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Towards adaptive time-resolved multivariate decoding in brain-computer interface rehabilitation after stroke

Jonatan Tidare

Mälardalen University

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School of Innovation, Design and Engineering

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Abstract

Stroke is a major cause of long-term disability, often resulting in severe motor impairments. Motor imagery has been proposed as a technique to engage motor networks and promote neuroplasticity, even in the absence of physical movement. Brain–computer interfaces (BCIs) can decode neural activity and provide feedback in a closed loop, supporting reinforcement-based motor learning. BCIs have shown modest but promising results, and their efficiency and usability can be improved by understanding how design choices influence human performance and clinical outcomes. Key challenges include achieving high signal precision through high-dimensional data, delivering real-time feedback under strict latency constraints, and managing non-stationary brain signals within and across sessions. This thesis presents an iterative and exploratory investigation of these challenges. Methods were first developed and validated in healthy participants and later implemented in a clinical intervention with stroke patients. Contributions include classification of motor imagery tasks involving one hand, characterization of motor signals in high-dimensional data, evaluation of system latency for real-time feedback, application of multivariate pattern analysis to capture temporal dynamics of the motor signal, introduction of a continuous metric for motor signal strength linked to visual representations, implementation of a method to set and maintain difficulty level during BCI training, evaluation of adaptive classification methods to maintain performance across sessions, and validation of these methods in a stroke case study. The findings advance understanding of how BCI design parameters affect usability and clinical relevance. By integrating neuroscience, machine learning, and principles of motor learning and neuroplasticity, this work contributes to the development of more effective and personalized BCI systems for stroke rehabilitation.

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To Emelie, Liam, and Jack.

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List of papers

This thesis is based on the following papers, which are referred to in the text by their Roman numerals.

I **Discriminating EEG spectral power related to mental imagery of closing and opening of hand.**
Tidare, J., Leon, M., Xiong, N., & Astrand, E.
In 2019 9th International IEEE/EMBS Conference on Neural Engineering (NER) (pp. 307-310). IEEE. © 2019 IEEE.

II **Feature selection of EEG oscillatory activity related to motor imagery using a hierarchical genetic algorithm.**
Leon, M., Ballesteros, J., Tidare, J., Xiong, N., & Astrand, E.
In 2019 IEEE Congress on Evolutionary Computation (CEC) (pp. 87-94). IEEE. © 2019 IEEE.

III **Evaluation of closed-loop feedback system delay - a time-critical perspective for neurofeedback training.**
Tidare, J., Åstrand, E., & Ekström, M. C.
In Proceedings of the 11th International Joint Conference on Biomedical Engineering Systems and Technologies (BIOSTEC 2018) - BIODEVICES; ISBN 978-989-758-277-6; ISSN 2184-4305, SciTePress, pages 187-193. DOI: 10.5220/0006598301870193

IV **Time-resolved estimation of strength of motor imagery representation by multivariate EEG decoding.**
Tidare, J., Leon, M., & Astrand, E.
In 2021 Journal of Neural Engineering, 18(1), 016026. © IOP Publishing. All rights reserved.

V **Exploration of using “distance-to-bound” to manipulate the difficulty during motor imagery BCI training after stroke – A clinical two-cases study**
Tidare, J, Astrand, E., Plantin, J. and Palmcrantz, S.
In medRxiv. https://doi.org/10.1101/2025.11.13.339460. Available under a CC-BY-NC 4.0 International license.

VI **EEG non-stationarity across multiple sessions during a Motor Imagery-BCI intervention: two post stroke case series.**

Astrand, E., Plantin, J., Palmcrantz, S., & Tidare, J.
In 2021 10th International IEEE/EMBS Conference on Neural Engineering (NER) (pp. 817-821). IEEE. © 2021 IEEE.

Contents

Part I:
Thesis

1. Introduction

Stroke continues to be one of the most prevalent causes of long-term disability globally, often resulting in motor impairments that severely limit independence and quality of life. Conventional stroke rehabilitation is effective, but the complexity of adverse effects following a stroke leave many unable to return to work, or even a life of independence. If the stroke is severe, the person may not be able to participate in stroke therapy. Stroke incurs an economic burden both personally and societally, and there is a pressing need to explore technologies that can respond to the specific needs of stroke survivors.

Brain-computer interfaces (BCIs) offer a novel approach to rehabilitation by enabling direct communication between neural activity and external devices, bypassing damaged motor pathways. In stroke rehabilitation, BCIs are typically used to support motor imagery tasks, in which patients imagine movements while receiving feedback based on their brain signals. This feedback loop can promote neuroplasticity and reinforce motor recovery. However, many clinical BCI systems are limited by simple and static designs that fail to account for individual variability and dynamic changes in brain activity. To fully realize their potential, BCIs must evolve into adaptive systems that respond to the user in real time.

Maintaining an optimal level of difficulty is critical in rehabilitation, as tasks that are too easy may lead to disengagement, while overly difficult tasks can cause frustration and fatigue. In the context of BCIs, this balance is particularly challenging due to the variability in brain signals and the cognitive demands of motor imagery. This thesis presents a method for estimating difficulty level from EEG data, allowing for real-time adjustments to task difficulty. The approach was first investigated in a study with healthy participants, demonstrating that continuous metrics for EEG-based signals can describe dynamic patterns of brain activity.

A major technical hurdle in BCI development is the non-stationarity of EEG signals. Brain activity patterns can shift over time, complicating classification and reducing system reliability. To address this, the thesis explores adaptive classification techniques that adjust to changing signal distributions without requiring frequent recalibration. By integrating real-time signal analysis with adaptive algorithms, the proposed system maintains robust performance across sessions and users. This adaptability is crucial for clinical deployment, where consistency and personalization are essential. The final system was evaluated in a case study with two stroke patients, demonstrating its potential to deliver tailored, responsive rehabilitation experiences.

2. Background

This chapter provides the theoretical foundation for understanding BCIs in stroke rehabilitation. It introduces the neurophysiological principles underlying motor imagery (MI) and its relationship to brain activity measured through electroencephalography (EEG). These concepts are essential for understanding how neural activity can be translated into feedback for BCI-based rehabilitation. The chapter concludes by outlining current trends and challenges in the field.

2.1 Stroke

Stroke is the second leading cause of death and disability worldwide, as reported in the annual Global Stroke Fact Sheet by Feigin et al. [1]. These reports indicate that approximately 6.5 million people die from stroke each year, and more than 100 million individuals live with its long-term consequences. Rehabilitation requires substantial time and effort, and many survivors are unable to return to work or lead an independent life. The tragedy and loss affect not only the individual, but also their family and social network. In addition to its personal toll, stroke imposes a significant economic burden on society. Lost productivity and income, hospital and caregiver expenses, diagnostic procedures, physiotherapy, and follow-up appointments burden both individual finances and public health systems. It is estimated that as much as US$891 billion annually (more than 1% of global GDP) is lost due to the effects of stroke [2].

The term stroke refers to a broad group of disorders involving vascular injury to the central nervous system [3]. A stroke can be either ischemic or hemorrhagic. An ischemic stroke is caused by a blood clot that obstructs blood flow to specific brain regions. A hemorrhagic stroke occurs when a blood vessel ruptures, allowing blood to leak into the brain. Disrupted cerebral blood flow can rapidly trigger pathological neuronal events, ultimately leading to cell death. The region of dead brain cells, known as the lesion, loses its ability to send, receive, and transmit synaptic signals. This disruption leads to functional impairments, which may include deficits in movement, speech, or cognition [4, 5]. At stroke onset, individuals may stumble or fall, experience numbness or weakness in the face or limbs (often on one side), have difficulty speaking or understanding speech, suffer from blurred vision, or develop sudden headaches [6, 7]. Immediate hospital care is essential. Every 10 minutes of earlier treatment saves approximately 19 million neurons from being destroyed [8], and results in an additional 39 days of disability-free life [9].

In the immediate aftermath of a stroke, ischemia causes energy failure in neurons, leading to cell death [10]. The lesioned brain region loses its ability to receive or transmit synaptic signals. Depending on the size and location of the lesion, various cognitive and motor functions may be impaired [11, 4]. In the following weeks, however, the brain undergoes a dramatic transformation. Neural plasticity increases, reflecting an enhanced capacity to recover and reorganize neuronal connectivity. A number of growth-promoting factors are released, facilitating neuronal repair and enhanced axonal growth in living neurons adjacent to the lesion (the peri-lesional area). During this period of spontaneous plasticity, stroke severity may be reduced [12].

This phase of heightened plasticity is commonly referred to as the sub-acute stage and typically spans from 7 days to 6 months post-stroke [13]. It presents a critical window for recovery through physiotherapeutic intervention [14]. Therapy focuses on practicing activities of daily living [15]. Early mobilization and balance training help individuals regain motor function and mobility. Cognitive skills may be practiced through reading, solving crosswords, using a calendar, or counting cars in a parking lot. Speech can be trained using progressively longer and more complex sentences, and may be supported with pen and paper, picture support, or body language [16, 17].

After six months, stroke typically enters the chronic phase. Brain plasticity returns to baseline levels, and further functional improvements are generally limited [18]. With normalized plasticity, any gains are usually achieved through compensatory strategies, meaning that patients learn to make more effective use of existing motor abilities. For example, a person may improve mobility by using crutches or a wheelchair more skillfully, or learn to make better use of the paretic hand despite its limitations [13].

So how does the brain recover? Historically, the brain was believed to be static: new neurons were thought not to grow after adulthood, and any loss of brain tissue was considered permanent. Today, we know this is not the case. New neurons can be generated in the brain, and synaptic connections may sprout to form new pathways. True recovery, or restitution, involves a series of neurobiological changes [19]. New neurons are formed in the peri-lesional area, replacing injured cells, and new blood vessels develop to support tissue repair. Axonal sprouting alters the cortical sensory and motor maps, forming new neural pathways. Distant brain regions that were functionally disrupted by the lesion may also recover, a process known as reversal of diaschisis [20].

Therapies administered during the sub-acute phase of stroke benefit from heightened plasticity and may even extend the duration of this plastic window [18]. Some interventions include brain stimulation or pharmacological treatment, but one form of therapy is universally accessible: activity-dependent plasticity [21].

Activity-dependent brain plasticity is a theory describing how the brain rewires itself during repetitive task performance, and is closely related to motor learning theory [22]. Repetitive practice can support stroke recovery by guiding the brain to effectively relearn motor pathways that encode motor behavior. By practicing a motor task at the stroke patient's current ability level and gradually increasing its difficulty, significant improvements in motor function can be achieved [23]. Importantly, activity-dependent brain plasticity can occur throughout life, even in old age [24, 25]. This is why older adults are encouraged to walk, spend time with family and friends, and engage in mentally stimulating activities such as solving sudoku. By participating in social, intellectual, and physical activities, many age-related conditions associated with neuronal cell death may be counteracted. An engaging environment promotes the generation of new neurons and the formation of new synaptic pathways [26, 27, 28].

However, in reality, recovery is not straightforward. Stroke often results in a range of disabilities, both cognitive and motor-related [29]. In addition, psychological conditions such as depression may emerge alongside functional impairments, leading to reduced activity levels and diminished motivation [30]. Severe disabilities, such as hemiplegia, can limit voluntary movement, speech, and responsiveness to the extent that the stroke survivor may be unable or unwilling to fully participate in physiotherapeutic practice or social activities [31]. In the most severe cases, individuals may experience complete locked-in syndrome, characterized by the absence of any residual motor function and no potential starting point for motor recovery. These patients typically remain in a locked-in state with markedly reduced quality of life [32]. Yet even under such circumstances, there is hope. Activity-dependent plasticity is driven by activity, but the underlying synaptic changes are caused by brain activity itself [33]. It is well established that the brain encodes memories during sleep and undergoes reorganization even in the absence of overt behavior [34, 35]. Moreover, evidence suggests that mental imagery during wakefulness can activate neural circuits to a degree that promotes plasticity and the formation of new neural pathways [36].

2.2 Motor Imagery

Mental imagery has been extensively studied in sports science. The imagined performance of various tasks can produce real and measurable physiological effects [37, 38]. It has been shown to improve performance in activities such as golf [39], tennis [40, 41], basketball [42], and even to increase muscle strength [43, 44]. The outcomes are striking: physical skills can be learned, at least to some extent, without actual physical execution. In addition, research suggests that mental imagery may benefit cognitive performance [45] and support treatment of psychological disorders [46]. In stroke rehabilitation, mental imagery has been proposed as an alternative or complementary therapy [47]. If mental practice can facilitate the learning of motor tasks, and stroke recovery depends on the brain relearning motor-relevant neural pathways, then imagery could plausibly contribute to improved outcomes for stroke survivors. Indeed, several studies have demonstrated that mental imagery can have positive effects in stroke rehabilitation [48]. Focusing on motor tasks, one may ask whether there are more or less effective ways of performing imagery, and how the brain responds to real and imagined activities.

Mental imagery of motor tasks, or MI, refers to the mental rehearsal of physical activities without overt bodily movement. MI can be performed using several techniques: kinesthetic or visual, first-person or third-person, and movement-oriented or goal-oriented approaches. Kinesthetic MI focuses on bodily sensations, how it feels to move, muscle tension, and the perception of body position and posture. Visual MI, by contrast, emphasizes the mental image of the task being performed, which can be imagined from either a first-person or third-person perspective. Movement-oriented MI concentrates solely on the execution of the movement, while goal-oriented MI includes elements related to the activity, such as the golf club, the ball, and imagining its trajectory through the air. In sports, third-person and goal-oriented imagery have been found to be particularly effective for ballistic activities such as throwing or hitting balls [49, 40]. However, kinesthetic MI has been shown to activate motor-related brain areas more strongly than other types of MI [50]. Additionally, kinesthetic MI activates similar and overlapping motor regions in the brain compared to the corresponding real movements [51]. For this reason, kinesthetic MI is commonly regarded as the preferred technique in stroke rehabilitation.

However, the absence of visual feedback makes MI difficult to evaluate. Real movements can be observed, and a physiotherapist can provide guidance and physical assistance during task execution. This is not possible with MI. Instead, brain imaging techniques are required to observe and assess MI performance. Brain activity can be measured by detecting blood oxygenation levels using, for example, functional magnetic resonance imaging (fMRI) [52] or functional near-infrared spectroscopy (fNIRS) [53]. Alternatively, the electromagnetic fields generated by synaptic activity in the brain can be recorded using magnetoencephalography (MEG) [54] or EEG [55]. The focus here is on EEG, due to its portability and high temporal resolution.

2.3 Electroencephalography

EEG is a non-invasive method for recording the electrical activity generated by the brain [56]. With EEG, brain activity can be recorded and used to communicate or control an external device [57]. EEG has long been used to diagnose epilepsy, which is characterized by strong spiking activity across multiple

EEG channels [58]. It is also commonly used in sleep research [59]. An EEG cap (figure 2.1A) is often used to pre-position the electrodes before placing the cap on the participant's head. Using a cap improves consistency across measurements and studies. EEG experiments typically follow the international 10–10 system for standardized electrode placement [60] (see figure 2.1B of electrode placements). After the cap is in place, an electrolytic gel is applied to ensure proper electrical contact between each electrode and the scalp. While dry EEG electrodes are available, they often suffer from increased signal noise [61]. Wet (gel-based) electrodes provide higher signal quality and are commonly used in EEG research.

Before discussing the motor signal in EEG data, we need to understand how the motor signal is generated by the brain. Given the importance of hand function in stroke rehabilitation, the hand motor signal will be the focus moving forward.

According to the Open Neuroscience Initiative [62], a simplified overview of motor control involves several brain areas working together to generate the motor signal for hand movement. Prior to movement, the premotor area (PM) prepares the action. The primary motor cortex (M1) then sends a motor command that travels down the spinal cord to the hand, resulting in movement. During execution, the cerebellum and the basal ganglia contribute by adjusting and regulating the motion [62]. However, EEG primarily captures activity from cortical surface regions [63]. Therefore, EEG signals recorded during hand movement mainly reflect activity in PM and M1 (see figure 2.1C). Within M1, neurons are organized somatotopically, meaning that distinct regions correspond to different body parts. This organization is often illustrated by the cortical motor homunculus, a figure that visually represents the somatotopic map [62] (see figure 2.1D). Due to the contralateral organization of the brain, the hand motor area in the left hemisphere represents the right hand. Based on this homunculus and the international 10–10 system for electrode placement, right hand activity would be expected in electrodes C1 and C3.

On a molecular level, the EEG signal arises when large assemblies of neurons synchronize their firing rates [63]. It is estimated that between 10000 and 50000 neurons dominate the EEG signal [64]. Kirschtein and Köhling [65] outline this process. Neurons communicate with one another by altering their membrane potential, a change mediated by ion pumps that allow ions such as sodium to pass through the neuronal membrane. These polarity shifts are small, lasting only about 1 ms, which is too brief to be detected by EEG. However, neurons possess axons and dendrites that branch outward, forming connections with thousands of other neurons. The synapse is the junction where an axon (output) meets a dendrite (input). At the synapse, the signal is transmitted via neurotransmitters such as glutamate, which are released from the axon. When neurotransmitters bind to receptors on the dendritic end, ions flow through the postsynaptic membrane (dendrite end). This causes a change in potential in the extracellular space near the synapse and generates an electric current inside the dendrite. An equivalent charge flows through the dendrite closer to the soma (cell body), effectively creating an extracellular dipole of ions. The postsynaptic potential can last up to 10 ms, which is long enough to synchronize in large assemblies of neurons and register in EEG recordings. The cerebral cortex contains large neurons known as pyramidal cells, which in

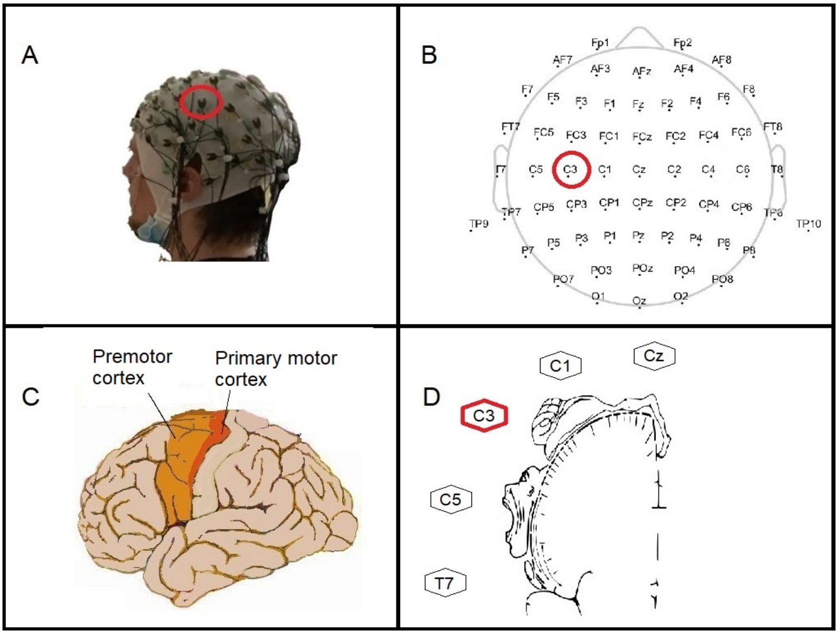

Figure 2.1. From Scalp to Cortex: Mapping the Hand Area via EEG Electrodes. The figure illustrates the anatomical and technical relationship between EEG electrode placement and the motor representation of the hand. These panels demonstrate how electrode C3 captures neural activity from the hand area in the left hemisphere, linking scalp-level measurements to underlying motor function. Note that electrode placement in panel D is approximate, not exact. A) The author wearing an EEG cap, demonstrating practical electrode positioning. Electrode C3 is highlighted with a red circle. B) The international 10–10 system. Electrode C3 is highlighted with a red circle, located over the left primary motor cortex. C) A lateral view of the human brain with premotor cortex and primary motor cortex marked. The primary motor cortex contains the somatotopical map of motor function. D) The motor homonculus, revealing the somatotopical map. Central electrodes are depicted above the hemisphere, and C3 is highlighted with a red edges. The position of electrodes relative to the brain are approximations, and not anatomically exact. **Image credits:** Image A: “Human motor cortex” by Pancrat, derivative work by Iamozy, licensed under [CC BY-SA 3.0](https://creativecommons.org/faq/). The image has been edited and is shared under the same license. Image D: “Motor homunculus” by ralf@ark.in-berlin.de, licensed under [CC BY-SA 4.0](https://creativecommons.org/faq/). The image has been mirrored and annotated with EEG channel labels. The modified version is shared under the same license.

the primary motor cortex (M1) are responsible for voluntary movement. These neurons have long (apical) dendrites oriented perpendicular to the cortical surface. The postsynaptic potentials of pyramidal cells are the primary source of the signal recorded by EEG [65].

2.4 Sensorimotor Rhythm

Brain signals measured with EEG are commonly analyzed as oscillatory activity, or rhythms. A brain rhythm is characterized by its frequency and spatial distribution. These rhythms are typically categorized into five frequency bands: Delta (0–4 Hz), Theta (4–8 Hz), Alpha (8–12 Hz), Beta (12–30 Hz), and Gamma (>30 Hz). The spatial distribution may involve one or several electrodes, and the rhythms reflect underlying synaptic activity. An increase in oscillatory activity following an event, such as gripping with one hand, is referred to as event-related synchronization (ERS), whereas a reduction in oscillatory activity is referred to as event-related desynchronization (ERD) [66]. The spatial and frequency patterns of ERD and ERS during hand MI (or the corresponding movement) describe the motor signal in the brain, known as the sensorimotor rhythm (SMR).

Typically, the SMR generated during hand MI produces ERD in both the Alpha and Beta bands, particularly in EEG channels C3 and C4 [67]. The SMR is identified by averaging multiple repetitions of a hand task, such as gripping. The SMR of a single repetition is difficult to observe in raw EEG activity (Figure 2.2A), but by extracting relevant features such as Alpha power and averaging across many repetitions, the typical Alpha ERD can be observed over time (Figure 2.2B). To visualize the spatial pattern, Alpha power can be extracted from both MI performance and an idle task (control condition), and the difference displayed as color in a topographic map (Figure 2.2C). Alternatively, the topography can be generated by comparing the task with baseline activity measured before task onset.

The typical motor signal of hand movements has been thoroughly established by Gert Pfurtscheller and colleagues [66] and reproduced by other researchers in both healthy subjects [68, 69] and individuals with brain lesions [70, 71, 72]. Pfurtscheller et al. [73] demonstrated that hand movements produces ERD in the Alpha and Beta bands within the localized somatotopic hand area, whereas foot activity produces ERS in the same region. This suggests that focusing on one type of activity may inhibit surrounding areas [74].

Contralateral ERD begins up to two seconds before voluntary movement and becomes bilateral during movement execution [75]. This preparatory activity originates in premotor and supplementary motor areas, not primary motor cortex. MI has been compared with the motor preparation signal but has also been shown to activate the primary motor cortex and generate bilateral activity, similar to actual movement [76]. After MI completion, ERS is measured in the hand areas of the brain, marking a rebound of oscillatory activity [74].

High Alpha and Beta power indicate cortical idling, meaning that the region is not actively processing information. Consequently, Alpha ERD reflects increased synaptic activity [77], and MI of hand movements produces ERD in both Alpha and Beta bands over the hand areas of the brain [78].

The specific frequency components of hand SMR were first identified near 10 Hz and 20 Hz [78], then refined to the ranges 9–14 Hz and 18–26 Hz (subsets of Alpha and Beta), although variations such as 8–12 Hz and 18–25 Hz

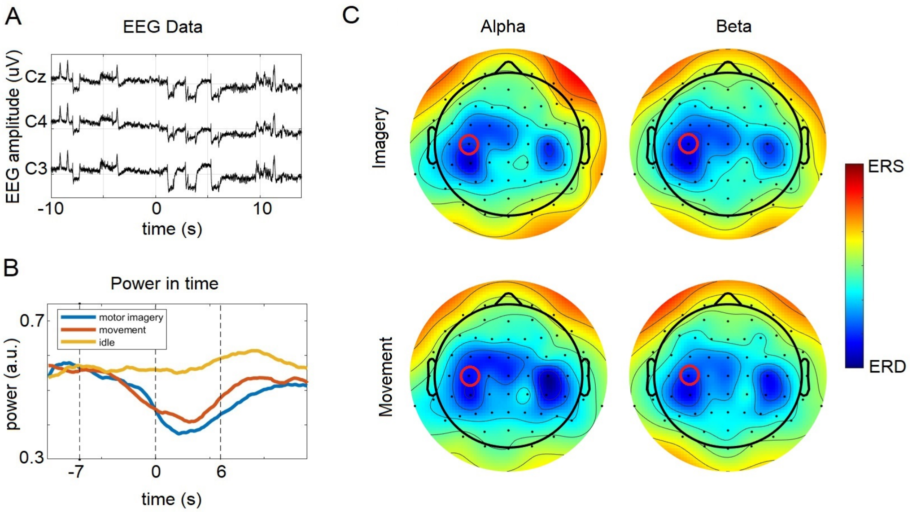

Figure 2.2. EEG Signatures of Hand Motor Activity: From Channels to Cortical Patterns. This figure illustrates EEG data and derived features related to right-hand motor activity. The data presented here were recorded from the author during a single calibration session. The task instruction was presented at time = -7 s. The task onset occurred at time = 0 and lasted until time = 6 s. A) Raw EEG signals, i.e., unprocessed signals from three central electrodes (C3, Cz, C4), during a single repetition of a motor imagery task involving one hand, sampled at 1000 Hz. B) Spectral Alpha power (8–12 Hz) in channel C3 is compared across three conditions: movement, motor imagery, and an idle task. Power was extracted using fast fourier transform (FFT) on sliding windows of 250 ms length with a 100 ms step. Data were averaged across 60 trials (20 per task) and smoothed using a moving average window of size 100. C) EEG patterns of the sensorimotor rhythm. Data from imagery and movement are contrasted with data from the idle task. The typical motor signal described in the literature is reproduced here. The SMR characteristic is specifically event-related desynchronization (ERD), centered contralaterally or bilaterally in central electrodes. In these four topographies, ERD is bilateral but stronger in the contralateral hemisphere during imagery. For movement, the activity is nearly bilateral. The activity is not strictly limited to C3 or C4 but is distributed over a broader area, including surrounding electrodes.

have also been reported [69] due to the exact SMR varying between individuals [79]. Furthermore, Beta appears to be more localized than Alpha during ERD-related performance [66] and slightly anterior to the Alpha component [80, 74]. However, McFarland et al. reported that the Beta component is centered near the vertex (Cz) rather than exhibiting bilateral activity [76].

The individual SMR may be more accurately characterized using high-dimensional data. A higher-resolution power spectrum can be extracted from numerous EEG channels (e.g., 32 or more), resulting in a large set of features that describe task-related activity in the EEG data [81]. The advantage of such high-dimensional data is that it may more precisely reflect the motor signal of an individual. The human brain is highly unique, with differences in size and spatial organization. Somatotopic maps can vary [82], meaning that even with identical electrode placement, the hand area may not occupy the same position across individuals [79]. Furthermore, stroke patients frequently exhibit disrupted patterns. Lesions introduce slow-wave activity and hemispheric asymmetry, which disrupts the typical ERD by producing excessive activity in low frequencies and a distorted topographical pattern [83, 84]. Additionally, the brain is protected by three membranes (meninges), the cranium, the periosteum, and the scalp layers. As the electrical signal propagates through these protective layers, it diffuses and spreads—a phenomenon known as volume conduction [85]. Cap placement and electrode-to-scalp connectivity may also vary between sessions, introducing noise and variability in the expected ERD and ERS patterns. Finally, the well-established SMR signal, characterized by Alpha and Beta ERD, may not represent the complete MI pattern but rather the most reproducible and generalizable component. By increasing the number of channels [86] and by expanding the frequency range [87], the MI signal becomes more discernible.

2.5 Decoding the Brain Rhythm

Identifying patterns in high-dimensional data poses a challenge for humans, but not for machines. Machine learning techniques enable computers to automatically detect patterns in data. Multivariate pattern analysis is a methodology in which machine learning algorithms construct models that classify data based on the most discriminative features in the data [88]. To identify the pattern associated with a hand task in EEG, multiple repetitions of the task must be recorded. A control task is then recorded for comparison. An idle or relax task is suitable for establishing a baseline of EEG activity. These repetitions of hand and idle tasks are used as training data for the classification algorithm. The resulting classifier model can be interpreted as a boundary, or hyperplane, in feature space [89]. This model can then accept new data samples and classify them. Depending on which side of the boundary a new sample falls, it is classified as either motor or idle activity. Importantly, the model itself represents the features that predict motor activity. Thus, it serves as a high-resolution representation of the motor signal.

When classifiers predict the class of novel data, the output is typically categorical. However, the distance to the decision boundary, known as distance-to-bound (DTB), contains additional information. DTB is a continuous metric that reflects the contribution of all features in the data, and a low value may indicate uncertainty. In EEG-controlled robot navigation, low-probability predictions can be rejected to reduce false positives, which in turn improves robot control [90]. Conversely, a high DTB value may indicate greater certainty. It is reasonable to believe that MI is not a binary process. Rather, it can vary continuously over time. DTB provides a more nuanced approach to analyzing patterns in EEG data [91]. With a continuous metric for single repetitions of MI activity, trials can be ranked according to the strength of pattern expression.

A classification algorithm generally attempts to model a decision boundary such that all samples of one class fall on one side and all samples of the other class on the opposite side. In practice, this is rarely achievable. Class distributions often overlap, meaning no boundary can perfectly separate them. While non-linear classifiers can theoretically model any data, this typically leads to overfitting, which degrades performance on unseen data [92]. EEG data is particularly challenging because it is noisy, non-stationary, and the amount of training data is insufficient to eliminate spurious correlations. For these reasons, linear, regularized classifiers still dominate BCI research [93].

When the classifier cannot perfectly separate all samples, it instead aims to minimize error. The specific approach varies by algorithm, but the general goal is to produce an unbiased model. An unbiased model balances classification accuracy across classes. However, due to the non-stationarity of EEG signals, this balance may not hold throughout a session. One of the major challenges with EEG data is drift. Drift results from a static shift in the EEG signal, causing all classifier decision values to increase or decrease. In other words, the entire data distribution shifts toward one side of the boundary. This leads to a classifier biased toward one class. In practice, this means that data containing clear MI activity may be classified as idle, or data lacking MI may be classified as MI.

Classifying the motor signal in the brain using machine learning tools also addresses the challenge of MI being difficult to observe and guide. By classifying EEG in real time, a computer can use the classification result to provide feedback on the MI, effectively enabling the imagery to be observed. And this is a BCI.

2.6 Brain-Computer Interface

A BCI is a system that records signals from the brain and translates them for communication and control [57]. BCIs have been used to type on a computer [94], to navigate robots [95], wheelchairs [96], and quadrocopters [97], to achieve continuous three-dimensional control [98], to play games [99], to move within virtual reality environments [100], and to support motor recovery in stroke rehabilitation [101]. Stroke rehabilitation using EEG-based systems is a growing research field, and several promising studies have highlighted opportunities for neurotechnology-supported care [101]. Rehabilitation approaches are often based on MI practice. The goal is to trigger activity-dependent plasticity by closing the motor learning loop [56]. Learning motor tasks relies on reinforcement learning: repetitively practicing a task and refining performance based on visual and sensory feedback.

Several types of feedback have been investigated, including visual [102], auditory [103], tactile [104], electrical [105], robotic [106], and brain stimulation [107]. Visual and auditory feedback can be delivered using a standard laptop computer, offering the advantage of not requiring additional hardware. However, sensory feedback may be more effective for clinical outcomes, as it engages sensory nerve pathways from the limb being rehabilitated [108].

During BCI practice, users perform many repetitions of one or several tasks. Feedback is provided for each repetition and can be either delayed or real-time. Early BCI experiments relied on delayed feedback, meaning that the user first completed a task (e.g., movement or motor imagery), which could last several seconds. Feedback was then provided based on the EEG activity recorded during the entire task. The advantage of this method is that longer time windows reduce white noise, and EEG signal processing methods tend to perform better with extended data segments. EEG data typically has a very low signal-to-noise ratio (SNR) [109]. Real-time feedback (also referred to as concurrent or ongoing feedback) can be provided if the system maintains a time window of the most recent EEG data. A simple implementation might update the feedback every second by analyzing the preceding one-second segment. A smoother and more responsive experience can be achieved using a sliding window approach. For example, with a step size of 100 ms, feedback can be updated ten times per second while still analyzing a one-second window. However, even real-time feedback introduces latency, as the time window must be recorded and the signal processed and classified before feedback is generated.

The latency of real-time feedback is influenced by both the length of the time window and the computational time required to analyze EEG data. Reducing latency involves shortening the time window and minimizing signal processing. However, these adjustments can compromise signal quality. Shorter time windows contain fewer cycles of rhythmic brain activity, such as the SMR, which limits decoding accuracy. To accurately represent rhythmic behavior in EEG data, the time window should accommodate 7–8 cycles of the target frequency [110]. The lower bound of the SMR is 8 Hz, and fitting eight cycles requires a minimum window length of one second. Using a shorter window is likely to reduce signal quality. In contrast, longer time windows support more accurate decoding of EEG signals [111]. Meanwhile, real-time feedback with low latency has been shown to more effectively promote cortical activation in BCI users [112], which may be beneficial for clinical outcomes in rehabilitative BCI applications.

2.7 Trends and Challenges

A motor signal can be more accurately represented by increasing both spatial and temporal resolution. However, high dimensionality poses a challenge when decoding MI from EEG data. A typical BCI session may last one to two hours and yield approximately 100 repetitions of MI task performance. In a simple two-class problem, 50 MI repetitions are contrasted with 50 idle repetitions, which is sufficient for univariate data analysis. With 64 EEG channels and 30 frequency levels, the number of features reaches 1,920. When the number of features exceeds the number of repetitions (i.e., data samples), the problem becomes ill-posed [113], similar to an underdetermined system of equations where there are more variables than equations. It is simply not feasible to record thousands of repetitions during a BCI session.

High dimensionality combined with a low signal-to-noise ratio of EEG can lead to spurious correlations and overfitting of the classification model [114, 115]. Feature reduction methods such as principal component analysis (PCA) or linear discriminant analysis (LDA) generate linear combinations of features that maximize variance, allowing for the selection of a smaller feature set. However, combining features may retain randomly correlated components in the training data. In contrast, feature selection methods aim to identify a subset of representative features, thereby excluding weakly correlated ones. Nevertheless, the issue persists, as spuriously correlated features may still be selected [116]. Comparison to prior work is also limited for high-dimensional MI signals, since established MI patterns typically focus on the most common features. The high-resolution pattern of a motor signal is likely subject-specific and remains poorly understood. Despite this, validation against known MI patterns is still useful for confirming the presence of MI-related activity in the data.

A BCI designed for stroke rehabilitation is a real-time system intended to close the loop for reinforcement learning. This form of rehabilitation relies on Hebbian plasticity and learning, which describe enhanced synaptic activation resulting from simultaneous neuronal firing [101]. Hebbian plasticity, particularly spike-timing dependent plasticity, operates within very short time frames, typically up to 20 ms [117, 118]. By this definition, the feedback latency of a BCI system must not exceed 20 ms in order to effectively trigger Hebbian plasticity. This presents a challenge, as most signal processing methods used to detect MI in EEG data require longer time windows. Many BCI experiments record one second or more of data before initiating analysis and providing feedback. Certain signal processing techniques, such as bandpass filtering, are unsuitable for very short time windows. Moreover, extracting power features from brief segments is problematic when too few cycles of the wave fit the window.

However, motor learning is not limited to Hebbian plasticity. Reinforcement learning can occur over longer time scales due to mechanisms such as eligibility traces and reward signals, including dopamine, which serve as tags for reinforcing specific synaptic connections [119]. Learning can also take place with greater latency between the event and the feedback. Some BCI experiments provide delayed feedback, allowing for the recording of a complete MI task lasting several seconds before feedback is delivered [120]. Motor learning with delayed feedback is not uncommon. Consider, for example, a sport like golf: the time between executing a motor action (hitting the ball) and receiving feedback (observing where it lands) does not prevent skill acquisition. Nevertheless, real-time feedback has been shown to enhance implicit motor adaptation, whereas delayed feedback primarily supports strategic learning [121]. Furthermore, feedback delay has been found to negatively correlate with cortical feedback effects [112]. The trade-off between accurate and timely feedback must be considered when designing a BCI.

Many BCI experiments rely on classification algorithms to model the MI signal and provide feedback that informs users when they perform correctly and guides them toward producing stronger MI signals [122]. Classification accuracy is a standard metric for evaluating BCI performance. However, a significant portion of individuals are unable to achieve high accuracy, sometimes performing at chance level. These individuals are sometimes referred to as BCI illiterates [82], due to their inability to generate decodable cortical patterns in EEG data. Because relevant feedback is essential for effective BCI rehabilitation, some studies include a screening session to exclude participants who fail to reach a minimum performance threshold [120]. Nevertheless, evidence suggests that low to moderate BCI performance may still be sufficient to achieve clinical benefits [123]. Unlike conventional physiotherapeutic practice, few BCI experiments incorporate adjustable difficulty settings. In stroke rehabilitation, task difficulty is typically matched to the patient's motor function and gradually increased as recovery progresses. If BCI experiments implemented configurable difficulty levels, BCI-based rehabilitation could be further individualized.

The non-stationarity of EEG signals presents a challenge, as MI signals vary both between individuals and across sessions [79]. Individualized classification models have adequately addressed inter-subject variability, but each person's EEG data may still differ from one session to another. Additionally, the MI pattern appears to change depending on whether the subject receives feedback during MI performance [124]. This is problematic because many BCI experiments train the classification model using data from a calibration session where no feedback is provided. Such data may be unsuitable for effective BCI rehabilitation. To address this issue, various adaptive classification algorithms have been tested. An adaptive classification model can incorporate new data during the BCI session and update its parameters accordingly. Adaptive classifiers often outperform static classifiers. However, this means the classification model changes during the session, which could be confusing for the BCI user [93]. This situation is referred to as the two-learner problem, where both the human and the BCI system adjust their behavior in response to each other. Another concern is whether an adaptive classifier might change to the extent that it no longer provides relevant feedback. Further research is needed to understand what causes the differences between feedback and non-feedback EEG data, and to determine which type of data is most relevant for BCI rehabilitation.

3. Related Work

In this chapter, I compare four randomized controlled trials (RCTs) of BCI-based rehabilitation with stroke patients. These studies are of high quality and clearly describe their methods, particularly in relation to the challenges identified in the previous chapter: high dimensionality, real-time demands, difficulty level control, and adaptive classification.

3.1 High Dimensionality

Increasing frequential and spatial dimensionality may improve the ability to capture and represent the MI signal in the brain. Despite this potential, many RCTs rely on uni- or low-dimensional data. Ramos-Murguialday et al. [125] investigated the relevance of contingent feedback compared to irrelevant feedback. Their hypothesis was that relevant feedback, delivered close to the time of an intended hand movement, would lead to clinical improvement. The feedback was based on univariate data, specifically the SMR measured in the Alpha frequency band (8–13 Hz). The signal was recorded from ipsilesional channels, although the exact channels were not specified. Pichiorri et al. [126] also used near-univariate data to provide feedback while examining the impact of BCI feedback on MI performance compared to covert MI practice. EEG data were recorded from 31 channels, and feature relevance was calculated using class covariance. A neurophysiologist then selected one or a few individual features for each stroke patient. The selection was based on the expected SMR signal in the Alpha or Beta frequency bands from ipsilesional channels. Both studies classified MI using a threshold applied to the SMR rhythm.

Ang et al. [120] evaluated the ability of a BCI system to close the reinforcement loop and promote clinical gains. In their study, the test group received feedback from a robotic orthosis when MI was detected, while the control group received robot-assisted movement training during volitional movement tasks. MI was detected using 27 EEG channels and 9 frequency bands, resulting in a total of 243 features for classification. The FBCSP algorithm was used to generate feature pairs that maximize the variance ratio between classes. Although only four feature pairs (eight features) were selected, these features were derived from combinations across the full feature set. As a result, they represent a much richer signal than uni- or low-dimensional data. Frolov et al. [127] also classified MI using a relatively large number of EEG electrodes

(30), but only one frequency band spanning 5–30 Hz. In essence, their approach provided higher spatial resolution in the MI feedback, but not higher frequential resolution. Their hypothesis and study design were similar to those of Ramos-Murguialday et al., in that the control group received robotic feedback that was unrelated to the EEG motor signal.

3.2 Real-Time Feedback

Real-time feedback mirrors conventional physiotherapy, where the visuomotor system is engaged during motor task performance. It may also enhance performance and help guide BCI users toward producing more distinct motor-related EEG patterns [128]. Additionally, there is evidence that low-latency feedback in BCI systems can be beneficial when learning to control cortical signals [112].

Ang et al. [120] did not provide real-time feedback. Instead, EEG data were recorded during 4.5 seconds of MI performance, followed by one second of signal processing. If MI was detected, feedback was delivered as a pre-defined trajectory of robot-assisted movement. However, the control group did not receive delayed feedback. Since the study aimed to investigate the effect of closing the neurofeedback loop, the control group received training with the robotic orthosis only. If the robot failed to detect a volitional movement within two seconds after a practice repetition, it initiated movement assistance automatically. Pichiorri et al. [126] also provided delayed feedback, although their design included real-time feedback that was visible to the operator. During the calibration session, the patient viewed a computer screen with a cursor at the bottom and a green arrow covering the top half. The cursor moved upward, and when it passed over the green arrow, the patient performed MI. During BCI training sessions, only the operator could see a similar screen with a cursor and a goal. The patient performed MI for ten seconds, and MI was decoded every 100 ms using the most recent one-second time window. Positive MI predictions directly controlled the cursor's speed. If the cursor reached the goal within ten seconds, delayed feedback was presented to the patient. The intention was to allow the operator or therapist to use the real-time feedback as a tool to guide the patient's MI performance.

Both Ramos-Murguialday et al. [125] and Frolov et al. [127] provided patients with real-time feedback. In their experiments, feedback was updated every 40 ms and 100 ms, respectively. Positive feedback triggered movement of the hand or arm orthosis along a predetermined path. All RCTs followed a cued recording protocol, which dictates when the participant starts and stops MI performance.

3.3 Controlling for Performance

Controlling the difficulty level in BCI-based stroke rehabilitation offers several advantages. It allows for a gradual increase in task complexity as patients improve, which mirrors conventional physiotherapy practices. It also provides an opportunity to investigate the relationship between user performance and clinical outcomes more systematically. Instead of correlating performance with improvement, performance could be treated as a fixed parameter in experimental design. For participants with very low BCI performance, a reduced difficulty level may help increase motivation to engage with the BCI system and continue practicing. This approach could make BCI-based rehabilitation more accessible and better tailored to individual needs.

Ramos-Murguialday et al. [125] and Ang et al. [120] did not control for user performance. However, Ang et al. manipulated the difficulty level in an earlier study [129]. In that study, the test group received positive delayed feedback if no MI was detected in two consecutive repetitions. This design choice artificially increased BCI performance.

Pichiorri et al. [126] also manipulated performance levels. When calculating the threshold for MI detection, it was set so that idle activity would only produce positive feedback by chance in 5% of cases. This method was previously tested with success in an earlier study [130]. However, they did not explicitly define a difficulty level. Instead, they controlled the rate of false positives. Because difficulty was manipulated by limiting false positives, the actual bias of the classification model is unknown.

Frolov et al. [127] provided both visual and robotic feedback to patients. While difficulty level was not controlled within the classifier, the feedback mechanism was biased. Movement of the exo-hand was determined by the ten most recent classifier predictions. If at least four of the ten predictions indicated MI, positive feedback was given by slowly extending the fingers with the exo-hand. Maximum speed of hand opening was achieved if all ten predictions indicated MI, resulting in full extension within five seconds. This design biased the system toward producing more frequent positive feedback.

Incorporating a difficulty level is almost entirely absent, except for a few performance-altering design choices. Introducing such a mechanism could create opportunities to engage and motivate low-performing participants while providing appropriate challenges for high-performing individuals.

3.4 Adaptation and Non-Stationarity

Adaptive BCIs are capable of incorporating new data into the model during training. This adaptation can help the system track signal drift and reduce inter-session variability, which may improve stability and enhance overall BCI performance. Adaptive designs may use novel data alongside calibration data, or rely exclusively on same-session data to eliminate the need for a separate calibration phase [131]. Adaptation can be implemented by adjusting specific BCI parameters or by fully retraining the classification model [132]. However, the computational demands of adaptive classification must be carefully considered, especially in real-time applications.

Ramos-Murguialday et al. [125] used an adaptive classifier. The model maintained a history of the most recent 15 seconds of idle and MI activity, and updated the MI detection threshold based on the zero-mean distance between the two distributions. Because the history size was fixed, retraining had a low computational cost. The purpose of this approach was to adapt to changes in the shape of the MI and idle distributions over the course of training. Frolov et al. [127] also employed an adaptive classification method. After each block consisting of two MI and two rest repetitions, the model was retrained using all available data. This meant that the amount of training data increased progressively throughout the session. In contrast, KK Ang et al. [120] and Pichiorri et al. [126] did not use adaptive classification. Their models relied entirely on training data collected during a separate calibration session.

4. Research Overview

This thesis is divided into two main parts using different study populations: healthy participants and chronic stroke patients. Methods for analyzing temporal dynamics were first developed using data from the healthy population and then implemented and tested in real BCI experiments with stroke patients.

In the first part, methods and experimental design were developed with healthy participants. I evaluated approaches for same-hand MI classification using established EEG preprocessing techniques, including spatial filtering, independent component analysis, and wavelet-based power spectral density (PSD). Topographical analysis of Alpha and Beta activity was performed, and a feature reduction method was tested to select informative features without compromising signal integrity. A custom BCI framework was built to assess real-time feedback, focusing on system latency and uncertainty. Multivariate pattern analysis was used to explore temporal variability in single MI repetitions, and MI patterns, quantified as DTB, was visually compared with topographical expression.

In the second part, these methods and designs were implemented in a BCI experiment with stroke patients (clinicaltrials.gov ID: NCT03994042). Signal processing was streamlined to support real-time feedback. FFT replaced wavelet analysis, spatial filtering was pre-computed, and short time windows of 250 ms were used. Feedback training data included both calibration and same-session data. DTB was used to set and maintain difficulty levels, and a new method was developed to quantify spatial pattern shifts. Lesions were localized using MRI and considered in EEG analyses. Adaptation using same-session data was evaluated by comparing performance with a static model trained only on calibration data.

There is an ongoing study involving 15 stroke patients, in which we investigate a calibration-free BCI system with rapid model convergence (clinicaltrials.gov ID: NCT04847089). Model characteristics, DTB, and classification accuracy are tracked to study convergence and potential maladaptive learning.

4.1 Problem Formulation

Many clinical BCI experiments rely on simple methods for classifying EEG data, such as measuring mu rhythm amplitude over a single electrode. While this approach captures established motor signals in EEG, it provides limited information. By increasing spatial and frequential resolution, a more complete and accurate representation of the motor signal may be achieved, which in turn can enhance the relevance of BCI feedback. However, high-dimensional data is more likely to include task-irrelevant information, especially in small datasets, and places greater demands on signal processing methods. This can result in increased latency within the BCI system, which negatively affects the reinforcement learning loop. If the delay between motor performance and feedback becomes too long, the user may struggle to associate the feedback with their action, thereby hindering learning.

Controlling the difficulty level is rarely implemented in MI-based BCI (MI-BCI) experiments, despite being a common practice in conventional stroke therapy. Gradually increasing task difficulty allows training to match the patient's ability and adapt as the patient improves. One approach to controlling difficulty in BCI is to bias the classifier. MI-BCI experiments often aim for unbiased classification, which ensures that feedback is based on accurate motor-related brain signals. However, this design can result in low-performing individuals receiving little or no relevant feedback. When classifier accuracy approaches 50%, it becomes unclear whether positive feedback reflects genuine motor signals or random brain activity. Still, low accuracy does not necessarily imply that feedback is unrelated to motor intent. It may simply indicate that the individual is unable to produce a clear motor signal more than half the time. Visual inspection and comparison with prior literature may reveal that even low-performing users, sometimes referred to as "BCI illiterates", are capable of generating distinct motor signals, albeit infrequently. By biasing the classifier, the system could ensure that positive feedback is only delivered in response to strong and clearly identifiable motor signals. Alternatively, difficulty could be reduced for low-performing users to help maintain motivation and engagement with the BCI system.

For clinical MI-BCI therapy, patients typically participate in a series of BCI sessions. EEG signals are non-stationary and subject to both inter- and intra-session variability, which can lead to drift in the model output. Adaptive classifiers are well suited to address this issue. Adaptation can be achieved by incorporating data from the current session or by excluding training data from previous sessions entirely. The model may be adjusted, for example by updating the detection threshold, or by retraining it completely. This raises an important question: how can a classification model mitigate inter- and intra-session variability while avoiding maladaptive reinforcement or divergence across a series of BCI sessions? The focus of this research has been formulated into the following three research questions (RQs).

1. **How can a BCI account for high dimensionality and real-time demands?**
   In paper 1, I present the first results from my EEG recording protocol and signal analysis processing methods. I validate the data against prior knowledge in the literature and investigate same-hand separability. In paper 2, I investigate a genetic algorithm for feature reduction which

preserves original features. In paper 3, I test various configurations in a BCI framework to investigate real-time properties.

2. **How can the difficulty be controlled online in a BCI?**
   In paper 4, I thoroughly explore temporal dynamics of MI in EEG signals, and validate the feature selection from the genetic algorithm with the visually observed MI pattern. Distance-to-bound is proposed as a continuous measure of the variable MI signal strength, and the distribution of MI data samples presents an opportunity to bias the classifier to achieve an arbitrary performance level. In paper 5, this method for controlling difficulty level is implemented and tested in a pilot study with two stroke patients. However, the signal processing methods had to be adjusted to meet real-time criteria, as discussed in Paper 3.
3. **How can adaptive classification mitigate non-stationarities in the EEG data within and between sessions?**
   In paper 5, we propose an adaptive classification algorithm. The majority of training data is collected during a calibration session, but a shortened version of passive data collection occurs on the BCI training session. By including a small amount of same-session data, inter-session variability is reduced. In Paper 6, we evaluate this adaptation by comparing the method with a non-adaptive classification method, i.e. using only training data from a different session.

4.2 Research Method

This research was conducted using Design Research Methodology (DRM) in combination with Exploratory Data Analysis (EDA). DRM is a framework that structures the research process for developing and evaluating an artifact, such as a product or process. It typically consists of four iterative steps: (1) setting research goals, (2) conducting a descriptive study I, (3) performing a prescriptive study, and (4) conducting a descriptive study II. The DRM methodology can be seen in figure 4.1.

In this research, each DRM cycle begins with the definition of an initial goal and corresponding deliverables. The first goal was to investigate the feasibility of classifying same-hand MI tasks in EEG data. The deliverables for this cycle included the type of EEG recording protocol and the validation procedures necessary to achieve the goal. Subsequent goals focused on exploring a difficulty level for MI-BCI training and adaptive classification in rehabilitation. The deliverables for these cycles primarily consisted of the design of the BCI intervention.

The first descriptive study (Step 2) typically involves a literature review to survey the state of the art and identify gaps in existing knowledge. This step is complemented by meetings aimed at refining the research objectives. It often overlaps with the goal-setting step, as insights gained from the literature and discussions with supervisors contribute to a more clearly defined research goal.

The prescriptive study (Step 3) is the phase in which the artifact is developed and tested within its intended context. My research is highly experimental, involving human participants and iterative development of the BCI. Across multiple DRM cycles, I have developed a BCI framework that includes hardware stress tests, an offline recording protocol, a BCI with adjustable difficulty levels, and a BCI with fully adaptive classification. Development occasionally feeds back into earlier stages, as practical challenges reveal new design considerations. The recording protocol, both offline and online, dictates how EEG data is collected. In my studies, I use a cue-based data collection protocol. Participants waited for a visual cue on a computer screen indicating which type of MI task to perform and when to begin. Each task was performed for a fixed duration, producing one repetition (also referred to as a trial). Each repetition ended after a set time, followed by a brief pause before the next repetition began. A typical session lasted approximately 2–3 hours, with active recording lasting up to 1.5 hours. From each session, approximately 200 repetitions were recorded. This protocol was used to collect offline EEG data from healthy participants and to guide MI practice for stroke patients during the BCI studies.

The second descriptive study (Step 4) involves evaluating the artifact in relation to the research goals, typically resulting in one or more publications. In this phase, Exploratory Data Analysis (EDA) is applied to gain deeper insights into the data and to inform improvements for subsequent DRM iterations. EDA is an approach aimed at maximizing understanding of a dataset and uncovering its underlying structure, generally through data visualization [133]. In this research, EEG data are visualized using topographies and graphs to explore the characteristics of motor-related signals. Additionally, classifier weights and feature selection outputs are visualized to better understand how machine learning models differentiate patterns, in contrast to visual inspection by researchers. One common example of EDA in BCI experiments involves working with high-dimensional EEG data. Training a classifier directly on EEG data avoids assumptions about the presence of SMRs, allowing the data itself to guide model development. This contrasts with classical data analysis, where models are built based on predefined assumptions about the data. For instance, BCI experiments that classify mu and Beta rhythms recorded over electrodes C3 and C4 rely on assumptions about spatial and frequency-specific structure in the data.

In this research, EEG data are also treated as qualitative data when observing topographies of the MI versus idle contrast. Although EEG data are inherently numerical, the interpretation of spatial patterns is qualitative, and comparisons with topographical patterns reported in the literature constitute a qualitative assessment. Visual inspection enables researchers to identify typical MI-related EEG patterns, even when the expected bilateral ERD does not

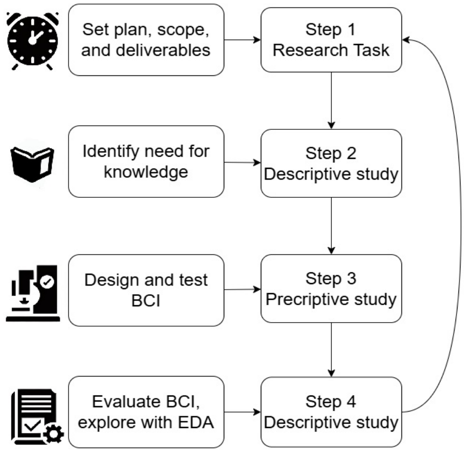

Figure 4.1. Design Research Methodology (DRM). The image shows a DRM in four steps, using EDA in the final descriptive study.

appear precisely over the same electrodes. This approach offers advantages, as variability in expected patterns may arise due to factors such as EEG cap misplacement, differences in head shape, electrode impedance, the thickness and structure of underlying tissues, and individual variation in the location of motor areas in the brain.

While statistical generalization may not be applicable in case studies such as this one, analytical generalization can be used to propose theories that help explain observed phenomena. For example, in the stroke study, paper V, Patient 1 exhibited a typical ERD pattern that was shifted posteriorly in the ipsilesional hemisphere. According to the literature, brain lesions are known to produce slow waves. A visualization of low-frequency activity revealed a region with strong low-frequency content overlapping the lesioned area and covering the typical ERD region on the affected side. Furthermore, natural recovery after stroke often involves peri-lesional areas compensating for lost function. Based on analytical generalization, I suggest that the posterior shift in the patient's ERD pattern was caused by the lesion, and that the peri-lesional region toward the back of the head either retained activity or had taken over function from the damaged area. While this does not constitute evidence, such analytical generalization can advance research by prompting new questions. For instance, if the lesion has spatially displaced MI-related EEG activity, would rehabilitation be more effective if feedback is provided at the new location, or should it target the original, lesioned region?

4.3 Validation of Results

Internal validity of data. The BCI design and EEG recording protocol were based on experimental setups described in the literature, and the EEG equipment was used in accordance with both the manufacturer's operating manual and prior experience in the laboratory. To further ensure data validity, EEG topographies were visually inspected and compared with previously published findings. This provided qualitative support for the validity of the recorded data.

Internal validity of BCI performance. In this work, BCI performance was evaluated in terms of both classification accuracy and clinical relevance. Classification accuracy reflects how well the classifier generalized to unseen data within the dataset, and was assessed using k-fold cross-validation. Additionally, accuracy was measured under online conditions, which is considered the gold standard for validation. Since BCIs are inherently real-time systems, offline performance tends to be higher than online performance [93, 134]. Publicly available datasets suffer from low validity, as repeated use across research groups may lead to inflated performance due to overfitting. In the context of MI-BCIs for stroke rehabilitation, however, classification accuracy is not the primary outcome of interest. Instead, clinical recovery measures are prioritized, with the Fugl-Meyer Assessment (FMA) being the most commonly used evaluation tool [135]. For this reason, FMA scores were analyzed and explored throughout the clinical intervention trials.

Analytical generalization. This research is primarily exploratory and based on case studies, which allows for analytical generalization. While large-scale studies provide evidence for the effectiveness of MI-BCIs, case studies offer insights into underlying mechanisms, the ”how” and ”why” In this work, EEG data were collected from a small number of participants and analyzed using a variety of methods. The results were interpreted in relation to existing literature. At times, theoretical models suggested by the literature prompted new analyses, while novel findings led to the formulation of alternative models. This iterative process between data exploration and theoretical framing generates valuable knowledge that supports continued research. Nevertheless, it should be noted that statistical generalization is not possible in these studies due to the small sample size and the absence of control groups.

4.4 Ethical Perspectives

The potential benefits of developing alternative and complementary rehabilitation methods justify the inconvenience experienced by participants. These methods can enhance independence and improve quality of life for hundreds of millions of individuals worldwide, and the underlying technology has advanced substantially in recent years. With continued technological progress, rehabilitation approaches are becoming more accessible and reliable while also contributing to scientific knowledge. Potential improvements include reduced preparation time, simplified setup, streamlined procedures for operators, and training protocols that are both engaging and enjoyable. The primary ethical considerations for stroke patients relate to the time commitment and physical endurance required to complete an intervention.

All studies included in this work adhered to the principles outlined in the Declaration of Helsinki (2013) and received ethical approval from the Swedish Ethical Review Authority in accordance with national regulations governing research involving human participants. All participants were provided with comprehensive information regarding the purpose, procedures, potential risks, and benefits of the research, and written informed consent was obtained prior to participation. Participation was entirely voluntary, and patients were informed of their right to withdraw from the study at any time without prior notice or explanation.

5. Contribution

This chapter is divided into two parts. The first part is a presentation of each included paper with a short summary and my own contribution. The second part discusses my scientific contributions related to each reseach question.

5.1 Contribution of Included Papers

This section presents all six included papers with a short summary followed by my contribution to each paper.

Paper I

Discriminating EEG spectral power related to mental imagery of closing and opening of hand.
Tidare, J., Leon, M., Xiong, N., & Astrand, E.
In 2019 9th International IEEE/EMBS Conference on Neural Engineering (NER) (pp. 307-310). IEEE.

Summary: ElectroEncephaloGram (EEG) spectral power has been extensively used to classify Mental Imagery (MI) of movements involving different body parts. However, there is an increasing need to enable classification of MI of movements within the same limb. In this work, EEG spectral power was recorded in seven subjects while they performed MI of closing (grip) and opening (extension of fingers) the hand. The EEG data was analyzed and the feasibility of classifying MI of the two movements were investigated using two different classification algorithms, a linear regression and a Convolutional Neural Network (CNN). Results show that only the CNN is able to significantly classify MI of opening and closing of the hand with an average classification accuracy of 60.4%. This indicates the presence of higher-order non-linear discriminatory information and demonstrates the potential of using CNN in classifying MI of same-limb movements.

Author Contribution: Main author, main developer of recording protocol, recruited and recorded data from participants, performed signal processing and regression analysis, manuscript draft and review.

Paper II

Feature selection of EEG oscillatory activity related to motor imagery using a hierarchical genetic algorithm.

Leon, M., Ballesteros, J., Tidare, J., Xiong, N., & Astrand, E.

In 2019 IEEE Congress on Evolutionary Computation (CEC) (pp. 87-94). IEEE.

Summary: Motor Imagery (MI) classification from neural activity is thought to represent valuable information that can be provided as real-time feedback during rehabilitation after for example a stroke. Previous studies have suggested that MI induces partly subject-specific EEG activation patterns, suggesting that individualized classification models should be created. However, due to fatigue of the user, only a limited number of samples can be recorded and, for EEG recordings, each sample is often composed of a large number of features. This combination leads to an undesirable input data set for classification. In order to overcome this constraint, we propose a new methodology to create and select features from the EEG signal in two steps. First, the input data is divided into different windows to reduce the cardinality of the input. Secondly, a Hierarchical Genetic Algorithm is used to select relevant features using a novel fitness function which combines the data reduction with a correlation feature selection measure. The methodology has been tested on EEG oscillatory activity recorded from 6 healthy volunteers while they performed an MI task. Results have successfully proven that a classification above 75% can be obtained in a restrictive amount of time (0.02 s), reducing the number of features by almost 90%.

Author Contribution: Structured and preprocessed EEG data, parts of data analysis, data interpretation, authored parts of manuscript.

Paper III

Evaluation of closed-loop feedback system delay a time-critical perspective for neurofeedback training.

Tidare, J., Åstrand, E., & Ekström, M. C.

In 11th International Conference on Biomedical Electronics and Devices, - BIODEVICES 2018-Part of 11th International Joint Conference on Biomedical Engineering Systems and Technologies, BIOSTEC 2018; Funchal, Madeira; Portugal; 19 January 2018 through 21 January 2018 (pp. 187-193). SciTePress.

Summary: Neurofeedback in real-time has proven effective when subjects learn to control a BCI. To facilitate learning, a closed-loop feedback system should provide neurofeedback with maximal accuracy and minimal delay. In this article, we propose a modular system for real-time neurofeedback experiments and evaluate its performance as a function of increased stress level applied to the system. The system shows stable behavior and decent performance when streaming with many EEG channels (36-72) and 500-5000 Hz, which is common in BCI setups. With very low data loads (1 channel, 500-1000 Hz) the performance dropped significantly and the system became highly unpredictable. We show that the system delays did not correlate linearly with the stress-level applied to the system, emphasizing the importance of system delay tests before conducting real-time BCI-experiments.

Author Contribution: Main author of paper, designed and developed BCI system, conducted tests, drafted and reviewed manuscript.

Paper IV

Time-resolved estimation of strength of motor imagery representation by multivariate EEG decoding.

Tidare, J., Leon, M., & Astrand, E.

In 2021 Journal of Neural Engineering, 18(1), 016026.

Summary: Objective. Multivariate decoding enables access to information encoded in multiple brain activity features with high temporal resolution. However, whether the strength, of which this information is represented in the brain, can be extracted across time within single trials remains largely unexplored. Approach. In this study, we addressed this question by applying a support vector machine (SVM) to extract motor imagery (MI) representations, from electroencephalogram (EEG) data, and by performing time-resolved single-trial analyses of the multivariate decoding. EEG was recorded from a group of healthy participants during MI of opening and closing of the same hand. Main results. Cross-temporal decoding revealed both dynamic and stationary MI-relevant features during the task. Specifically, features representing MI evolved dynamically early in the trial and later stabilized into a stationary network of MI features. Using a hierarchical genetic algorithm for selection of MI-relevant features, we identified primarily contralateral Alpha and Beta frequency features over the sensorimotor and parieto-occipital cortices as stationary which extended into a bilateral pattern in the later part of the trial. During the stationary encoding of MI, by extracting the SVM prediction scores, we analyzed MI-relevant EEG activity patterns with respect to the temporal dynamics within single trials. We show that the SVM prediction score correlates to the amplitude of univariate MI-relevant features (as documented from an extensive repertoire of previous MI studies) within single trials, strongly suggesting that these are functional variations of MI strength hidden in trial averages. Significance. Our work demonstrates a powerful approach for estimating MI strength continually within single trials, having far-reaching impact for single-trial analyses. In terms of MI neurofeedback for motor rehabilitation, these results set the ground for more refined neurofeedback reflecting the strength of MI that can be provided to patients continually in time.

Author Contribution: Main author, main developer of recording protocol, recruited and recorded data from participants, analysed data and proposed ideas during discussions, drafted and reviewed manuscript.

Paper V

Exploration of using "distance-to-bound" to manipulate the difficulty during motor imagery BCI training after stroke – A clinical two-cases study
Tidare, J., Johansson-Alvarez, M., Plantin, J., Palmcrantz, S., & Astrand, E
medRxiv, 2025, 2025.11. 05.25339460.

Summary: Objective: Motor Imagery-based Brain-Computer Interfaces (MI-BCIs) is a promising technology for neurorehabilitation after stroke. However, many face challenges in using a BCI because they fail to produce discriminable patterns in their brain activity. Personalizing the BCI task difficulty could help the learning process of these users but there is currently very limited knowledge on which methods can be used online. Our aim was to explore a distance-to-bound approach for adapting MI BCI task difficulty in real time.

Approach: Two chronic stroke patients performed 12 BCI training sessions over 4 weeks during which they performed MI of open– and close hand movements and received continual visual feedback based on multivariate decoding of ongoing electroencephalogram (EEG) activity. We increased the difficulty and maintained it by adapting it in real time based on distance-to-bound decoding metrics and using a multiple-session design we investigated the stability of this approach and how it related to MI-related EEG activity of each patient.

Main results: We show that patients had to produce stronger Alpha and Beta event-related desynchronization (ERD) activity across the sensorimotor cortical areas of the brain to receive positive feedback. In addition, we show that the online adaptation converged within sessions as well as accommodating for drift in the data both within and between sessions. We suggest that the distance-to-bound approach can effectively be used to control BCI task difficulty and potentially guide patients to produce functionally relevant activity patterns. However, from our results, stronger sensorimotor ERD activity did not consistently correlate to improved motor function. Clinical assessments showed that both patients improved in motor function (+4 and +8.7 change in Fugl-Meyer assessment for upper extremity), however, the correlation to sensorimotor ERD activity was positive for one patient and negative for the other (Pearson's rho = 0.95,-0.80, p = 0.05, 0.18). These results indicate that the translation of distance-to-bound outputs to feedback needs to be individually tailored considering the stroke lesion and EEG activity profiles for each patient.

Significance: This study provides valuable insights and considerations for BCI difficulty adaptation in the aim of developing more effective training protocols in BCI-based stroke rehabilitation.

Trial registration: The study was registered at clinicaltrials.gov (NCT03994042) and complied with local rules and regulations according to the Swedish Ethics Review Authority (dnr. 2019-01577).

Author Contribution: Main author, main developer of BCI for stroke case study, recorded data from participants, performed signal analysis, proposed ideas during discussions, drafted and reviewed manuscript.

Paper VI

EEG non-stationarity across multiple sessions during a Motor Imagery-BCI intervention: two post stroke case series.

Astrand, E., Plantin, J., Palmcrantz, S., & Tidare, J.

In 2021 10th International IEEE/EMBS Conference on Neural Engineering (NER) (pp. 817-821). IEEE.

Summary: Clinical Electroencephalogram (EEG) Brain-Computer-Interface (BCI) rehabilitation largely depend on reliable information extraction from steadily evolving brain features. Non-stationary EEG feature behavior is considered a major challenge and a lot of effort has been devoted to developing adaptive methods to accommodate for this nonstationarity. However, learning- and plasticity-related mechanisms throughout a BCI intervention are additional sources of non-stationarity, that even though expected, we know very little about. In this work, we explore the evolution of Motor Imagery (MI) information extraction across multiple sessions, in two stroke patients, using a fixed and an adaptive Support Vector Machine (SVM) model. We show different behavior of the fixed SVM model for the two patients, indicating that for one patient, relevant MI-related EEG features shifted throughout the intervention. This observation calls for further investigations to better understand the evolution and shift of features across sessions, as well as the impact of using adaptive methods from a clinical outcome perspective.

Author Contribution: Authored parts of paper, prepared data for analysis, discussed results, reviewed drafted manuscript.

5.2 Discussion on Scientific Contributions

This section discusses the scientific contributions of the thesis in relation to the research questions. The aim is to critically examine how the findings address each question and to reflect on their implications for BCI design in stroke rehabilitation. The discussion is organized by research question, emphasizing the contributions in relation to the background and related work.

How can a BCI account for high dimensionality and real-time demands?

BCIs in stroke rehabilitation are primarily designed based on Hebbian plasticity mechanisms. A critical component is the accurate detection of motor-related brain signals, followed by the immediate delivery of feedback to reinforce coactivational neuronal activity. However, the literature rarely reports the use of high-dimensional data in this context. Most commonly, feedback is based on a small number of features or low-dimensional representations. This may be due to the fact that well-established MI patterns in BCI research are centered around a few key features, namely, bilateral or contralateral ERD in the Alpha and Beta frequency bands. For example, Bauer et al. [106] recorded EEG from 31 channels but derived robot control from only three channels within the Beta range (16–22 Hz). For resting-state analysis, only electrodes C3 and C4 were considered. Similarly, Ramos-Murguialday et al. [125] and Pichiorri et al. [126] measured motor signals using one or a few features. Importantly, both studies demonstrated the significance of relevant feedback by including control groups that received unrelated or sham feedback. These groups did not exhibit the same positive outcomes, underscoring the importance of meaningful feedback. In a study with healthy participants, Zich et al. [136] provided further evidence for the effectiveness of EEG-based feedback. Their results showed physiological changes measured with both EEG and fMRI: feedback led to stronger contralateral ERD in EEG and a stronger contralateral BOLD response in fMRI.

In this research, we hypothesized that high-dimensional data may contain richer information for describing EEG signals. Using 62 EEG channels and 30 frequency coefficients, we recorded MI tasks involving opening and closing one hand from seven healthy participants (paper I). The focus was on agonistic and antagonistic movements of the same hand, with relevance for rehabilitation, similar to the approach in [126]. Our analysis revealed highly overlapping EEG patterns for the two tasks. To investigate task separability, we compared two classification methods: linear regression and a convolutional neural network. The results showed poor separability between MI open and MI close. Consequently, in all subsequent research, we pooled data from both tasks, following the same rationale as in [126].

Moving forward, we aimed to better understand the features that drive classification performance. Prior research has shown that high-dimensional data can improve MI classification [87], and that certain frequency bands, such as Gamma, may be modulated by Alpha rhythms [137]. This interaction could explain why frequencies outside the SMR range enhance classification when combined with SMR features. Our findings in paper IV support this notion, demonstrating that the full power spectrum outperforms any individual frequency band. However, we sought a method to more effectively interpret the motor signal's representation in high-dimensional EEG data. While Frolov et al. and Ang et al. [127, 120] provided feedback based on multivariate data, both employed feature reduction techniques that project variance onto a lower-dimensional space. Although these methods reduce dimensionality, they also transform and combine original features, which can obscure interpretability. Another limitation is that high-dimensional EEG data contain substantial redundancy. Without penalizing this redundancy, reduced feature sets may disproportionately favor large effects, typically those associated with SMR patterns, while overlooking subtler but potentially meaningful signals.

This led to the work presented in paper II, where we investigated a hierarchical genetic algorithm (hGA) combined with the minimum Redundancy Maximum Relevance (mRMR) objective function. By reducing redundant features and prioritizing those that contribute to informative MI patterns, we hypothesized that a more detailed representation of motor imagery would emerge. The hGA algorithm performed well, achieving high classification accuracy while reducing the number of features by approximately 90%. This reduction also resulted in faster computation times, which is advantageous for low-latency feedback. However, the primary value of hGA lies in its ability to identify a compact subset of representative features that collectively describe the MI signal in high-dimensional EEG data. We used these hGA-selected features to conduct in-depth analyses of the MI signal. In paper IV, we visualized population-wide hGA features as a function of time and compared them with classification accuracy, revealing how the SMR evolves temporally. Among healthy participants, we observed that the bilateral ERD pattern typically emerged after approximately 1.5 seconds. In paper V, we applied hGA to identify subject-specific patterns. Here, hGA features, combined with spectral power topographies, highlighted the activity identified as the MI signal. Across these three papers, we demonstrated that hGA is a powerful tool for analyzing high-dimensional EEG data, both at the individual and population levels.

BCIs are inherently online systems, designed for real-time feedback. However, researchers rarely report the exact latency of their systems, even in BCI experiments involving real-time feedback. For instance, Ramos-Murguialday [125] used 500 ms windows, while Frolov et al. and Pichiorri et al. [127, 126] employed 1-second windows, yet none of these studies provided details on system latency. Nevertheless, several design choices in these studies reflect considerations of computational efficiency. Frolov et al., [127] for example, implemented a Bayesian classifier based on EEG covariance matrices due to its computational speed, despite its slightly lower performance compared to other classifiers. There is, however, research addressing the impact of delayed visual feedback in motor tasks. Kim et al. [138] investigated latency effects in telerobotic surgery, where participants performed tasks such as threading a needle through 2 cm rings. When visual feedback was artificially delayed, performance declined. In their experiment, latency was gradually increased up to 400 ms—a relatively low delay in the context of BCI performance. Belinskaia et al. [112] directly examined the effects of delayed feedback in BCI users. They introduced artificial delays of 250 ms and 500 ms, in addition to a baseline system delay of 244 ms. Their findings showed that delayed feedback negatively impacted feedback-induced cortical changes, with total latencies of 494 ms and 740 ms resulting in reduced learning effects. These results suggest that learning to modulate brain rhythms through feedback is highly sensitive to latency.

To address the demands of real-time processing, I developed a framework for a BCI system capable of operating with low latency. The system measured a total delay of just under 100 ms when using 72 EEG channels and a sampling frequency of 1 kHz. During development, Classification computation time was measured at less than 50 ms, resulting in an overall latency below 150 ms. This latency is approximately 100 ms lower than the system delay reported by Belinskaia et al. [112], and would likely be sufficient to support strong learning effects in BCI training. However, this delay was measured using a window size of 50 ms. In typical BCI experiments, time windows are often 500 or 1000 ms long, which would result in feedback latencies approaching or exceeding the 740 ms threshold observed in Belinskaia et al.'s worst-case condition. To mitigate this, we experimented with shorter time windows in our studies. In paper IV, we used the Morlet Wavelet transform to extract time-resolved features and analyzed 500 ms windows to investigate temporal variability in the MI signal. For the online BCI studies, described in paper V, several modifications were made to the signal processing pipeline to enable fast real-time feedback. The data window was shortened to 250 ms, and the bandpass filter was replaced with a DC removal method, subtracting the mean of the raw EEG signal in each channel. Additionally, the wavelet transform was replaced with a FFT. The full system latency with 250 ms data windows was just under 300 ms. We validated this approach by reproducing near-typical MI-EEG patterns in the data, demonstrating that very short EEG data windows are feasible for BCI feedback based on PSD.

How can the difficulty be controlled online in a BCI?

As outlined in Chapter 3.3, difficulty adjustment is largely absent in BCI experiments. Online adaptation of difficulty remains an underexplored area, despite its potential to enhance user motivation and engagement. To effectively control and gradually adapt difficulty, it is necessary to measure momentary MI activity on a continuous scale.

Some researchers have attempted to measure a continuous metric for the MI signal. In studies using univariate measures, feedback is often based on a threshold, as seen in Ramos-Murguialday et al. [125]. However, the feedback remains binary—crossing the threshold results in a discrete step forward in feedback. Zich et al. [136] implemented continuous feedback using the DTB metric, where a horizontal feedback bar on the screen grows or shrinks depending on the DTB value. Despite its continuous nature, DTB does not necessarily reflect the strength of the MI signal. EEG data are inherently noisy, and high-dimensional datasets may contain spurious correlations, leading classifiers to model noise rather than meaningful signal. Moreover, research in cognitive neuroscience has shown that features containing decodable information are not always representative of underlying cognitive processes in the brain [139]. Therefore, fluctuations in DTB may be driven by features both related and unrelated to the MI task.

We aimed to investigate which features drive the decoding of MI in EEG data. In paper IV, we explored the DTB metric as a measure of MI. Our results showed that DTB can represent the MI pattern as a continuous measure, similar to classification accuracy. A key advantage of DTB is that it can be computed for individual predictions, unlike classification accuracy, which requires aggregation across trials. This enabled us to examine temporal variability within single trials and group them according to their temporal profiles, that is, how the pattern evolves over time. We found that this temporal variability corresponded with visually observed topographical patterns, indicating that the MI signal fluctuates in strength during sustained MI performance. These findings provide evidence that DTB accurately reflects expected MI patterns and captures their temporal dynamics.

With DTB showing strong potential as a continuous measure of MI signal, we conducted a BCI experiment with a controlled difficulty level. At higher difficulty, only MI predictions with high DTB values received positive feedback. This design aimed to promote stronger MI patterns and reduce false positives, resulting in less frequent but more relevant feedback. In paper V, we demonstrated that DTB can successfully regulate difficulty in BCI experiments. By collecting DTB values from MI repetitions and recalculating the 60th percentile online, the system maintained an average performance of approximately 40% for both participants across all sessions.

However, this design also effectively caps participants' classification accuracy at 40%, which is considered low. Previous studies have shown that high performance is linked to better clinical outcomes [140], although not entirely. Prasad et al. found that good motor improvements were accompanied by only moderate BCI classification performance [123]. A plausible explanation is that high-performing users are able to generate relevant brain activity that is successfully decoded and fed back by the BCI system, thereby closing the reinforcement learning loop. In contrast, low performers, or BCI illiterates, may not benefit from feedback because they are unable to generate clear MI-related activity. We challenge this assumption. Emerging evidence suggests that the brain does not operate in a persistent, continuous manner as implied by averaged signals, but instead functions in an activity-silent mode [141]. In memory research, for example, brain activity occurs in short bursts during encoding and retrieval [142]. These findings imply that meaningful neural activity may be transient and sparse, rather than sustained, which has implications for how BCI systems interpret and respond to MI signals. In a BCI experiment where participants learned to modulate Alpha rhythms, it was found that the Alpha wave was not a persistent oscillation with gradually increasing amplitude. This apparent persistence was shown to be an artifact of averaging. Instead, the increase in Alpha activity was explained by a higher rate of short bursts of activity which clarified how users learn to generate stronger

Alpha signals [112]. If MI of hand movements operates in a similar fashion, with activity-silent patterns emerging in short bursts, then so-called BCI illiterates may simply fail to produce a sufficient number of bursts during an MI repetition to achieve accurate BCI performance. However, by observing topographical patterns at high DTB values, there remains a possibility for typical MI patterns to emerge, even in low-performing users.

In paper V, we observed a particularly interesting effect in the first patient. During the initial week of BCI feedback, the patient did not exhibit typical MI-related EEG patterns. However, in the following weeks, a distinct and clear contralateral ERD emerged. Despite this improvement, the patient never exceeded statistically significant classification accuracy with the BCI system, as measured by unbiased decoding performance. Although anecdotal, this outcome suggests that MI-BCI therapy may be beneficial even for individuals considered BCI illiterate. In conclusion, using DTB is a feasible and reliable method for adjusting difficulty levels in BCI training. It shows strong potential for increasing inclusivity in stroke rehabilitation, particularly for individuals who might otherwise be excluded during screening due to low initial performance.

How can adaptive classification mitigate non-stationarities in the EEG data within and between sessions?

To address non-stationarities in EEG data, adaptive classifiers update their prediction models online. This approach not only helps track feedback-induced changes but also expands the typically limited training dataset [143, 144]. Adaptive classification in BCI is primarily supervised, meaning that new data are collected along with corresponding labels. Ramos-Murguialday et al. [125] implemented an adaptive strategy in which the BCI maintained a rolling history of the most recent 15 seconds of EEG data. Frolov et al. [127] retrained their classifier after every four repetitions, using all available data up to that point, which has been shown to be advantageous in BCI applications [145].

In our work, we initially pursued a semi-adaptive approach. In our first online BCI case study (paper V), we describe how the classification model was trained using both calibration data and same-session data recorded immediately before the BCI training commenced.

Changing from a calibration session to feedback is known to alter MI-related EEG patterns during motor imagery [146], and we reproduced this effect in our study. The altered MI pattern manifests as drift in the classifier output, and an adaptive approach can track this drift to maintain classifier performance. In our study, the FBT successfully tracked drift throughout the session, effectively compensating for non-stationarity both within and between sessions.

In paper VI, we further analyzed adaptive classification. Two methods were compared: a non-adaptive approach, which used only calibration data, and an adaptive approach, which incorporated same-session training data. We found that including same-session data improved drift compensation and, to some extent, classification accuracy, compared to using calibration data alone. These findings demonstrate that even a small amount of same-session data can mitigate a substantial portion of both inter-session and intra-session variability, as evidenced in a multi-session clinical BCI intervention.

However, an important question arose as we analyzed the data from the case study: is calibration data necessary for training? Sultana et al. [147] demonstrated in an offline comparison study that a small number of MI repetitions may be sufficient to produce an initial model, which can then be adaptively updated. This finding suggests that calibration sessions could potentially be omitted from BCI rehabilitation interventions. The initial repetitions used to train the first BCI model could be recorded while providing random feedback, ensuring that the feedback effect is present from the beginning of the session. This will be investigated in the ongoing MISA study with 15 participating stroke patients.

6. Future Work

There are numerous opportunities for future work following this thesis. First, the ongoing MISA study (ClinicalTrials.gov ID NCT04847089) will evaluate the effects of a calibration-free BCI design. Beyond this, significant potential exists for improving BCI design by systematically examining how feedback is provided. Many design choices are currently based on theoretical assumptions or arbitrary decisions rather than empirical evidence. Research in motor learning has extensively investigated how visuo-motor adaptation, visual latency, and the provision of abundant feedback influence learning. Understanding how these factors affect MI-BCI training contexts would be essential for advancing the field.

6.1 Ongoing Stroke Study

The MISA study aims to provide a more comprehensive answer to the third research question: "How can adaptive classification mitigate non-stationarities in the EEG data within and between sessions?" In paper VI, we demonstrated that including same-session data significantly reduces inter-session drift and may improve classification accuracy. The expected results from the MISA study will reveal the implications of omitting the calibration session entirely.

Calibration-free BCI. There have been attempts to reduce or eliminate the calibration session [148, 149]. While the results appear promising, further investigation is needed to understand the possible consequences. The MISA study uses a calibration-free design. The protocol is similar to the previous protocol used in the two-cases stroke study, but the model uses no calibration data. Instead, the first two trials in each session provides random feedback. After that, the initial model is trained, using 50 overlapping windows of 250 ms from each previous trial. The control condition, idle, was replaced with a motor observation (MO) task. By replaying the feedback given during the previous MI repetition, visual stimulation was present in both tasks, making it less likely to drive classification. A pure idle task was still recorded for analytical comparison, but classification was performed between MI and MO. After each pair of MI-MO trials, a new classification model is trained from scratch. The result will reveal how fast the model converges onto a stable solution, i.e., a model that no longer meaningfully changes with additional data. We can also explore if there are negative effects on the training from having a subpar model in the early stages of the training.

The protocol is similar to the one used in the previous two-case stroke study, but the model does not rely on calibration data. Instead, the first two trials in each session provide random feedback. After these trials, the initial model is trained using 50 overlapping windows of 250 ms from each previous trial. The control condition, idle, was replaced with a motor observation (MO) task. By replaying the feedback given during the previous MI repetition, visual stimulation was present in both tasks, reducing the likelihood of it driving classification. A pure idle task was still recorded for analytical comparison, but classification was performed between MI and MO. After each pair of MI–MO trials, a new classification model is trained from scratch. The results will indicate how quickly the model converges to a stable solution, that is, a model that no longer changes meaningfully with additional data. We will also examine whether there are negative effects on training caused by having a suboptimal model during the early stages.

Maladaptative convergence. Without a calibration session, a model is initially built on a very small amount of data, the two-learner problem could lead to maladaptive convergence, a situation in which the BCI reinforces irrelevant EEG patterns, thereby guiding the individual to generate more low-quality data. This issue is particularly critical in stroke rehabilitation, where the primary goal of classifying the motor signal is to reinforce relevant motor activity. If artifacts drive classification, rehabilitation cannot be expected to occur.

Due to the multiple sessions conducted over four weeks, we can determine whether the model converges similarly across different days. The goal is for the model to rapidly converge, as more data become available, onto a pattern that accurately represents the motor signal in the brain. The cue-based design, combined with clear instructions to perform MI, should guide the subject to focus on the correct MI task, thereby ensuring that the MI signal is present in the data. Nevertheless, the subjects are aware that the system aims to decode MI and that successful decoding will cause the screen hand to move to its final pose. This reflects the principle of reinforcement learning. It is reasonable to assume that a stricter gaze during MI could be modeled, thereby reinforcing ocular noise in the EEG data along with the motor signal. This reduces the relevance of the feedback, as it is influenced by both relevant data (SMR signal) and irrelevant data (noise).

One interesting outcome of this study will be determining whether the model converges to a similar solution in each session. With volatile beginnings, the model could potentially capture any type of noise present early in the session and reinforce that behavior. However, if the design is successful, we expect each session to converge to a similar model that represents the MI signal of each stroke patient. A second outcome will involve further analysis of the final model in each session to identify deviations from expected patterns or the presence of typical noise such as EMG or EOG. For these analyses, the raw data may not be particularly informative, as the presence of noise does not necessarily indicate that it was rewarded through feedback. Instead, examining the model weights will provide greater insight into which patterns were reinforced and whether noise was modeled.

Learning-induced cortical changes. Feature selection can improve classification accuracy but restricts the range of models that the classifier algorithm can train. The theoretical basis for BCI-based rehabilitation is that the brain becomes more plastic and enables synaptic reorganization. If synaptic reorganization occurs, it is possible that the brain's typical MI patterns in the EEG data will change. Limiting the available features to a subset that works early may be counterproductive and hinder learning, as the new pattern may not be rewarded by the old model.

In the MISA study, we do not perform feature selection with hGA. Instead, the SVM model is trained on all available features, leaving it to the classifier to penalize noisy features while promoting informative ones. Because the entire model is retrained every two repetitions, spatial changes in the MI signal are allowed. Analyses of the data will reveal whether spatial shifts in the model actually occur by comparing model convergence across sessions. Post-experiment comparisons may indicate whether hGA-based feature selection would have been superior for decoding MI or whether it would have limited the ability to accurately represent the MI pattern.

Evolution of the motor signal in time. The quality of the data may vary over time, and some segments may be better suited for classifier training. Data within a single repetition also varies temporally, as shown in paper IV, and the temporal variability of EEG has been reported previously [150]. For this reason, the first second of EEG data is sometimes removed from analysis, and for the same reason, it should also be excluded from the training dataset. However, it should be acknowledged that removing the first second of data can decrease classification accuracy, since no data represent the volatile initial phase of MI performance, and early classification accuracy will therefore be expectedly low. Nevertheless, accuracy during the larger portion of MI repetitions may be higher due to a better representation of persistent MI performance, which constitutes nine out of ten seconds of each repetition.

Furthermore, EEG data with feedback differs from EEG data without feedback, as reported in the literature [146] and in paper V. However, the question remains as to why feedback data is different. One possible explanation is that feedback data is recorded within the same session, whereas calibration data comes from another session, introducing inter-session variability. This explanation is not supported by our data, since we have multiple sessions and the difference between feedback and non-feedback is evident in each session, including calibration sessions after the training phase in paper V. Another potential explanation is the visual stimulus. Observing feedback on a screen could generate a signal that interferes with the MI pattern. However, early MISA analyses do not support this, as we contrast MI with MO. MO always followed MI, and during MO, the subject idled while watching the feedback provided during the previous MI repetition. This means that we replayed the exact same visual stimuli for the stroke patient. Our preliminary analyses revealed that MO is similar to the idle task without stimuli, albeit with weak Alpha and Beta ERD over occipital and sensorimotor cortices, indicating that visual stimuli from feedback observation in our study had little to no effect on EEG patterns. This finding is consistent with the literature, which shows that visual imagery and observation of motor tasks fail to produce typical MI patterns [151].

A more plausible explanation for the difference could be the conscious expectation of feedback and the intent to influence it. No difference was found between subjects observing realistic (hand) feedback and those observing abstract (bar) feedback [152], indicating that the modulation of EEG is driven by the use of feedback rather than by its visual characteristics. It is also well established that the brain generates additional signals in response to feedback, such as the error-related potential [153]. This error signal occurs when a participant fails to control a BCI successfully, for example, by selecting the wrong letter in a speller BCI or turning in the wrong direction during a robot navigation task [154].

In the MISA study, we aimed to balance the training data by including both feedback and non-feedback segments. A modification to the protocol prevented any visible feedback during the first four seconds of MI performance. This allowed same-session MI data to be extracted that either contained or lacked visible feedback, although the subject still performed as if feedback was expected. In the study, the classifier builds its model from equal parts feedback and non-feedback data, excluding the first second of each repetition. Post-experiment analyses will enable us to assess the effects of including different portions of the signal. Some plausible hypotheses are: (1) more data improves performance, (2) feedback data is superior because it mimics the context in which the person uses the BCI, and (3) the first second contains volatile and somewhat inaccurate data for classification. These hypotheses are not mutually exclusive.

6.2 Exploring System Designs

Motor learning research is well advanced in theories regarding feedback types and their effects on learning. It is essential to re-evaluate these theories in the context of mental imagery and integrate them with measurements of cortical rhythms to design more effective feedback strategies for BCI rehabilitation.

Combined imagery types. Combined motor imagery may be more effective than pure kinesthetic imagery, as demonstrated in a multi-experiment sports study that combined internal–external imagery with kinesthetic imagery [155]. Research on the motor homunculus has also shown that specific motor areas in the brain correspond to goal-oriented movements rather than individual muscles. For example, stimulating the hand area of a primate triggers the motion of bringing the hand to the mouth, as if eating food [156]. If the natural organization of motor activation is goal-oriented, then feedback during MI-BCI should perhaps be goal-oriented as well, as seen in some BCI experiments and in conventional stroke rehabilitation [157]. This contrasts with the idea of practicing tasks at the level of a stroke patient who may not be able to perform simple actions such as gripping or opening the hand voluntarily. Should MI practice match the person's physical ability? Or is it advantageous to practice MI on complex, goal-oriented tasks even if they exceed the person's current physical capabilities?

Ultra-short latency. Ultra-short latency could be explored using EEG microstates, which are brief quasi-stable patterns lasting as little as 37 ms [158]. As measured in the full system latency in paper III, with 50 ms time windows, the latency is as short as 100 ms, which is remarkably low. If MI could be accurately decoded within such short windows, feedback could become highly intuitive, potentially offering greater benefits than achieving higher classification accuracy.

Learning with latency. Learning to control a BCI could be explored in healthy participants by having them play a game where MI signals serve as input. Latency in motor learning has been investigated in simple computer game tasks [159], where the test group experienced an artificial 333 ms delay between device input and in-game actions. While this latency hindered performance, it did not necessarily impair motor learning. However, it is important to note that in these experiments, there was no uncertainty regarding classification accuracy. In paper III, we show that latency in BCI systems is uncertain. This suggests that a better BCI design might prioritize ensuring consistent latency, even if it is not minimized.

Direct continuous feedback. A more continuous approach to feedback could be explored. Instead of using 32 discrete images of hand poses ranging from closed to open, the continuous output of the classifier could be mapped directly to the corresponding video frame of the hand movement. Due to transient EEG activity, some smoothing would be required, but this approach would more accurately reflect strong MI signals rather than simply displaying a slowly moving hand progressing toward a fully opened or closed position. One RCT study reported using continuous feedback, where the DTB value directly influenced the length of a feedback bar on the screen [136]. Currently, even strong MI patterns can only move the hand one step at a time, which may hinder the user's understanding of the BCI.

Intermittent non-feedback. It may be advantageous to provide users with intermittent non-feedback repetitions during training. In some motor learning experiments, reduced feedback has been shown to benefit motor learning [160]. According to the Guidance Theory, a user may become overly reliant on feedback to the extent that their internal performance model fails to develop [161]. This suggests that practicing without feedback can sometimes be beneficial. However, for complex motor skills, abundant feedback does not appear to have a detrimental effect [162]. Therefore, if MI of a movement is perceived as complex, abundant feedback may still be superior. It is also possible that performance improves simply because practicing without feedback better mimics real-world conditions. For example, if stroke patients perform MI at home at their own leisure, they would do so without feedback. Practicing under similar conditions could therefore enhance independent MI training.

Gamification for motivation. There is also a trade-off between providing high-quality feedback and maintaining the accessibility of feedback available on a computer screen. Computer screens offer a wide range of interactive games, which can make training more engaging and enjoyable, thereby sustaining interest and motivation. Games also enable creative ways to adapt difficulty levels, such as adding dimensions like flying a virtual helicopter. Virtual games can be played collaboratively, allowing social interaction among multiple stroke patients. While EEG equipment is costly, therapy could become more affordable if several patients engage in MI-BCI training simultaneously, with recovery potentially enhanced through social engagement. However, some stroke patients have expressed that they do not particularly enjoy competition because stroke-related disabilities vary greatly between individuals. Games can be tailored to each person's abilities, and cooperative modes can replace competitive ones, reducing stress or anxiety for participants.

Interactive phase for user agency. Another relevant idea for BCI rehabilitation design is to incorporate asynchronous control (not cue-based) as a phase in the training. During measurements with stroke patients, some have expressed curiosity about the system's actual accuracy. A few even reported deviating from the protocol and performing the wrong task intentionally to "test" their sense of agency over the system. It is understandable that users want to know how much control they truly have. Even proficient BCI users may receive frequent errors. Stroke patients should have the opportunity to test the system. An asynchronous mode could be introduced as a "play phase." This phase could last for one or several minute and allow users to try various MI strategies at their own pace and experiment with the system. Such an approach may reduce their inclination to interfere with actual training repetitions. Based on my conversations with stroke patients, they would greatly appreciate the chance to explore the system at their own pace.

7. Conclusion

In this work, I have presented the iterative development of a rehabilitative MI-BCI system. Two studies were conducted: one with healthy participants and another with individuals who had experienced a stroke. This thesis aimed to address three research questions: 1) How can a BCI account for high dimensionality and real-time demands? 2) How the can difficulty be controlled online in a BCI? 3) How can adaptive classification mitigate non-stationarities in EEG data within and between sessions? The first two questions are adequately addressed in Papers 1 through 6, while the third question is addressed in Papers 5 and 6.

This research addresses a critical knowledge gap within the BCI research community. While other researchers have conducted RCTs to evaluate the effectiveness of MI-BCI therapy, and numerous experiments have successfully improved classification accuracy of MI using publicly available EEG datasets, my work focuses on exploring and explaining the connection between MI tasks, cortical patterns, and behavioral adaptations. By integrating visual representations with numerical measurements, this research bridges the gap between visual-qualitative and statistical-quantitative knowledge. In particular, I aim to visualize the machine's perspective, for example, by analyzing classification models to enhance our understanding of how machine learning algorithms acquire and represent knowledge. These insights provide valuable information and new perspectives on designing more effective and personalized BCIs.

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