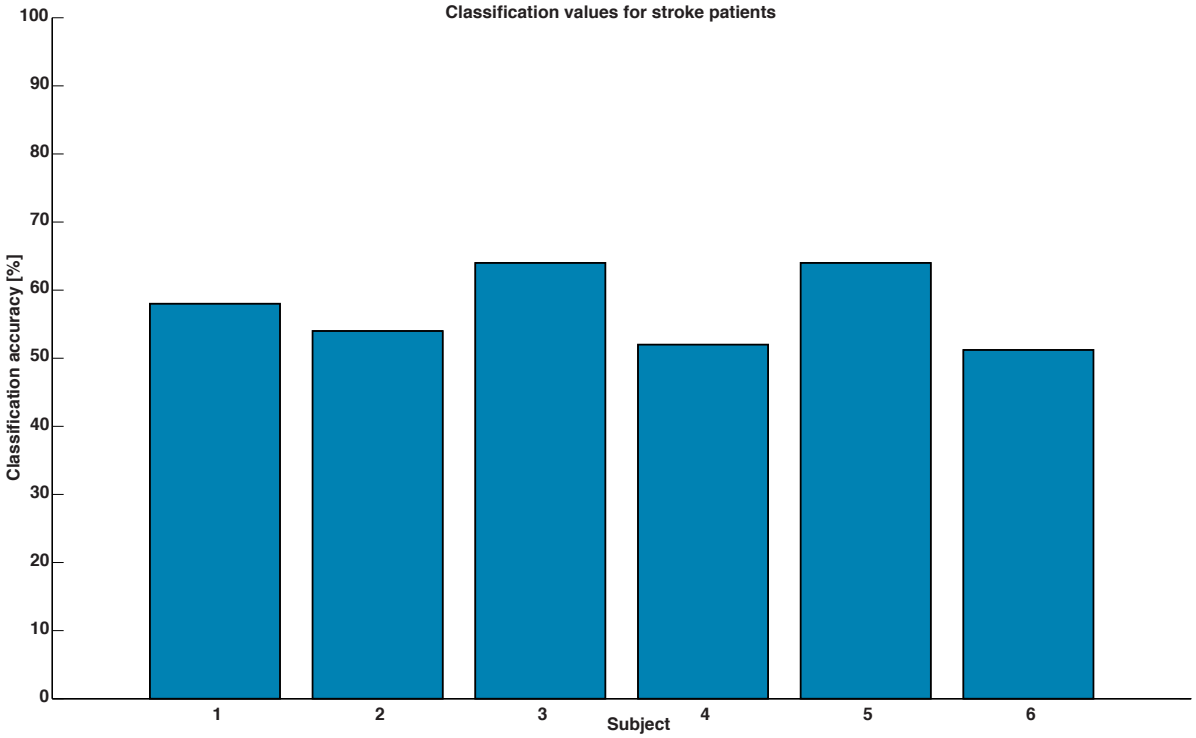

Figure 10.2: Classification for individual patients

11

System performance

11.1 Healthy volunteers

The three different system performance results for test 1-3 in weekly data are presented in Table 11.1, 11.2, and 11.3. A detailed visualisation of all the sessions is available in Figure 11.1. The overall mean system performance for the four weeks for all the subjects for test 1 is 45 ± 2 %, test 2 is 43 ± 2 %, and test 3 is 46 ± 3 %. The false positives per minute(FP/min) were 2 ± 0.1 %, 1.5 ± 0.1 %, and 1.4 ± 0.3 % for test 1-3 respectively. The results of the control was 45 ± 14 %, 43 ± 6 %, and 41 ± 7 % with a FP/min of 1.4 ± 0.8 %, 1.3 ± 0.6 %, and $1. \pm 0.5$ % for test 1-3 respectively. The system performance for test one are the most consistent and generally higher accuracies and lower std each week.

System performance test 1												
	Correctly detected and classified [%]						*FP/min*					
Week	1	2	3	4	Break	8	1	2	3	4	Break	8
mean value	46	45	47	42		45	2	2.2	2	2		1.3
std.	9	6	6	11		14	0.7	0.7	0.8	0.7		0.8

Table 11.1: Test 1 focuses on testing using previous data, but no prior training that session. The overall mean value for the healthy volunteers is 45.09 ± 2.02 with a FP/min of 2.05 ± 0.12

System performance test 2												
	Correctly detected and classified [%]						*FP/min*					
Week	1	2	3	4	Beak	8	1	2	3	4	Break	8
mean value	42	45	43	39		43	1.5	1.6	1.6	1.4		1.3
std.	9	9	5	9		6	0.8	0.9	0.8	0.8		0.6

Table 11.2: Test 2 focuses on testing using only data recording during that session. The overall mean value for the healthy volunteers is 43.4 ± 1.94 with a FP/min of 1.51 ± 0.08

System performance test 3												
	Correctly detected and classified [%]						*FP/min*					
Week	1	2	3	4	Break	8	1	2	3	4	Break	8
mean value	49	44	44	44		41	1.9	1.2	1.3	1.4		1
std.	8	10	8	9		7	0.6	0.7	0.6	0.8		0.5

Table 11.3: Test 3 focuses on testing using all previous data and training just prior to the test. The overall mean value for the healthy volunteers is 45.57 ± 2.93 with a FP/min of 1.43 ± 0.31

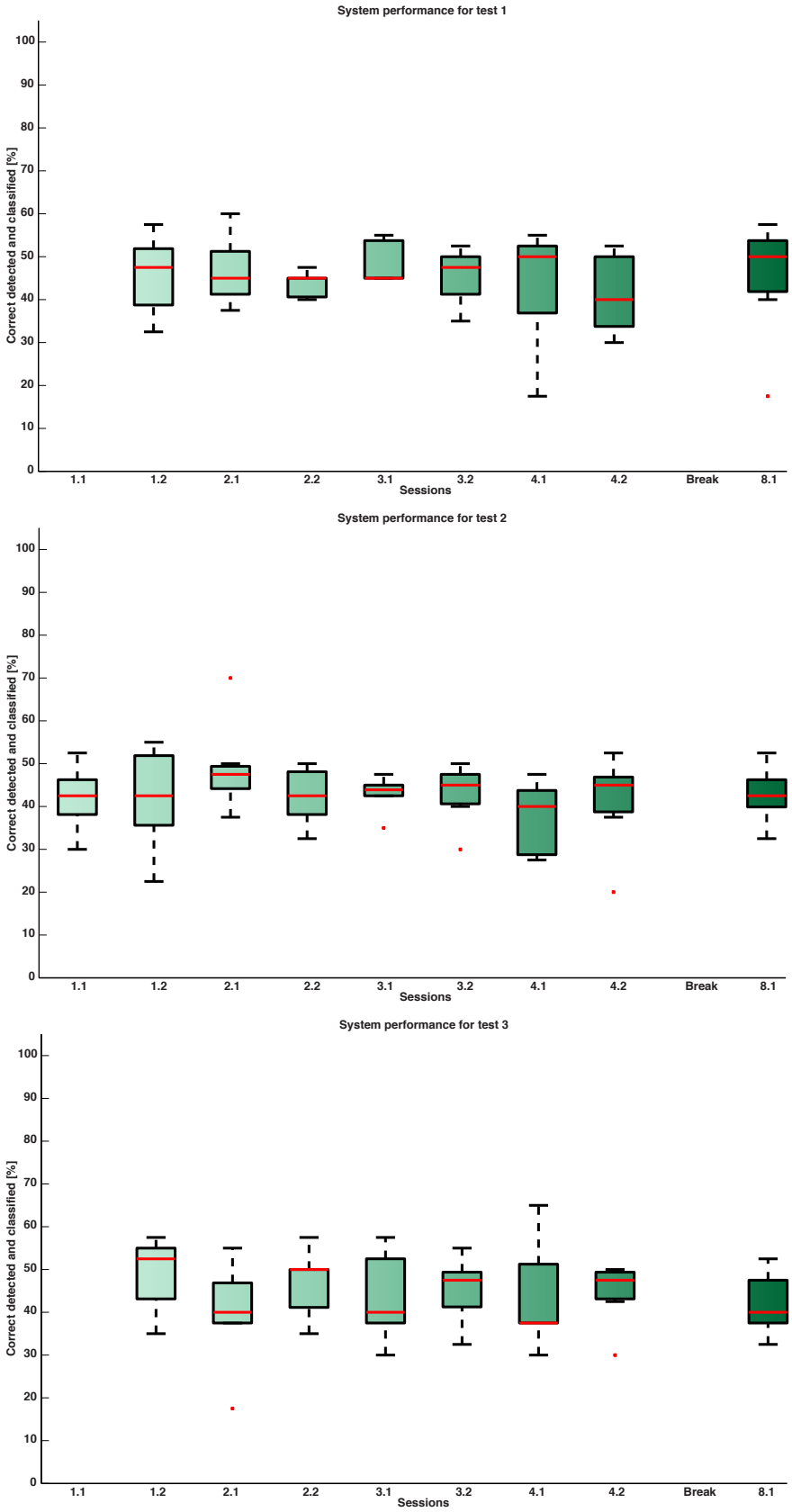

Figure 11.1: The boxplots are divided into 25 % and 75 % quartiles showing the median value in a red line and whiskers depicting the extreme datapoints not considering outliers shown by red dots. System performance for the three different tests. Session 1.1 for test one and three are not present since these were not recorded during the first session.

11.2 Patients

The mean system performance for the six subjects is 50.38 ± 8.64 with a FP/min of 0.77 ± 0.33 each patients system performance can be seen in Figure 11.2. The system performance is very consistent except for subject 4, this subject had slightly lower detection and classification accuracy than the others resulting in a lower system performance.

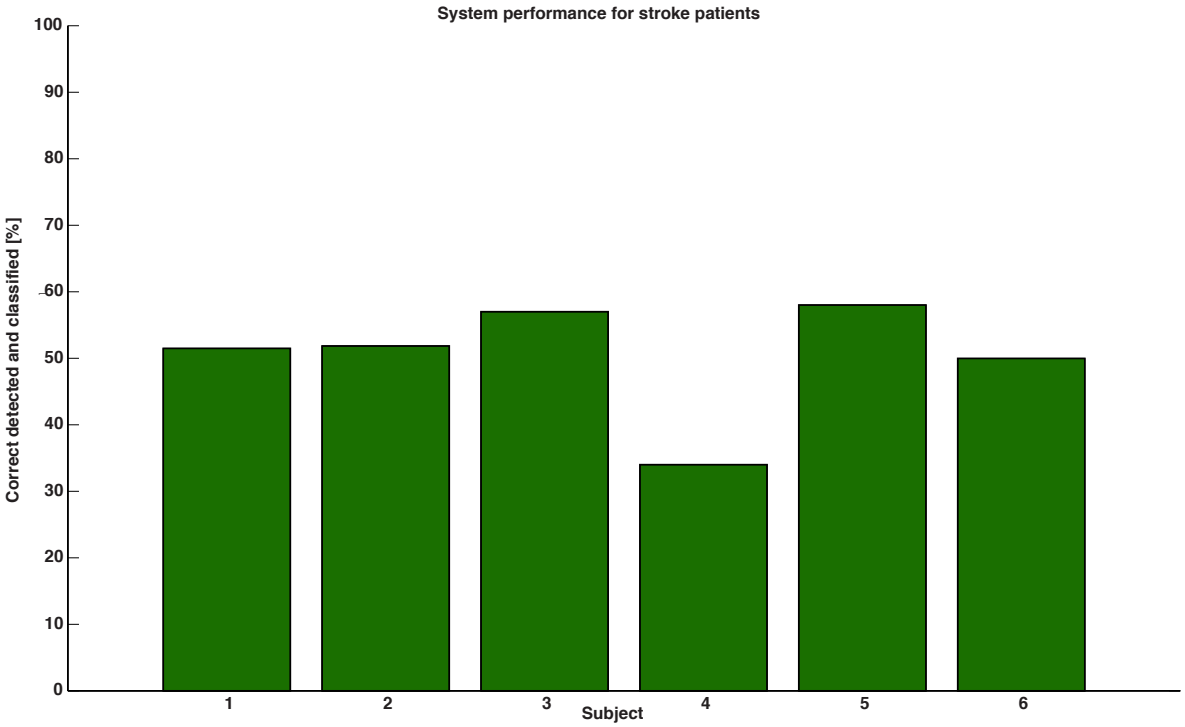

Figure 11.2: System performance patients

12

MRCP

12.1 MRCP changes over time for healthy subjects

Looking at the changes over time Figure 12.1 and Figure 12.2 show grand averages over time for the fast and slow movements of healthy volunteers, respectively. The MRCPs are shown for week one 1.1 and 1.2, week two 2.1 and 2.2 and so on for four weeks with a four week break and lastly a control for one session 8.1. The MRCPs are grand averages of all healthy volunteers and are included to visualise changes over time. The individual sessions are mixed and do not show any changes over time for fast or slow movements. The MRCPs from the control sessions are mixed between the sessions recorded during the four weeks for both fast and slow movements. This indicates, that there are no trends in the development of the MRCP. The amplitudes are not increasing or decreasing during the four week sessions or after a four week break.

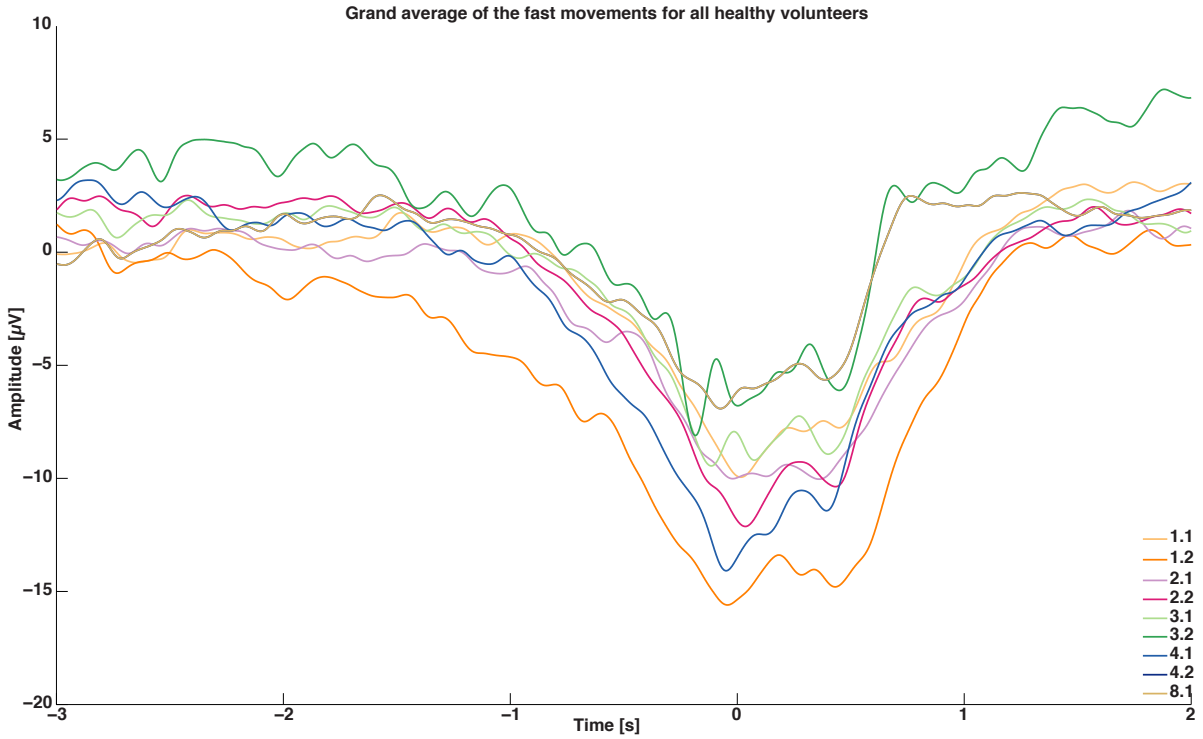

Figure 12.1: Grand averages of the fast MRCP movements of of the healthy volunteers for each session. 1.1 and 1.2 were recorded during the first week, 2.1 and 2.2 were recorded during the second week and so on. 8.1 is a control session recorded four weeks after 4.2. The movement onset is at time (0). The figure is based on 1942 MRCP sweeps each subject had on average 277 ± 17 sweeps.

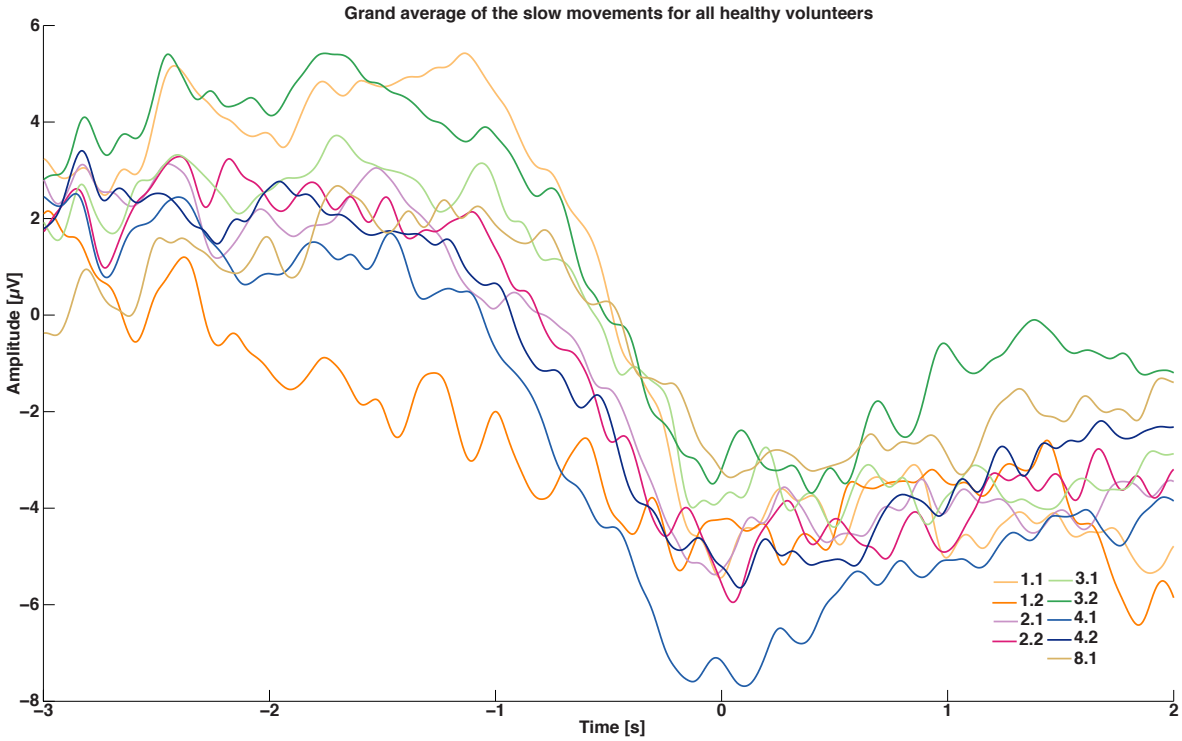

Figure 12.2: Grand averages of the slow MRCP movements of of the healthy volunteers for each session. 1.1 and 1.2 were recorded during the first week, 2.1 and 2.2 were recorded during the second week and so on. 8.1 is a control session recorded four weeks after 4.2. The movement onset is at time (0). The figure is based on 2058 MRCP sweeps each subject had on average 294 ± 38 sweeps.

12.2 Different force levels of MRCP compared

Figure 12.3 and Figure 12.4 show differences in MRCP between fast and slow movements for healthy volunteers and patients, and between the four different MRCP recordings from patients respectively.

12.2.1 Healthy volunteers and patients

The grand average MRCPs shown in Figure 12.3 show the differences in amplitudes between healthy volunteers and patients for fast and slow movements. The differences between healthy and patients for fast and slow movements are smaller than the differences in Figure 12.1 and Figure 12.2 between the four week sessions of MRCP recordings. The morphology of the MRCPs are very similar for healthy and patients with a max peak negativity of 5 μV for slow movements and 10 μV for fast movements.

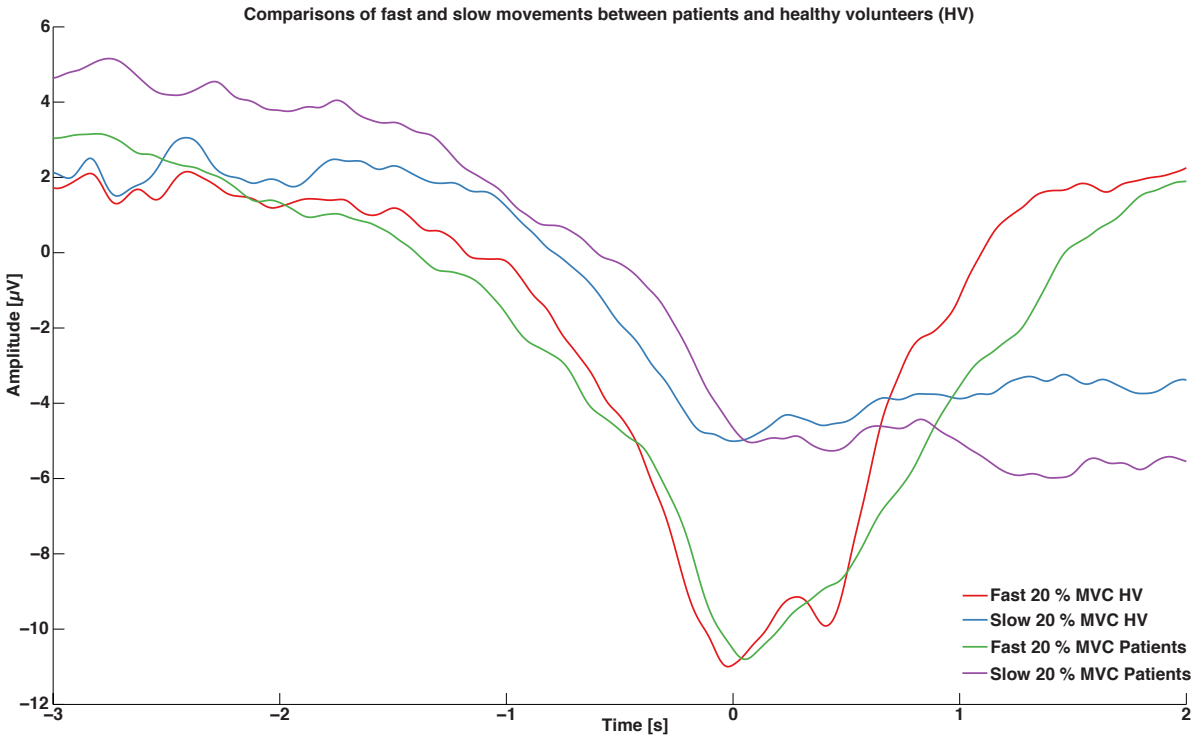

Figure 12.3: Comparison between grand averages of healthy volunteers and patients performing fast and slow movements at 20 % MVC, the recorded MRCPs are both from the first recording session. The movement onset is at time (0). The figure is based on 238 fast and 240 slow MRCP sweeps for healthy, and 291 fast and 283 slow sweeps for patients

12.2.2 Patients at different force levels

The grand average of the four kinds of movements patients performed are shown in Figure 12.4. This figure shows the slight differences between different forces exerted and the larger differences between speeds. The morphology of the MRCPs are very similar for different levels of force and same speed with a max peak negativity of 3.5-5 μV for slow movements and 10 μV for fast movements. Being able to select between all four types of movement allows for a larger difference between two classes and a higher classification accuracy. There are slight differences between the amplitudes of MRCPs for different MVCs for same speed movements. There are bigger differences between the force levels of slow movements at 20 and 60 % MVC than between the two types of fast movements.

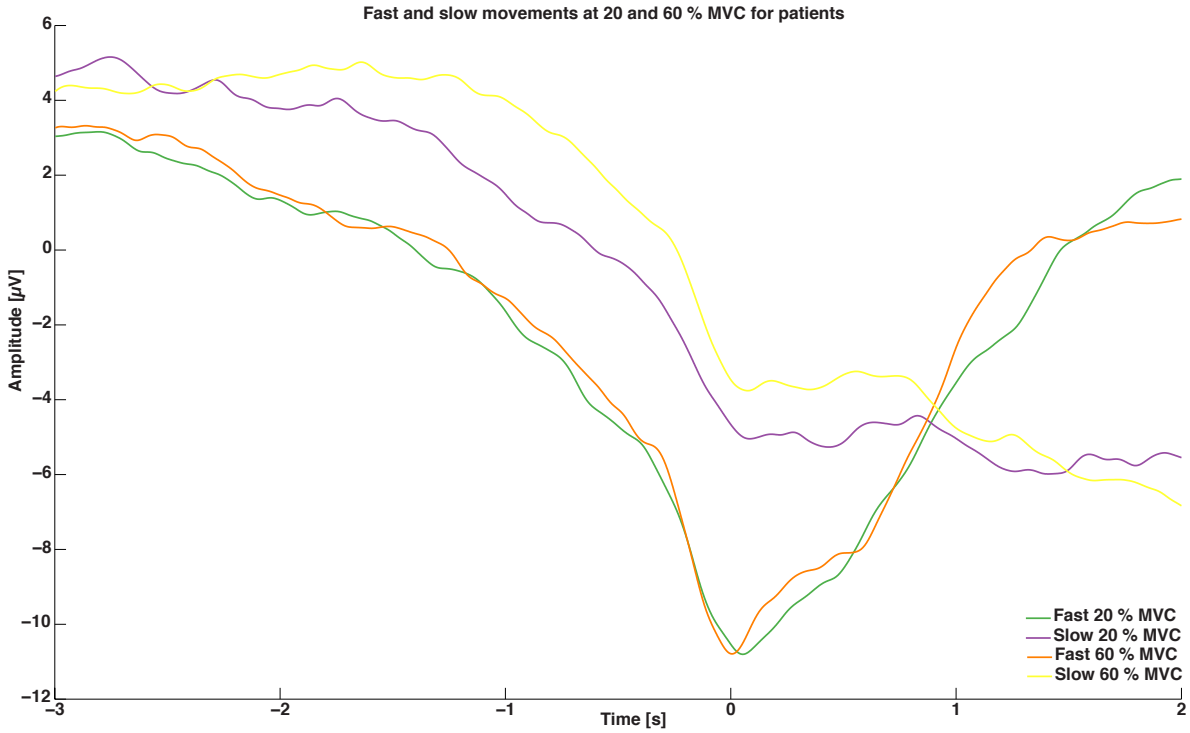

Figure 12.4: A grand average of the four different recordings performed for the patients fast and slow movements at 20 or 60 % MVC. The movement onset is at time (0). The figure is based on a total of 1154 MRCP sweeps.

Part IV

Synthesis

13

Discussion

13.1 Summary of results

The overall detections for test 1-3 through the first four weeks were: 81 ± 1 %, 78 ± 3 %, and 80 ± 2 % respectively. The overall detections for patients during a session was 88 ± 12 %. The overall classification for test 1-3 through the first four weeks were: 56 ± 3 %, 55 ± 2 %, and 57 ± 2 % respectively. The overall classification for patients during a session was 57 ± 6 %. The overall system performance for test 1-3 through the first four weeks were: 45 ± 2 %, 43 ± 2 %, and 46 ± 3 % respectively. The FP/min for healthy subjects were 2 ± 0.1 $\frac{FP}{min}$, 1.5 ± 0.1 $\frac{FP}{min}$, and 1.4 ± 0.3 $\frac{FP}{min}$ for test 1-3 respectively. For patients the overall detection was 88 ± 12 %, classification was 58 ± 6, and system performance was 50 ± 9 % with a FP/min of 0.8 ± 0.3 $\frac{FP}{min}$.

13.1.1 Summary of controls

The detection for all subjects during the control was 84 ± 15 %, 76 ± 9 %, and 80 ± 10 % for test 1-3. The classification was 53 ± 10 %, 56 ± 5 %, and 53 ± 9 % for test 1-3. The system performance was 45 ± 14 %, 43 ± 6 %, and 41 ± 7 %, the FP/min was 1.4 ± 0.8 $\frac{FP}{min}$, 1.3 ± 0.6 $\frac{FP}{min}$, and 1 ± 0.5 $\frac{FP}{min}$ both system performance and FP/min are shown for test 1-3 respectively.

13.2 Results

13.2.1 Performance of the BCI system

The changes over time for test 1-3 for detection, classification, system performance, and FP/min are all negligible. This suggesting that the system performance of the BCI system does not change over time for non complex foot movements for healthy subjects. The differences between test 1-3 show differences in the detection and classification performances for the three different tests. Test two used only data recorded during that session and had the lowest performance of the three, this indicates an advantage of using all available data from previous sessions to classify movements as well to be preferred. Test three scored the highest performance of the three, this test used all available data and trained the subject before performing the test. This indicates that using more available data to detect and classify movements along with a training of the different kinds of movement needed to be performed during the test, makes them more easily differentiated thereby increasing the performance of the BCI. The performances from the control study are very similar to the ones during session 1.1 to 4.2, an interesting fact to note is that test one only relies on previous recorded data, the performances from this control shows that after four weeks with no training the MRCPs have changed very little resulting in similar performances of the BCI, suggesting that no training is needed.This was also supported by the performance of the stroke patients that showed relatively good BCI control in the first session

Previous systems working with detection and classification of MRCPs have worked in either an online or offline capacity. The offline studies have reported detection rates of 83 ± 8 % for healthy volunteers [Niazi et al., 2011], 81 % also for healthy volunteers [Jochumsen et al., 2013]. Niazi et al. [2013] tested individual and averaged across all subjects templates for both healthy and stroke patients. They achieved 71 ± 6 % and 55 ± 12 % detection accuracy for

individual templates for healthy and stroke patients respectively, and 69 ± 21 58 ± 11 using an averaged detection template for healthy and stroke patients respectively. Online studies focusing on detection of MRCPs have detection accuracies of 67 ± 8 % [Niazi et al., 2012], 79 ± 11 % by [Xu et al., 2014a], and 73 ± 10 % [Xu et al., 2014b]. The three online studies mentioned have lower detection accuracies than the offline BCIs and the detection accuracies in this project. This is because they detect imagined movements instead of real movements, these have a lower detection accuracy than real movements [Niazi et al., 2011]. It has only been possible to find offline studies focusing on classification of MRCPs. These are 86 ± 3 % correctly classified Farina et al. [2007], 84 ± 9 % correctly classified by Gu et al. [2009a], 70 ± 3 by Gu et al. [2009b], and 75 ± 9 % correctly classified by Jochumsen et al. [2013]. Lastly only one other article dealt with system performance by looking at the number of correctly detected and classified movements. Jochumsen et al. [2013] had a system performance of 64 ± 13 %. The detector performed well compared to other studies both for patients and healthy volunteers making it reasonable to assume that the system performance is high enough for inducing cortical plasticity if combined with e.g. functional electrical stimulation. However, the lower limit for inducing plasticity is not known [Grosse-Wentrup et al., 2011]. Niazi et al. [2012] were able to induce plasticity by using peripheral electrical stimulation and found significant increase in corticospinal plasticity for the target muscle. Xu et al. [2014b] used an active ankle-foot orthosis to induce cortical neural plasticity. The systems focusing on classification of movement speed and or force all performed at a higher accuracies than the method performed in the current project. This is due to the fact that they were offline systems classifying movements from the movement onset. The detector used in the present system does not necessarily detect movements at the movement onset, if the MRCP is detected earlier or later than the movement onset it is much more difficult to classify the movements based on the nature of the the features used for classification. The detection latencies reported in other studies are -125 ± 309 ms with respect to movement onset Niazi et al. [2012], 315 ± 165 ms between detection and movement Xu et al. [2014a], and -317 ± 73 ms with respect to movement onset Jochumsen et al. [2013]. This means the classifier will have a window that is up to 300 ms off compared to the actual movement onset. The classification accuracies performed were all above the theoretical chance level of 50 %, a more precise way of accounting for chance level is to include a certain confidence interval depending on the number of trials. The actual chance level for a two class system performing 20 trials per class and a significance level of 5 % is 65 % [Müller-Putz et al., 2008]. This means the classifier is performing below chance level.
A strength of this project is the time needed to train the subject. The actual time needed for the subject to perform 30 repetitions of two different kinds of movements is roughly 10 minutes, this is enough data for the BCI system to properly detect and classify movements. Adding a number of these 10 minutes training sessions yields higher accuracies which in the long run might make it unnecessary to perform initial training as shown by the performance of test 1 in session 8.1. This use of more data recorded in smaller training sessions could be a possible training strategy for patients, the detector works reasonably well early on, but has a slight increase in performance with more training samples. It is not known how high or stable in terms of standard deviation BCI performances need to be in order to induce plasticity and therefore how much or little data is needed.

13.2.2 Performance required to induce plasticity

It is not known how high accuracies are needed from BCI systems to induce plasticity [Grosse-Wentrup et al., 2011]. As mentioned in Section 13.2.1 both Niazi et al. [2012] and Xu et al. [2014b] achieved significant increases in cortical plasticity with detection rates of 79 ± 11 % and 73 ± 10 % respectively. Krakauer [2006] reports the importance of randomising movements to be able to generalise clinical training and increase retention. They report increases in retention even though the initial performance decreases from performing different movements. This means that even though the classification accuracy is below random performing multiple, and randomised movements might help improve retention for patients. A possible study that could be performed

is only detecting movement onsets, but still asking the subject to perform different movement speeds. Then stimulating fast or slow movements randomly to see if this increases plasticity and retention more than just performing the same movement throughout the experiment with a single stimulation intensity. This simple classification performed at random might be enough to help increase retention, it could however also discourage the subject from trying to create more normal movement patterns.
The performance of the BCI is very stable for all three tests one of the reasons why the performance is so stable is the nature of the MRCP and the type of movement performed. Slow and fast dorsiflexions were chosen because they are very simple movements and highly automated at least in healthy subjects. Because of this the cortical potentials responsible for creating the movements are also very unlikely to change. Changes in cortical activity reflect changes in motor control, so because of this the MRCP should not change unless the amount of effort needed to plan and perform the task changes [Lang et al., 1992].

13.2.3 Performance of healthy vs. patients

Focusing only on the first session test 2 for the healthy subjects and the session with patients suffering motor impairments all measures detection, classification, system performance, and FP/min higher for patients than healthy subjects. The reason for only comparing test 2 session 1.1 for healthy subjects is that this test and session is the one most similar to the session performed with the patients. The difference in performance can be accounted for since the detector threshold for the detection template described in Figure 8.1 on page 27 was optimised allowing more false positives to obtain a higher true positive rate for each stroke patient, and not for the healthy volunteers. The two classes the classifier was trained on for the stroke patients were chosen between four different movements fast or slow at 20 or 60 % MVC, amongst these the two movements with the largest differences in slope and amplitude were chosen, a grand average of the four different MRCPs can be seen in Figure 12.4 on page 48. The healthy volunteers only performed fast and slow movements at 20 % MVC, this was chosen to ensure that the healthy volunteers did not fatigue during the three tests. The timing between the movements were 5 seconds for the patients, and 15 seconds for the healthy volunteers. This difference in timing was chosen to minimise the time patients needed to concentrate, reducing fatigue during the test, this short break however possibly masked false detections as true positives, simply because of the short interval between movements. On the other hand longer breaks for healthy volunteers allowed for a easier differentiation between false positives and true positives during the notation of movements, resulting in a higher amount of false positives.
To sum up, the session performed with the patients was tested using a best case scenario for rehabilitation and potential increase in plasticity. The sessions with the healthy volunteers were designed to investigate changes in performance of the system with as little change of the subjects performance as possible. It can be problematic to compare healthy volunteers and patients suffering a stroke affecting their motor cortex, since the cortical regions of the patients might be damaged. Grosse-Wentrup et al. [2011] also concludes that the focus of experimental work should be on patients not healthy subjects. An unexpected finding is however the fact that there are very small differences in MRCPs between healthy and patients for similar movements and levels of force as shown in Figure 12.3 on page 47. This suggests a small difference between the MRCPs of healthy and patients, which might make studies between healthy and patients more comparable.

13.3 Method

13.3.1 Variation of data

Large standard deviations across subjects were visible both for the healthy subjects and patients. This could be due to the features extracted from the MRCP that are based on temporal and physiological features of the MRCP. The amplitude of the MRCP is dependant on level of

intention from the subject [Shibasaki and Hallett, 2006]. The subjects were not given any visual feedback of the speed or force of their movements, because of this the difference between fast and slow movements might have become smaller making it more difficult for the classifier to differentiate the different speeds of the foot movements.

13.3.2 Effects of training

It does not seem like there is any training effect from the healthy subjects for this type of experimental setup. The MRCP did not change over the course of the four weeks for the healthy subjects. The fast and slow movements described in Section 7.1 were not complex movements that needed to be learned by the healthy subjects. Because of this the differences between fast and slow movements did not change making it easier or more difficult for the BCI system to classify movements, this resulted in minute changes of performance for the BCI. The three different tests in each session except for the first focused on different amounts of data available to the BCI system. There was little if any difference between the three tests indicating that there might not be any need to train subjects before each session thereby minimising the time each individual session lasts.
There was no effect of training for the healthy volunteers because of the non complex movements. It is possible to record and differentiate MRCPs while performing motor imagination [do Nascimento et al., 2006]. Motor imagination would for most people be a completely new skill to learn, it would therefor take time to be able to master the movement, and be able to automate the movement in the same manner as simple fast and slow dorsiflexions. Motor imagination would be novel movements, and might over time change the MRCP. As long as performance of a movement increases the amplitude of the MRCP should also increase. Once the performance of the movement plateaus the MRCPs should either remain the same or decrease [Taylor, 1978]. The performance of the patients movement will during recovery increase, thereby most likely also increase the amplitude of the MRCP. Lang et al. [1992] concluded that cortical activity reflect changes in motor control, and since the effort needed to perform movements is larger for patients at the beginning of recovery than later during recovery this should be reflected in changes in the MRCP.

13.3.3 Methological considerations

Allowing more false positives for stroke subjects resulted in higher detection accuracy, that combined with the two kinds of movement with the largest difference resulted in higher performances for stroke subjects. Implementing this for healthy subjects has resulted in higher performances as well [Jochumsen et al., 2013]. It was however not the aim for the healthy subjects to achieve the highest possible detection accuracy, rather to investigate changes over time of the performance of the BCI system. Using visual feedback to the subject might help train their brain signals by adding a new channel of feedback for patients with damage to the motor cortex [Daly and Wolpaw, 2008]. A possible way of optimising the outcome is introducing feedback to the subject. Neither the patients or the healthy volunteers were given any feedback of the computers detection or classification accuracy, being able to tell the subject if their movements were correctly detected and classified might be able to help the subject train to achieve a better detection and classification accuracy. Another way of increasing the accuracy of the performed movements is giving a visual feedback of force and speed to the subject during the testing phase.

13.3.4 Signal processing

The detection accuracy of this study was very high, but the classifier performed below chance level so more effort should be put into optimising the signal processing of the classifier. Only six features were used to distinguish movement speeds during the testing. The six features used were applied to a single channel created using a spatial filter. Applying the features to each of the nine channels would result in 54 features which would possibly result in higher

classification accuracies. Investigating the frequency domain might also show more features capable of classifying differences between movements. Also subject-dependent features (on the contrary to the subject independent-features) may be extracted, and those that carry the most discriminative information can be used in the testing session. These steps would add a high level of features and might make it possible to select a number of subject specific features, selecting a subgroup of features resulting in the highest classification and still keeping a low classification latency for the individual subjects.

13.4 Limitations

The longitudinal study was only performed on healthy subjects, the no training effect might not translate to patients. Improvement of motor function might affect the MRCP for patients over time, the large similarities in MRCPs between healthy and patients does however suggest that there are only small differences between the potential for healthy and patients. The sample size of six patients suggested the possibility of using MRCP as a control signal, a larger sample size of patients might be more representative of the stroke population. Lastly the detection latencies were not recorded during the experiments which means the detection latencies could only be estimated from previous studies.

13.5 Implications

The MRCP does not change over time for healthy volunteers, and the BCI system used works on stroke patients from the first try without previous training. The MRCPs for healthy and patients are very similar which suggests that MRCP based rehabilitation can be used with very low training time and not change over time minimising the need for more training data and by combining it with functional electrical stimulation cortical plasticity may be induced which potentially can be used for neurological rehabilitation of stroke patients.

14

Conclusion

The aims of this project were for healthy subjects: What is the effect of training of a BCI system over time and does the MRCP of healthy subjects for non complex movements change over time. Three tests were performed to investigate the effects of training a BCI system over time. The system was able to detect and classify movements early on with little training, after the first session it was possible to achieve as high system performance without training as with training. The highest performances were seen with previous training data and subject training during the session prior to testing, this was also the test that required the most training time each session. Because of the low complexity of the foot movements the MRCPs did not change over time for healthy volunteers, this was also evident since the performance of the BCI system did not fall during the control session four weeks after the last MRCP recording.

Another aim of the project was to investigate how the BCI system performed detecting differences in speed based on MRCPs for patients suffering a stroke. The BCI system was able to detect and classify movements from the patients after a single session making it possible to use MRCP based BCI systems from the first training session. This seems promising for further studies investigating neurorehabilitation based BCI systems that detects movement speed and force from MRCP.

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Appendices & Listings

Conference paper for BCI Conference 2014

While performing experiments and recording data from healthy volunteers and patients my supervisors and I submitted an article for the 6th International Brain-Computer Interface Conference in Graz, the article is appended below. The article deals with the same detector and classifier as in the main project, and parts of the data recorded for the main project are presented in the conference paper.

Online detection and classification of movement kinetics

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Abstract

Over the past years brain-computer interface (BCI) technology has been proposed as a means for neurorehabilitation. To induce Hebbian-associated-like plasticity, the movement-related cortical potential (MRCP) can be detected from the continuous brain activity to trigger timely appropriate inflow of somatosensory feedback from electrical stimulation. The aim of this study was to detect online the MRCP from the continuous brain activity and decode two types of movements that were performed with different levels of force and speed (2x50 movements). 5 healthy subjects and 1 stroke patient performed/attempted to perform the movements. The system correctly detected and classified 65±3 % and 51 % of the movements for the healthy subjects and patient, respectively. The findings suggest that it is possible to detect movements and decode kinetic information online. This may have implications for stroke rehabilitation where task variability may be introduced to optimize the retention of relearned movements.

1 Introduction

Stroke is the main cause of adult disability in high-income countries worldwide; therefore, several techniques have been proposed to reverse motoric impairments [1]. Over the past years, brain-computer interfaces (BCI) have been proposed as tools that can be used in neurorehabilitation [2, 3]. Recently, it was shown that plasticity could be induced by using the movement-related cortical potential (MRCP) as a control signal in a BCI that provides somatosensory feedback from electrical stimulation [4, 5]. The MRCP is a low-frequency brain potential associated with executed and imagined movements [6]. The potential can be observed in the electroencephalogram (EEG) up to two seconds before a voluntary movement; therefore, it has been proposed for BCIs that are used for induction of Hebbian-associated-like plasticity [4, 5]. The MRCP also contains kinetic information of the executed or imagined movement such as the level of force and speed [6, 7]. This kinetic information may be utilized in designing more sophisticated rehabilitation protocols where variety of tasks is required. It has been shown that variety of tasks in a rehabilitation paradigm is good for maximizing the retention of relearned motor skills [8]. To implement this in BCI protocols, we need to detect the movement intention and classify different task parameter (force and speed) to activate correlated somatosensory feedback (through functional electrical stimulation). The detection and decoding of the MRCP has been performed offline in a previous study [7].

The aim of this study was to implement and test the feasibility of detecting the MRCP and discriminating between fast movements with a high level of force and slow movements with a low level of force.

2 Methods

2.1 Subjects

Five healthy volunteers (1 female and 4 males: 29±5 years old) and one stroke patient with lower limb paresis (77 years old, male, infarction, right site affected, 46 days since event). All the subjects gave their informed consent before participation, and the procedures were approved by the local ethical committee (N-20130081).

2.2 Experimental protocol

Each subject was seated in a chair, with the right foot fixed to a pedal with an attached force transducer. The training session started with recording of the maximum voluntary contraction (MVC) force followed by 50 repetitions of cued isometric dorsiflexions of the ankle for each of two movement types. The two tasks were [7]: i) 3 s to reach 20% of MVC and ii) 0.5 s to reach 60% of MVC. The subjects spend ~5 min to familiarize with each task. The order of the two tasks was randomized in blocks for each subject. To assist the subjects in performing the movements with the correct level of force and speed, they were visually cued by a custom made program (Knud Larsen, SMI, Aalborg University), where force was used as input. They were asked to produce force to match a ramp trace.

After the training session the detector (Section 2.4) and classifier (Section 2.5) was built and the testing session started. In this session, the subjects performed 50 movements of each movement type randomly and in their own pace (they were instructed to separate two consecutive movements with at least 5 s). After they performed a movement they verbally expressed the movement type that was performed, this was noted and compared to the outcome of the computer prediction.

2.3 Signal acquisition

Ten channels of monopolar EEG were recorded (EEG amplifiers, Nuamps Express, Neuroscan) continuously from FP1, F3, Fz, F4, C3, Cz, C4, P3, Pz, and P4 according to the International 10-20 system (32 Channel Quick-Cap, Neuroscan). The signals were sampled at 500 Hz and analog to digital converted with 32 bits accuracy. The signals were referenced to the right ear lobe. Electrooculography (EOG) was recorded from FP1. The impedance of the electrodes was below 5 kΩ during the experiment.

2.4 Detection, feature extraction and classification

In the training and testing session, the EEG signals were bandpass filtered from 0.05-10 Hz with a 2^{nd} order Butterworth filter. A surrogate channel of the nine EEG channels was obtained by applying an optimized spatial filter to improve the signal-to-noise ratio (SNR) as proposed by Niazi et al. [9]. The movements were detected using a template matching technique [7, 9] where a template of the initial negative phase of the MRCP was matched to the surrogate channel. The template was extracted from an average of the 2x50 movements that were performed in the training session. The length of the template was 2 s, and was extracted from the peak of maximum negativity and 2 s prior to this point. The detection threshold was obtained for each subject using a receiver operating characteristic (ROC)

curve. The ROC curve was generated through 3-fold cross-validation of the training data. The detection threshold was selected to maximize the true positive rate (TPR), but on the expense of more false positive detections (FPs). The detector decisions were based on the likelihood ratio method (Neyman Pearson lemma) computed between the template and the surrogate channel. When the likelihood ratio exceeded the detection threshold, and the EOG activity was lower than 125μV, detection occurred. To reduce the number of FPs, the detector was disabled for 3 s after detection. The detection was evaluated through the TPR and number of FPs/min.

Six temporal features were extracted from the initial negative phase of the MRCP from the detection onset and 2 s prior this point. These features were: i+ii) slope and intersection of a linear regression fitted to the entire interval (-2 s until the detection onset), iii+iv) slope and intersection of a linear regression fitted to the last 0.5 s (-0.5 s until the detection onset), v) maximum negative amplitude and vi) mean amplitude.

The features were classified using a support vector machine (SVM) with a linear kernel. All trials from the training session were used to build the classifier that was used in the testing session. The classification accuracy was obtained for the correctly detected movements.

3 Results

The results are summarized in Table 1. The TPR was 85±4 % for the healthy subjects and 85 % for the stroke patient. The number of correctly detected and classified movement was higher for the healthy subjects (65±3 %) compared to the patient (51 %).

Healthy/stroke subject	TPR [%]	CA Correct	CA Incorrect	FPs/min
H 1	87	62	25	0.6
H 2	90	70	21	0.6
H 3	82	65	17	0.2
H 4	78	61	17	0.1
H 5	89	67	22	2.4
Mean±SD	85±4	65±3	20±3	0.8±0.8
S 1	85	51	37	0.9

Table 1: Performance of the system for healthy subjects and stroke patient.

The number of movements that were correctly detected, but misclassified was 20±3 % and 37 % for the healthy subjects and patient, respectively. On average less than 1 FP/min was registered.

4 Discussion

In this study, movements were detected and the kinetic information classified for healthy subjects with a performance of 65±3 % correctly detected and classified movements. The proposed techniques were also tested in a stroke patient, where 51 % of the movements were correctly detected and classified.

The detection performance was slightly higher compared to what has been found in previous studies where an online system was simulated [7, 9]; this may be explained by the selection of the detection threshold. In the previous studies the detection hold was based on the midpoint of the

upward convex part of the ROC curve to obtain a tradeoff between the TPR and number of FPs. In this study, the detection threshold was selected to increase the TPR, but on the expense of more FPs. The number of FPs was accounted for by disabling the detector for 3 s after detection.

The performance of the classifier to discriminate between the movement performed slightly worse than in the offline studies which may be explained by the lower detection threshold leading to an earlier detection of the movements and therefore less kinetic information can be extracted from the 2 s of data extracted prior the detection point. Detection latencies were not calculated in the current study, but it is expected to be in the range of ±100 ms [9].

The findings suggest that the BCI system can be used for neuromodulation where task variability can be introduced (two classes). The system performance is in the range of what has been reported to induce plastic changes [4], although it remains an open question what is the lower limit of performance of BCI system for plasticity [3]. The effect on the induction of plasticity should be investigated to see if current BCI protocols for this purpose can benefit from the introduction of task variability. Since induction of plasticity seems to be positive correlated with the system performance [4], it could be investigated how BCI training would affect the system performance.

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