BRAIN IN THE POSITION CONTROL LOOP FOR NEURO-MOTOR REHABILITATION

A Thesis

Submitted in partial fulfilment of the requirement for the Degree of

Master in Control System Engineering

(Electrical Engineering Department)

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May, 2024

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CERTIFICATE

This is to certify that the dissertation entitled **"Brain in the Position Control Loop for Neuro-Motor Rehabilitation"** has been carried out by ANWESA MONDAL (University Registration No.: 163526 of 2022-2023) under my guidance and supervision and be accepted as partial fulfilment of the requirement for the Degree of Master in Control System Engineering, offered by Electrical Engineering Department, Jadavpur University. The research results presented in the thesis have not been included in any other paper submitted for the award of any degree to any other University or Institute.

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DECLARATION OF ORIGINALITY AND COMPLIANCE OF ACADEMIC THESIS

I hereby declare that this thesis entitled **"Brain in the Position Control Loop for Neuro-Motor Rehabilitation"** contains literature survey and original research work by the undersigned candidate, as part of her Degree of Master in Control System Engineering, offered by Electrical Engineering Department, Jadavpur University. All information here have been obtained and presented in accordance with academic rules and ethical conduct. It is hereby declared that, as required by these rules and conduct, all materials and results that are not original to this work have been properly cited and referenced.

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Acknowledgement

I would like to express my earnest gratitude and sincere thanks to my thesis supervisor Prof. Amit Konar, Department of Electronics and Telecommunication Engineering, Jadavpur University, for giving me the opportunity to work under him and inspiring me to explore the fields of Control System Engineering, Artificial Intelligence and Brain-Computer Interface. I am indebted to him for his patient guidance, critical and constructive views and untiring support that shaped my work.

I am also grateful to Prof. Smita Sadhu (Ghosh), Prof. Ranjit Kumar Barai, Prof Madhubanti Maitra and Prof. Sayantan Chakraborty, Department of Electrical Engineering, for all the guidance and knowledge that they have imparted during the tenure of the course.

I would also like to thank my senior Ms. Baishali De, PhD scholar at Artificial Intelligence Laboratory, Department of Electronics and Telecommunication Engineering, Jadavpur University for the guidance throughout the project. It was a wonderful experience working alongside her.

Lastly, I am thankful to my parents Prof. Lakshmi Kanta Mondal and Mrs. Rinku Mondal, for their continuous support, encouragement and unending faith in my abilities.

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PREFACE

This thesis delves into the integration of Electroencephalography (EEG)-based Brain-Computer Interface (BCI) systems with robotic arm control, aiming to enhance the lives of individuals with motor impairments by enabling them to control the robot arm simply by thinking to do so. Motivated by the limitations of traditional BCI technologies, this research explores the potential of BCIs to offer more seamless and intuitive interactions.

The thesis begins by outlining the objectives, focusing on developing robust BCI systems, optimizing control strategies, ensuring user comfort, and evaluating performance. It emphasizes the importance of acquiring and pre-processing EEG data, which involves filtering and artifact removal to ensure high-quality signals for accurate interpretation. Feature extraction techniques are employed to translate EEG signals into actionable features, followed by classification of the signals into discrete categories of thought (for example, Right Hand Motor Imagery for moving the right arm, Left Hand Motor Imagery for moving the left arm, etc). These signals are used to control the movement of a robotic arm.

Four Brain-Actuated Control strategies are explored: Proportional Speed Control, Zero-Crossing Sensitive Speed Modulation, Takagi-Sugeno Fuzzy Logic Control and Learning Automaton Induced Takagi-Sugeno Speed Modulation. Proportional Speed Control offers quick responses but may cause oscillations; Zero-Crossing Sensitive Speed Modulation enhances stability by adjusting speed upon positional error crossing zero; Fuzzy Logic Control provides nuanced adjustments, enhancing adaptability and reducing cognitive load of the subject; and lastly, the parameters of the Fuzzy-Logic Control is defined using Learning Automton which gives greater precision and is further amplifies subject’s comfort.

The results highlight the strengths and limitations of each strategy, emphasizing the importance of adaptive designs that are convenient for patients with neuro-motor disabilities in BCI-based assistive devices. This research not only advances the technical field but also aims to significantly improve the quality of life for those relying on such technologies.

List of Publications

[1] B. De, A. Mondal, A. Konar and A. Saha, "Brain-Actuated Speed Modulation for Position Control of an Artificial Robotic Limb for Rehabilitative Application," presented in *3rd Int. Conf. on Control, Instrumentation, Energy and Communication*, Kolkata, Jan. 2024.

[2] B. De, A. Mondal, A. Konar and A. Saha, **"**Design of a Brain-Actuated 2-Loop Position Control of a Robot Arm for Neuro-Motor Rehabilitation," presented in *8th Int. Conf. on Computer and Devices for Communication*, Kolkata, Dec. 2023.

[3] A. Konar, B. De, A. Mondal and A. Saha, "Error-Induced Brain-Actuated Motor Command Generation for Speed-Profile Setting in a 2-Loop Position Control of a Robot Arm," presented in *2nd Doctoral Symposium on Intelligence Enabled Research*, Cooch Behar, India, Dec. 2023.

[4] B. De, A. Mondal, A. Konar and A. Saha, **"**Learning Automaton Induced Brain-Actuated Takagi-Sugeno Speed Modulation for Position Control of a Rehabilitative Robot Arm," to be presented in *IEEE-FUZZ World Congress on Computational Intelligence (WCCI),* Yokohama, 2024 (accepted).

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CHAPTER 1

Introduction to Brain-Computer Interface-Based Position Control

1.1 Introduction

In recent years, the confluence of neuroscience and engineering has given rise to technologies that seemed unimaginable a few decades ago. Among these, Brain-Computer Interfaces (BCIs) stand out as a profound innovation, enabling direct pathways for communication between the human brain and external devices. This technology not only promises revolutionary applications in medical therapies and enhancement of human capabilities but is also paving the way for advanced integrations with various control systems. One such integration is with position control systems, which are fundamental to a multitude of disciplines including robotics, prosthetics, and automated vehicle guidance.

Position control is essential wherever precise movement is required. In industrial robotics, it ensures that mechanical arms perform tasks with high precision. In vehicular automation, it keeps vehicles within their intended lanes. And in the world of prosthetics, it can mean the difference between a naturally moving limb and a static one. Traditionally, these systems rely on manual inputs or pre-programmed commands to operate. However, integrating these systems with BCIs introduces a layer of intuitive control, using human thoughts to guide and control these machines.

This thesis explores the novel concept of BCI-based position control, a cutting-edge integration that merges the intuitiveness of human thought with the precision of mechanical control systems. Through this integration, the thesis investigates how machines can not only augment human physical capabilities but also respond to human intentions in real-time, creating a symbiotic relationship between human cognitive functions and machine operations.

The importance of this technology is manifold. For individuals with severe mobility impairments, BCIs that can interpret thoughts and convert them into mechanical actions promise an unprecedented level of interaction with their surroundings. Imagine a paralyzed individual controlling a robotic limb or a wheelchair merely through their thoughts, bypassing the damaged neural pathways that once carried their commands. Furthermore, in industrial settings, such intuitive systems can lead to more efficient and safer operations, where machines can adapt to human commands in real-time, potentially reducing the cognitive load and physical demands on human operators.

However, the road to integrating BCIs with position control systems is fraught with challenges, both technical and ethical. Technically, the systems must be capable of high-speed, accurate interpretation of neural signals, which requires sophisticated algorithms and robust hardware. Ethically, questions about autonomy, privacy, and the potential for misuse arise. These concerns must be addressed alongside technological advancements to ensure that BCI-based systems are developed in a responsible and beneficial manner.

This thesis aims to lay down a comprehensive foundation for understanding BCI-based position control systems. It discusses the current state of technology, explores significant challenges, and hypothesizes about future developments. By delving into the technicalities, this thesis not only aims to showcase what has been achieved but also to illuminate the path forward, inviting further research and development in this interdisciplinary field.

Thus, the journey into integrating BCIs with position control systems is not just about building more advanced technologies; it's about redefining the boundaries of human-machine interaction. As this technology matures, it could redefine not only how we interact with machines but fundamentally alter our capabilities, enhancing and extending them beyond natural biological limits. Through this thesis, we embark on a detailed exploration of this fascinating frontier, aiming to contribute to a future where technology and human intention converge seamlessly.

1.2 What is Position Control?

Position control is an integral aspect of control systems engineering, crucial in fields requiring exact control over the movement and orientation of system components or entire systems. This section elaborates on the fundamentals of position control, its mechanisms, challenges, and its extensive application in modern technologies.

1.2.1 Fundamentals of Position Control

Position control pertains to the branch of control engineering that deals with controlling the position of an object in space to perform specific tasks accurately. This control process involves determining the position of a device or a component accurately and repeatedly, maintaining its position against dynamic forces, and manoeuvring it to desired locations under controlled speed and trajectories. The sophistication of position control systems varies greatly—from simple setups in machine tools to complex configurations in high-tech robotics and aerospace applications [1][2].

1.2.2 Core Mechanisms in Position Control Systems

Position control systems generally consist of sensors, actuators, and controllers:

- ***Sensors:*** These are crucial for acquiring real-time data about the system's current state. Common sensors in position control include encoders, which measure the angular position of rotating elements, and linear position sensors, which measure the movement of components along a path.

- ***Actuators:*** The physical devices that execute the commands issued by the control system, such as motors (stepper motors, servo motors) and hydraulic pistons, which alter the position based on received inputs.

- ***Controllers:*** Typically, a microcontroller or a digital signal processor (DSP) computes the desired response using a mathematical model. Controllers in position control systems use algorithms such as Proportional-Integral-Derivative (PID) control to adjust the control effort based on the position error—the difference between the target and actual positions. PID controllers, in particular, are prized for their simplicity and efficacy, adjusting the control outputs to minimize the position error over time [1][2].

1.2.3 Control Systems Engineering in Position Control

The efficacy of a position control system hinges largely on the principles of control systems engineering. This discipline ensures that systems perform their functions reliably, efficiently, and safely, adhering to desired behaviors amidst external disturbances and internal fluctuations. Control systems are designed based on mathematical models that predict the behavior of the system under various conditions. This predictive capacity is vital for designing controllers that can compensate for future states, enhancing the system's stability and performance.

Control systems in position control utilize both classical and modern control theory. Classical control methods, like PID control, provide solutions where the system dynamics are linear and relatively predictable. However, modern control approaches are employed when dealing with nonlinear systems or systems with complex dynamics that classical methods cannot adequately handle. These may include robust and adaptive control strategies that can accommodate system uncertainties and changing environmental conditions [13][14].

1.2.4 Challenges and Advances in Position Control

Implementing effective position control systems presents numerous challenges. The precision of position control systems can be affected by factors like mechanical backlash, sensor noise, and actuator saturation. Moreover, the environment in which the system operates can introduce variability, such as temperature changes affecting sensor accuracy or mechanical properties.

To address these challenges, recent advances in control systems engineering have focused on integrating more sophisticated computational techniques, such as model predictive control (MPC) and machine learning algorithms, which predict and adjust to the variable dynamics of the system in real-time. These technologies enable the design of more adaptive, resilient, and intelligent control systems that can optimize performance automatically in the face of system and environmental changes [8][9].

1.2.5 Applications of Position Control

The application of position control spans numerous domains:

- ***Robotics***: Position control is critical in robotics for tasks that require high precision, such as assembly line work, where robots need to position components precisely and consistently.

- ***Aerospace***: In aerospace, position control systems ensure the accurate positioning of satellite antennae, enabling them to maintain the correct orientation for communication. Similarly, in aircraft, flight control systems use position control to manage the positions of the control surfaces accurately.

- ***Automotive***: In automotive technology, position control is used in systems like electronic power steering and active suspension systems, which improve vehicle handling and comfort.

- ***Consumer Electronics***: Modern consumer electronics, including cameras and computer peripherals like printers, also rely on precise position control for functionality such as autofocus mechanisms and paper handling systems [5][10][21].

In summary, position control is a pivotal aspect of control systems engineering, facilitating the advancement and functionality of various technological innovations across multiple industries. As technology progresses, the role of sophisticated control systems in achieving precise and reliable position control becomes increasingly important, driving forward the capabilities of automation and intelligent machine design. The continuous evolution of control strategies, coupled with the integration of cutting-edge computational methods, is essential for meeting the ever-growing demands for higher precision and efficiency in industrial applications [1][2].

1.3 What is Brain-Computer Interface (BCI)?

A Brain-Computer Interface (BCI) represents an advanced technology that forges a direct communication pathway between the brain and an external device. This interface is a pinnacle of innovation in technology, blending neuroscience with computer science to interpret brain signals for controlling devices without any physical interaction. This section delves into the fundamental concepts of BCIs, exploring their types, operational mechanisms, applications, and the challenges inherent in their development.

1.3.1 Fundamental Concepts of BCIs

BCIs are engineered to decode neural signals, translating them into commands that can activate actions in a computer system or a connected device. Essentially, a BCI circumvents the conventional channels of communication—like nerves and muscles—which can be slow and may degrade over time due to diseases or injuries. Instead, it directly interprets brain activities that relate to intentions, thoughts, or emotions, and translates these into actionable commands.

The operation of a BCI begins with the acquisition of brain signals, which can be captured through invasive, semi-invasive, or non-invasive methods. Invasive techniques involve implanting electrodes directly into the brain tissue, offering high-resolution signals but raising significant risks and ethical questions [3]. Semi-invasive methods, which occur beneath the skull but not within the brain tissue, still provide relatively high signal clarity with fewer risks than fully invasive methods. Non-invasive techniques, such as EEG (electroencephalography), capture brain activity from the surface of the scalp. These are the most popular due to their safety, ease of use, and non-intrusive nature, although they suffer from lower resolution and greater susceptibility to noise [4].

1.3.2 Types of BCIs

BCIs can be categorized based on their signal acquisition method, the type of signals used, or their intended applications. Primarily, there are three types of BCI based on the source of signals:

1. Motor Imagery BCIs which capture brain signals generated when a user imagines performing a movement. These signals are processed to control external devices like computer cursors or robotic arms.

2. Visual Evoked Potential (VEP) BCIs utilize the brain's response to visual stimuli. For example, the repetitive flashing of lights can generate stable, predictable brain responses that are harnessed to control interfaces.

3. P300 BCIs employ the P300 wave, an EEG response that occurs approximately 300 milliseconds after the onset of a stimulus. This response is particularly useful for selecting items on a screen or in communication applications.

1.3.3 How BCIs Operate

BCI operation involves several key stages:

- ***Signal Acquisition***: The initial step involves capturing brain signals using one of the previously mentioned methods. The quality of these signals is critical, as it directly affects the BCI's accuracy and efficiency.
- ***Signal Processing***: Raw signals are then processed to filter out noise and enhance relevant features for interpretation. This typically involves signal enhancement, feature extraction, and dimensionality reduction techniques.
- ***Feature Translation***: Processed signals are decoded into commands understandable by external devices. These decoding leverages machine learning or pattern recognition algorithms to interpret the user's intentions from the signals.
- ***Device Control***: Ultimately, these translated signals are used to control an external device, whether it be a wheelchair, a virtual keyboard, or an artificial limb.

1.3.4 Applications of BCIs

The applications for BCIs are extensive and diverse, ranging from medical rehabilitation to entertainment:

Medical Applications: BCIs have significant implications for the medical sector, particularly for individuals with disabilities. They enable people with spinal cord injuries, stroke survivors, and those with conditions like ALS to control prosthetic limbs, computers, or wheelchairs, enhancing their ability to communicate and move independently.

Communication and Control: For individuals unable to speak or use their hands, BCIs provide alternative communication channels, enabling them to operate speech-generating devices or surf the internet.

Neuromarketing and Gaming: In consumer electronics, BCIs are being explored in gaming and virtual reality, offering new methods of interaction within gaming environments using mere thoughts. Additionally, neuromarketing utilizes BCIs to assess consumer reactions directly through brain activity.

1.3.5 Challenges in BCI Development

Despite promising advancements, BCIs confront significant challenges:

- ***Signal Acquisition and Interpretation***: The most formidable challenge is the quality and reliability of signal acquisition. Non-invasive methods, while safer and more user-friendly, yield less precise signals than invasive methods.

- ***User Training***: BCIs necessitate substantial user training for effective operation, as individuals must learn to consistently generate brain signals that can be accurately decoded.

- ***Ethical and Privacy Concerns***: As BCIs involve tapping into personal biological data, they raise serious ethical and privacy issues. The potential misuse of such data and concerns about information security are critical aspects that need addressing as the technology evolves.

Brain-Computer Interfaces stand at a compelling crossroads of technology, neuroscience, and human potential, offering vast prospects for enhancing human capabilities, especially for those with physical limitations. As research progresses, integrating advanced computational methods, improved sensor technologies, and sophisticated machine learning algorithms will further expand the capabilities of BCIs, making them more intuitive, efficient, and accessible [8][9].

1.4 Why is BCI-Based Position Control Important?

Brain-Computer Interface (BCI) technology, especially when integrated with position control systems, represents a significant breakthrough in how humans interact with and control their environment. The integration of BCI with position control mechanisms—where precise positioning of objects or devices is required—opens a vast realm of possibilities, from enhancing the quality of life for individuals with disabilities to advancing the fields of robotics and automation. This section explores the significance of BCI-based position control, detailing its applications, benefits, and potential future impacts.

1.4.1 Enhancing Accessibility for Individuals with Disabilities

One of the most profound impacts of BCI-based position control is its potential to transform the lives of those with severe physical disabilities. For individuals suffering from quadriplegia, advanced neurodegenerative diseases, or severe forms of cerebral palsy, even simple tasks such as moving around in a room or adjusting the position of a chair can be daunting if not impossible. BCIs that control these positional parameters can provide these individuals with unprecedented independence, reducing reliance on caregivers and improving their overall quality of life [3][6].

For example, wheelchair control through BCI allows users to direct their mobility device using brain signals alone, circumventing the physical limitations of their bodies. This technology does not merely add convenience but opens new avenues for interaction with the world that were previously inaccessible. In robotic arm control applications, BCIs enable precise movements, allowing users to perform complex tasks like picking up objects or manipulating tools, which are essential for personal care and professional activities [5][10].

1.4.2 Advancing Robotics and Automation

In the realm of robotics and automation, BCI-based position control systems serve as a bridge between human cognitive capabilities and mechanical performance. Such systems allow for a more natural, intuitive interface for controlling robots, which can be particularly beneficial in complex environments where traditional control mechanisms may fall short. For instance, in surgical robotics, BCIs could enable surgeons to control robotic instruments with their thoughts alone, potentially increasing the precision and reducing the fatigue associated with manual controls during long operations [6][12].

Moreover, BCI-based systems can improve the efficiency and safety of operations in hazardous environments, such as in nuclear decommissioning or underwater repairs, where direct human involvement is risky. Robots controlled via BCI can execute precise manipulations based on the operator's thoughts, combining human decision-making capabilities with the robot's mechanical precision.

1.4.3 Facilitating Research and Innovation in Neurotechnology

The development and implementation of BCI-based position control systems also drive advancements in neurotechnology and cognitive neuroscience. By analyzing how the brain communicates movement intentions to control external devices, researchers can gain deeper insights into the underlying mechanisms of motor control and brain functionality [4][9].

This research has broader implications, potentially leading to breakthroughs in understanding and treating neurological disorders such as Parkinson's disease, multiple sclerosis, or stroke rehabilitation. Each application of BCI-based control contributes to a body of knowledge that could revolutionize therapeutic strategies and improve outcomes for patients experiencing motor control issues.

1.4.4 Promoting Inclusivity and Societal Participation

BCI-based position control technologies promote inclusivity, enabling people with severe physical disabilities to participate more fully in society. By providing tools that help bypass physical limitations, BCIs can help level the playing field, allowing individuals to partake in educational opportunities, employment, and social activities that were previously challenging.

These technologies also help raise awareness about the capabilities and needs of people with disabilities, fostering a more inclusive society that values technological accessibility and innovation as key components of societal development.

1.4.5 Challenges and Ethical Considerations

Despite these benefits, the integration of BCI with position control systems is not without challenges. The accuracy and reliability of BCIs need significant enhancement to ensure safe and effective control in critical applications. There are also substantial ethical and privacy concerns that come with reading and interpreting brain signals, which require careful consideration and robust regulatory frameworks to ensure that these technologies are used responsibly [7][11].

BCI-based position control is more than just a technological innovation; it is a potential catalyst for profound societal change, offering new freedoms to those with physical limitations and advancing fields as diverse as medicine, robotics, and accessibility. As this technology continues to evolve, it will undoubtedly open up new frontiers for how humans interact with and control the physical world, making it a crucial area of focus for future research and application [8][10].

1.5 Simple Scheme of BCI-Based Position Control

The concept of Brain-Computer Interface (BCI) based position control embodies a significant technological synthesis, integrating the realms of neurology, control systems, and robotics. This section aims to demystify the basic operational scheme of a BCI-based position control system, detailing the components involved, the process flow, and typical applications where such systems are deployed. Understanding this scheme is pivotal for appreciating how BCIs can be used to manage and direct the positioning of devices or limbs in space.

1.5.1 Basic Components of BCI-Based Position Control Systems

A typical BCI-based position control system consists of several key components, each playing a critical role in translating user intentions into precise physical actions:

1. Signal Acquisition: The first step involves capturing brain signals, typically using non-invasive methods like electroencephalography (EEG). These signals are often weak and noisy, necessitating sophisticated signal processing techniques to extract meaningful data [9][11].

2. Signal Processing: Once acquired, the brain signals are subjected to various processing stages, including filtering, feature extraction, and classification. The objective here is to accurately decode the user's intention from the raw EEG data. Advanced machine learning algorithms, such as those outlined in references [8] and [9], are commonly employed to enhance the accuracy and reliability of signal interpretation.

3. Command Interface: The processed signals are then converted into commands understandable by the control system. This translation is crucial as it forms the bridge between human intentions and mechanical actions. The design of the command interface often depends on the specific application, whether it be robotic arm manipulation or wheelchair navigation [5][10].

4. Execution by Actuators: Following command generation, actuators or mechanical systems carry out the desired actions. These can include motors in a robotic arm or wheels in a mobility device, precisely controlled based on the commands derived from brain signals [5][10].

5. Feedback Loop: To ensure accuracy and safety, a feedback loop is often incorporated. This involves sensors providing real-time data back to the user, potentially through visual, auditory, or tactile feedback, allowing them to adjust their commands dynamically [6][12].

1.5.2 Operational Flow

The operational flow of a BCI-based position control system can be succinctly described in a series of steps that start with the user generating a mental command and end with the physical movement of a device or limb:

1. Initiation: The user focuses on a specific task, such as moving a cursor on a screen or directing a robotic arm to reach for an object. This mental activity generates distinct brain patterns that are detected by EEG electrodes.

2. Signal Detection and Processing: The EEG system captures these signals, which are then filtered and decoded using sophisticated algorithms to ascertain the user's intent. The effectiveness of this step hinges on the robustness of the signal processing algorithms and the clarity of the user-generated signals [3][9].

3. Command Generation: The decoded intentions are translated into specific commands tailored to the control system of the device being operated. This step requires seamless integration between the BCI system and the device's control architecture to ensure that the commands are both accurate and timely [10][12].

4. Action Execution: The commands are executed by the device's actuators, resulting in movement. For instance, a wheelchair might start moving forward, or a robotic arm might change its position to grab an item.

5. Feedback and Adjustment: Concurrently, the system provides feedback to the user, who can then adjust their mental commands based on the device's response. This feedback loop is essential for achieving precise control, particularly in complex tasks [6][12].

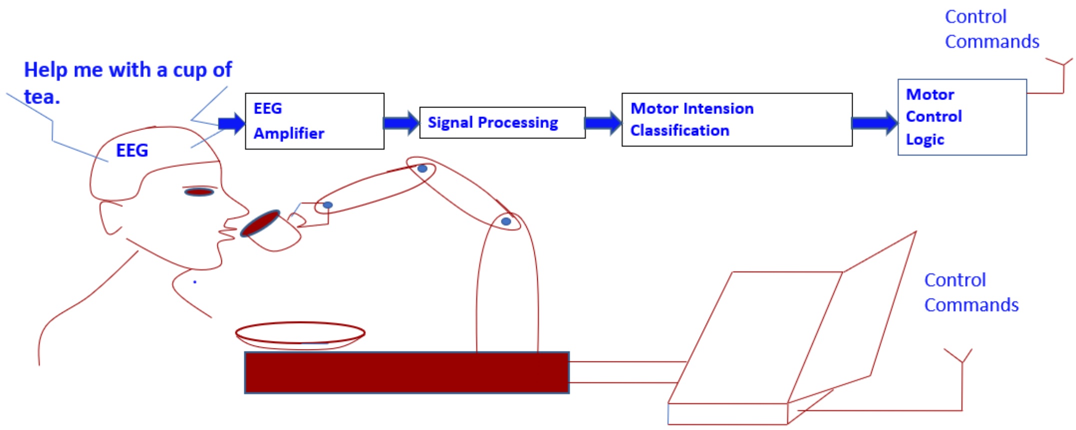

Fig 1.1 Schematic Diagram of BCI-based Position Control

1.5.3 Applications of BCI-Based Position Control

BCI-based position control systems find applications in various fields, each benefiting from the direct interface between human cognitive functions and mechanical execution:

- ***Medical Rehabilitation:*** For patients recovering from strokes or spinal cord injuries, BCIs combined with robotic exoskeletons can facilitate movement and rehabilitation exercises, enhancing recovery by engaging the patient's own neural pathways in the therapy [3][10].

- ***Assistive Technologies***: Wheelchairs, prosthetics, and other assistive devices equipped with BCI technology offer enhanced autonomy to individuals with severe physical disabilities, enabling them to perform daily tasks with greater independence [5][6].

- ***Industrial Robotics***: In industrial settings, BCI systems can allow operators to control robotic arms or other machinery via thoughts alone, potentially increasing safety and efficiency in environments where physical controls can be cumbersome or dangerous [10][12].

The simple scheme of a BCI-based position control system encapsulates a complex interplay of neurology, computer science, and mechanical engineering. By harnessing the power of human thought to directly control physical objects, this technology not only opens new avenues for individual autonomy and medical rehabilitation but also paves the way for innovations in various technological domains. As the field advances, further enhancements in signal processing, machine learning, and feedback mechanisms are expected to drive the efficacy and adoption of these systems across an even broader spectrum of applications [8][9][11].

1.6 Scope of the Thesis

This thesis explores the development and application of Brain-Computer Interface (BCI) technology for controlling robotic arms, with a particular focus on precision and responsiveness improvements through error-related neural feedback. The primary objective is to enhance the integration of human neural responses with robotic movements, enabling a more intuitive and effective control system for users, especially those with physical disabilities.

Chapter 1 is dedicated towards a detailed introduction to position control and the preliminary concepts of Brain-Computer Interface and how these two can be achieved. Next, Chapter 2 discusses the modes through which BCI can be achieved, that is the different methods of brain signal acquisition and the different brain signals from the various lobes of the brain. It also discussed the methods required for processing these raw brain signals. In Chapter 3, we discuss the various methods that we have applied to automatize the BCI system so as to improve system performance and reduce the cognitive load of the patients. We have designed four control strategies, each outperforming the former, in terms of required parameters. In Chapter 4, we discuss the merits and demerits of the current proposed schemes and any future prospect to improve upon the current position control system.

1.7 Conclusions

As we conclude our exploration into Brain-Computer Interface (BCI) based position control, it becomes evident that this field represents a significant crossroads of neuroscience, technology, and engineering, holding substantial promise for the future of human-machine interaction. Throughout this thesis, we have systematically analyzed various facets of BCI technology—from the fundamentals of position control and BCIs, to the implications of integrating these technologies into practical applications. Each section has not only delved into the technicalities and advancements but has also highlighted the importance and the potential that BCI-based position control systems carry.

In the initial sections, we discussed the concept of position control, which is essential for any robotic or mechanical system requiring precise movement. Position control, as grounded in the theories and applications elaborated in classic control system texts [1][2][13][14], forms the backbone of automation and robotics. The mechanisms that allow for such control involve complex feedback systems and sophisticated algorithms, ensuring accuracy and reliability in response to dynamic environmental conditions.

Transitioning from traditional control systems to BCIs, we explored how these interfaces bridge the gap between human cognitive intent and machine operations. BCIs decode neural signals, predominantly using EEG, to command and control external devices without physical movement [3][4][9]. This leap from manual control to thought-based command opens numerous possibilities in assistive technologies, particularly aiding those with mobility impairments. The integration of BCIs with position control systems signifies a notable advancement in creating more intuitive and naturalistic interactions with technology [5][6].

The discussions on the importance of BCI-based position control underscored not only the technological brilliance but also the profound societal impacts. These systems offer renewed independence to individuals with severe physical limitations, thus enhancing their quality of life and societal integration [5][6][7]. Moreover, the potential applications in medical rehabilitation, where patients can retrain and regain motor skills through BCI-controlled robotic systems, illustrate the therapeutic benefits of this technology.

However, with great technology comes great responsibility. We examined the technical challenges, such as the need for improved signal processing techniques and real-time response systems, which are critical for the wider adoption and effectiveness of BCIs [8][10][11]. Ethical concerns also form a significant part of the discussion, as the personal and private nature of neural data demands stringent safeguards against misuse and considerations for user consent [7].

Looking ahead, the potential for future enhancements in BCI technology is boundless. Integration with artificial intelligence could lead to more adaptive systems that learn from user behavior to enhance functionality and user experience [8][9][11]. Furthermore, as we merge these technologies with the burgeoning field of the Internet of Things (IoT), we could see a new era of smart environments responsive to thought commands, changing how we interact with our surroundings.

In essence, the journey through this thesis has not only presented a detailed analysis of BCI-based position control systems but has also set the stage for future research and development in this fascinating intersection of disciplines. As we continue to push the boundaries of what these technologies can achieve, it is imperative to foster an interdisciplinary approach that balances innovation with ethical considerations. The roadmap laid out by this thesis provides a foundation for future explorations, aiming to harness the full potential of BCI systems while conscientiously navigating the complexities they present. The promise of BCI technology, as explored in this thesis, is not just in its current capabilities but in its potential to redefine the limits of human-machine collaboration.

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Chapter 2

Brain-Signal Processing and Classification

2.1 The Human Brain: Lobe Functions

The human brain, an incredibly sophisticated and indispensable organ, governs a myriad of essential aspects of our everyday lives and our ability to survive and thrive. At the outermost layer of the brain lies the cerebral cortex, which is segmented into distinct regions or lobes, each with its own set of responsibilities. These lobes play vital roles in functions such as sensory perception, motor control, language processing, and higher cognitive functions like reasoning and decision-making.

A deeper understanding of these brain regions not only enriches our knowledge of human behavior but also serves as a cornerstone for advancements in the medical field. Such insights aid in the diagnosis and treatment of various neurological disorders, offering hope to countless individuals grappling with conditions that affect their brain function and quality of life.

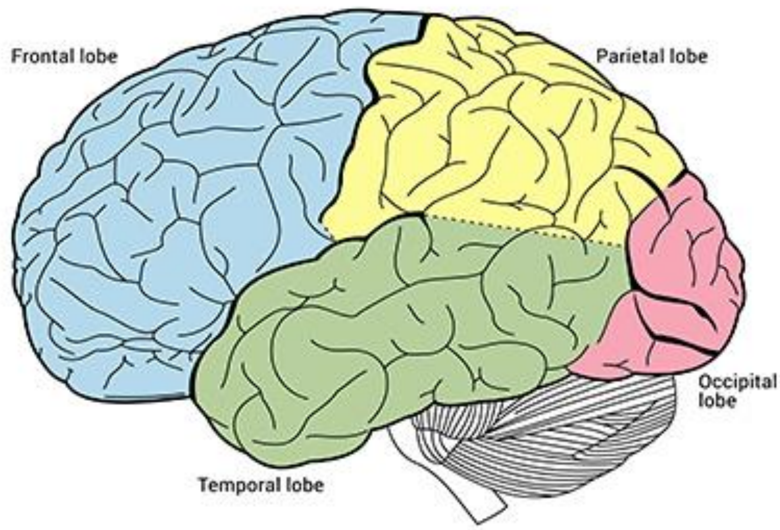

Fig 2.1 The different lobes of the brain

The human brain serves as a testament to nature's complexity, orchestrating an intricate dance of neural activity that underpins our very existence and daily activities. Divided into distinct lobes, each segment holds a vital role in regulating cognition, behavior, and sensory processing. As we unravel the mysteries of the brain's architecture, we unlock new avenues for understanding and addressing neurological challenges, bringing us closer to unlocking the full potential of the human mind.

(a) Pre-frontal Lobe:

The prefrontal lobe, nestled at the forefront of the brain within the frontal lobe, assumes a pivotal role in overseeing executive functions essential for navigating daily life. Often likened to the CEO of the brain, it orchestrates a complex symphony of cognitive processes and social behaviors. Decision-making, impulse control, emotional regulation, and judgment formation are among its primary responsibilities, intricately woven into the fabric of our psychological landscape ([7], [9]).

Moreover, the prefrontal lobe serves as a cognitive hub for tasks requiring nuanced thought processes, such as problem-solving, logical reasoning, and complex decision-making. Engaged extensively during activities demanding active memory utilization, it ensures seamless navigation through multifaceted cognitive challenges.

Beyond cognitive realms, this region plays a significant role in emotional regulation and social interaction, modulating our responses to external stimuli and shaping our interpersonal relationships. Its intricate interplay with other brain regions underscores its indispensability in human psychology, illuminating the profound impact of prefrontal function on our daily experiences and interactions with the world.

(b) Frontal Lobe:

Situated adjacent to the prefrontal lobe, the frontal lobe assumes responsibility for coordinating voluntary movements, regulating speech production, and facilitating higher cognitive functions. Often regarded as the brain's command center for action and creativity, it plays a pivotal role in orchestrating activities that demand innovative thinking and problem-solving ([7], [9]).

Moreover, the frontal lobe is intricately involved in short-term memory retention, crucial for recalling recent events or information. Its contribution extends to planning and anticipating the consequences of actions, enabling individuals to adapt effectively to new environments.

In essence, the frontal lobe serves as a hub for cognitive prowess, creative endeavours, and pragmatic decision-making, underscoring its significance in shaping our ability to interact with the world and manifest our thoughts into actions.

(c) Motor Cortex:

Nestled within the frontal lobe, the motor cortex serves as a vital hub for orchestrating voluntary movements by transmitting signals to the spinal cord. Positioned towards the rear of the frontal lobe, it acts as the brain's primary command center for physical activity, ensuring the precise execution of coordinated movements essential for daily functioning [7].

The motor cortex plays a pivotal role in the planning, regulation, and execution of voluntary movements. Through its intricate network of neurons, this region dispatches instructions to the spinal cord, prompting muscle contractions and facilitating movement. It comprises two main subdivisions: the primary motor cortex, which directly governs muscle actions, and premotor areas, which prepare muscles for specific actions.

This segmentation enables the motor cortex to facilitate smooth and coordinated movements necessary for a wide array of physical activities, ranging from basic motor tasks to complex actions requiring precision and dexterity. Ultimately, the motor cortex serves as a cornerstone for our ability to interact with the external environment, translating neural commands into tangible movements with remarkable efficiency and accuracy.

(d) Parietal Lobe:

Positioned just behind the prefrontal lobe, the frontal lobe plays a pivotal role in governing voluntary movements, speech production, and higher cognitive functions. Serving as the brain's command center for action and creativity, it is notably engaged during tasks demanding innovative thinking, such as problem-solving and artistic endeavors [7]. Furthermore, the frontal lobe contributes significantly to short-term memory retention, crucial for recalling recent events or information.

Beyond cognitive realms, this region aids in planning and anticipating the consequences of actions, essential for adapting to new environments and navigating daily challenges effectively. Its intricate interplay with other brain regions underscores its indispensability in shaping our ability to interact with the world and manifest our thoughts into actions, thereby highlighting the profound impact of the frontal lobe on our daily experiences and interactions.

(e) Occipital Lobe:

Situated at the posterior of the brain, the occipital lobe serves as the epicenter for visual processing, enabling us to perceive and comprehend the visual world around us. Often likened to the brain's camera, it functions as a sophisticated mechanism for capturing and analyzing visual stimuli [7].

Functioning as the brain's visual processing powerhouse, the occipital lobe deciphers incoming visual information from the eyes, discerning nuances such as color, light intensity, motion, and depth. Essential tasks like facial recognition, reading, and appreciating visual arts heavily rely on the seamless operation of the occipital lobe.

Despite its relatively compact size compared to other cerebral lobes, the occipital lobe wields considerable influence over our interaction with the environment, shaping our ability to navigate and interpret visual stimuli with precision and clarity.

(f) Temporal Lobe:

Located bilaterally on the sides of the brain, the temporal lobes play pivotal roles in auditory processing, language comprehension, and memory consolidation. Nestled beneath the temples, they serve as command centers for deciphering auditory stimuli and encoding memories for future recall.

Primarily responsible for recognizing sounds and understanding language nuances, the temporal lobes are indispensable for language comprehension and the appreciation of music. Moreover, they actively participate in the formation of long-term memories, crucial for educational learning and sustained information retention over time.

Beyond memory consolidation, the temporal lobes intricately intertwine memories with emotions, enriching our experiences with depth and sentiment. This integration of cognitive and emotional processes underscores the temporal lobes' multifaceted functions in shaping our perceptions, interactions, and memories of the world around us.

Each brain lobe, with its unique and interconnected functions, supports the diverse array of human thoughts, emotions, and behaviours. From solving complex problems in the pre-frontal lobe to storing cherished memories in the temporal lobe, each part contributes distinctively to the essence of being human. Expanding our understanding of these functions not only sheds light on our internal mechanisms but also assists healthcare professionals in addressing various brain conditions, thereby enhancing life quality.

2.2 The Different Brain Signals

The human brain communicates through intricate patterns of electrical activity, which can be recorded and analyzed to understand cognitive processes and neural functions.

Three significant brain signals, Motor Imagery (MI), Error-Related Potentials (ErrP), and Steady-State Visually Evoked Potentials (SSVEP), offer valuable insights into brain activity and have applications in neuroscience and technology.

2.2.1 Motor Imagery (MI) Signals:

Motor Imagery involves mentally simulating movement without physical execution, activating neural pathways akin to those engaged during actual movement. This cognitive process engages specific brain regions associated with movement planning and execution, notably the motor cortex, which exhibits distinct activity patterns during Motor Imagery tasks. These patterns manifest through two phenomena: Event-Related Desynchronization (ERD), characterized by a reduction in brain wave amplitude indicating active motor planning, and Event-Related Synchronization (ERS), marked by increased wave amplitude reflecting a pause in motor activity.

Hemispheric activation follows a contralateral pattern: imagining left limb movement activates the right motor cortex, while imagining right limb movement activates the left motor cortex.

The applications of Motor Imagery extend to neuro-prosthetics and Brain-Computer Interfaces (BCIs), offering potential benefits for individuals with disabilities. MI-based BCIs decode imagined movements into commands, enabling users to interact with technology or control prosthetic limbs through thought alone.

These findings not only deepen our understanding of brain function but also hold promise for improving the quality of life for individuals with motor impairments. Harnessing the power of Motor Imagery in assistive technologies opens new avenues for enhancing independence and mobility for those with physical disabilities.

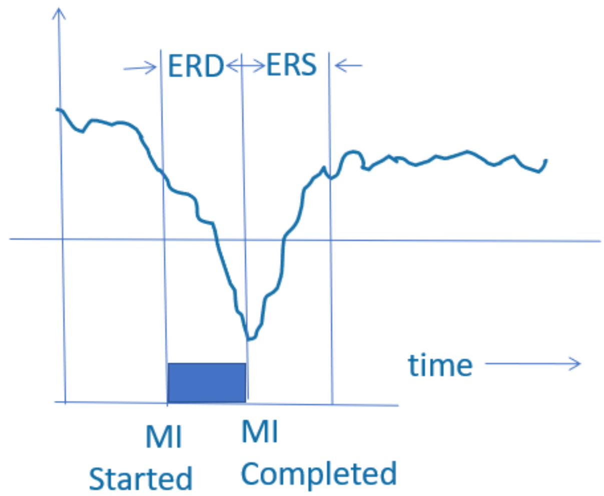

Fig 2.2 The Motor Imagery Signal

2.2.2 Error-Related Potentials (ErrP):

Error-Related Potentials (ErrPs) represent neuroelectric signals originating from a specific region of the brain called the medial frontal cortex. These signals are triggered when individuals recognize errors or receive feedback indicating the presence of an error. ErrPs provide valuable insights into the cognitive processes involved in self-monitoring and error correction within the brain.

When an error is perceived, ErrPs manifest as distinct patterns in electroencephalogram (EEG) readings. These patterns are characterized by sharp, negative deflections occurring shortly after the individual becomes aware of the mistake. ErrPs can be further classified into two main types: response ErrPs and feedback ErrPs.

Response ErrPs are elicited when errors occur in the individual's own actions. For example, if someone makes a mistake while performing a task, such as pressing the wrong button, a response ErrP may be observed in their EEG readings. Feedback ErrPs, on the other hand, are triggered by external feedback indicating the presence of an error. This could include receiving an error message on a computer screen or being informed verbally that an error has occurred.

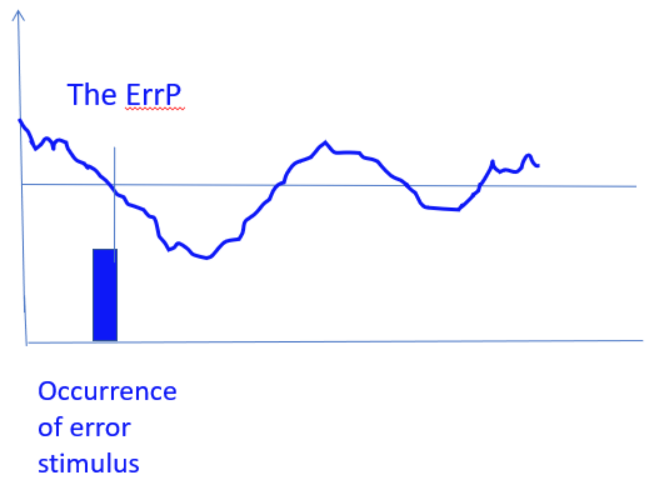

Fig 2.3 The ErrP signal

The integration of ErrP detection into Brain-Computer Interfaces (BCIs) holds significant potential for enhancing the adaptiveness and accuracy of these systems. For instance, in a BCI-controlled robotic arm, detecting an ErrP could prompt an immediate adjustment or correction of the movement being executed. This real-time error correction mechanism not only helps prevent mistakes but also enhances user safety and overall system performance.

In summary, ErrPs play a crucial role in understanding how the brain monitors and corrects errors, and their integration into BCIs represents a promising avenue for advancing neurotechnology and improving human-computer interaction.

2.2.3 Steady-State Visually Evoked Potentials (SSVEP):

Steady-State Visually Evoked Potentials (SSVEPs) are brain responses evoked by visual stimuli flickering at constant frequencies. These responses, primarily recorded over the occipital region, signify the brain's electrical activity synchronizing with the frequency of the stimulus. SSVEPs are renowned for their robustness and reliability, making them invaluable for Brain-Computer Interface (BCI) applications aimed at visual-based control tasks.

The integration of insights from Motor Imagery (MI), Error-Related Potentials (ErrP), and SSVEP signals enriches our understanding of brain function and expands the horizons of neurotechnology applications. From assistive devices for individuals with disabilities to cutting-edge BCIs, these signals hold immense promise for enhancing human health and quality of life.

SSVEPs offer a non-invasive and efficient means of interaction in BCIs. Their robust and high signal-to-noise ratio facilitates quick and reliable interpretation, ideal for real-time control systems. Users can control interfaces by directing visual attention to stimuli of varying frequencies, with each frequency corresponding to a distinct command, enabling seamless interaction without physical movement.

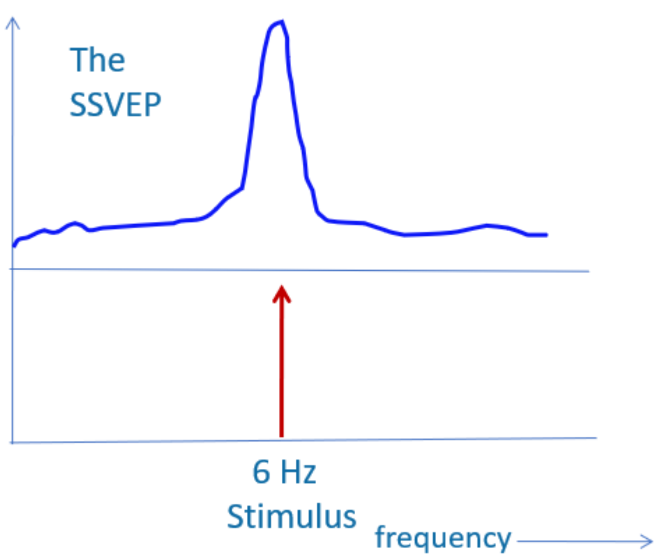

Fig 2.4 The SSVEP signal

Clinically, SSVEPs play a vital role in assessing the functionality of visual pathways and diagnosing visual impairments. By analyzing SSVEP responses, clinicians can gain insights into the integrity of the visual system, aiding in the diagnosis and treatment of visual disorders.

In summary, SSVEPs represent a powerful tool in neurotechnology, offering a reliable and non-invasive method for interfacing with the brain. Their versatility and effectiveness make them indispensable in a wide range of applications, from enhancing human-computer interaction to diagnosing and treating visual impairments.

Integrative Approaches and Future Directions:

Combining insights from MI, ErrP, and SSVEP signals not only enhances the functionality and efficiency of BCIs but also opens new avenues in neurotherapeutic applications. These integrated systems could lead to more naturalistic and intuitive user interfaces in assistive technologies, providing greater independence and improved quality of life for individuals with physical impairments. Further research into these signals will continue to expand our understanding of the brain and pave the way for innovative applications in medicine, rehabilitation, and human-computer interaction. Overall, the study and application of MI, ErrP, and SSVEP brain signals highlight the immense potential of neural technology in bridging gaps between the human brain and artificial systems, offering profound benefits across medical and technological fields.

2.3 Feature Extraction for Brain Signals

Understanding brain signals is crucial for unraveling the mysteries of the human mind and developing advanced technologies for neurorehabilitation, human-computer interaction, and cognitive enhancement. One fundamental aspect of analyzing brain signals is feature extraction, which involves identifying and quantifying relevant patterns or characteristics within the signals. In this essay, we explore the process of feature extraction for brain signals, drawing insights from recent research findings and referencing relevant studies.

Feature extraction plays a pivotal role in decoding and interpreting brain signals obtained through various neuroimaging techniques such as electroencephalography (EEG) and functional magnetic resonance imaging (fMRI). By extracting discriminative features from raw brain signals, researchers can identify meaningful patterns that correspond to specific cognitive processes, motor activities, or sensory responses [11].

2.3.1 Artifact Removal and Signal Filtering

Initial preprocessing of EEG data is essential to enhance the quality of the signals for feature extraction. Common disturbances such as eye blinking and muscle movements introduce significant artifacts which can obscure the true EEG signal. Independent Component Analysis (ICA) is widely used for artifact removal. ICA separates multivariate signals into additive, independent non-Gaussian signals, allowing for the isolation and removal of artifacts without affecting the underlying brain signals.

Following artifact removal, the EEG data is filtered to isolate the frequency bands relevant to each type of brain signal. This is typically achieved using narrow band spatial filters that are tuned to appropriate mid-frequencies and bandwidths. These filters help in reducing the influence of irrelevant frequencies and enhance the signal-to-noise ratio of the EEG recordings.

2.3.2 Feature Extraction from Brain Signals

Brain-computer interfaces (BCIs) revolutionize human-computer interaction by translating brain signals into actionable commands. A crucial step in this process is extracting meaningful features from electroencephalogram (EEG) signals associated with different brain activities. This chapter delves into the techniques used to extract features from motor imagery (MI), error-related potentials (ErrP), and steady-state visually evoked potentials (SSVEP) signals, as explored in the referenced literature and experiments.

2.3.2.1 Motor Imagery (MI)

Motor Imagery (MI) signals are crucial components in brain-computer interface (BCI) technologies, especially in the context of non-invasive EEG-based systems. These signals arise when an individual imagines performing a movement without physically executing it, activating similar neural pathways as actual movement. The predominant challenge in MI BCIs is the extraction of relevant features from raw EEG data that can effectively capture the underlying imagined action.

The feature extraction process for MI primarily targets sensorimotor rhythms, with a focus on the alpha (8-12 Hz) and beta (13-30 Hz) frequency bands. These bands are known to exhibit significant fluctuations during motor planning and execution, whether real or imagined. Techniques such as band-pass filtering are commonly employed to isolate these specific frequencies from the broader EEG spectrum.

Event-Related Desynchronization/Synchronization (ERD/ERS) analysis is another critical technique in the MI feature extraction arsenal. ERD refers to the decrease in band power associated with motor activity, while ERS denotes an increase. Analyzing these patterns provides insights into the timing and location of brain activity related to specific motor imaginations.

Furthermore, time-frequency transformations like wavelet transforms are utilized to capture both the frequency and temporal information from EEG signals. This is particularly important as the dynamic changes in brain activity during motor imagery occur over very short intervals. Wavelet transforms help in mapping these quick transitions effectively, providing a robust framework for decoding the user's intention in BCIs.

Motor imagery involves mentally simulating movements, activating similar brain regions as physical execution. Extracting relevant features from MI signals is pivotal for controlling devices via BCIs. Some of the techniques utilized are mentioned:

- **Common Spatial Pattern (CSP)**: CSP is a sophisticated technique akin to tuning a radio to capture clear signals. It leverages spatial filtering to highlight brain activity patterns relevant to MI tasks while minimizing noise. Think of it as tuning into the brain's frequency for specific movements ([15], [18]).

- **Filter-Bank Approach**: This approach breaks down EEG signals into different frequency bands, akin to sorting music into different genres. By applying CSP to each band separately, it enhances the system's ability to discern between different MI tasks. It's like fine-tuning the radio to different stations for better clarity ([15]).

2.3.2.2 Error-related Potentials (ErrP)

Error-related Potentials (ErrP) are another type of signal of interest in neuro-engineering, particularly in the development of adaptive BCIs. These signals are generated when an individual recognizes a mistake in the outcome of their action or when an external system error occurs. The ability to detect and respond to ErrPs can significantly enhance the interactive capabilities of a BCI, enabling it to correct errors in real-time.

Feature extraction for ErrPs involves precise segmentation of EEG data to capture the occurrence of an error. This segmentation is typically centered around the event where the error is detected, and involves the application of baseline normalization techniques to enhance the signal-to-noise ratio. This prepares the signal for further analysis where features such as the amplitude and latency of the ErrP peaks are scrutinized.

The amplitude and latency of these peaks are telling; they represent the intensity and timing of the brain's response to errors, respectively. These features are crucial for algorithms that aim to detect and classify ErrPs effectively, thereby facilitating quick corrective actions within the BCI framework. The method for ErrP feature extraction is Adaptive Auto-Regressive.

- **Adaptive Auto-Regressive (AAR) Parameters**: AAR parameters delve into the dynamic nature of EEG signals post-error. Think of it as analyzing the ripples in a pond after a stone is thrown. By examining these ripples, we gain insights into the brain's response to errors, aiding in error detection and system adaptation ([1]).

2.3.2.3 Steady-State Visual Evoked Potentials (SSVEP)

Steady-State Visual Evoked Potentials (SSVEP) are elicited by visual stimuli flickering at constant frequencies. In BCI applications, SSVEP signals are advantageous due to their robustness and relatively high signal-to-noise ratio. Feature extraction for SSVEP primarily focuses on identifying the frequency components corresponding to the visual stimuli.

Techniques like Fourier Transforms or Power Spectral Density (PSD) analysis are pivotal in isolating these frequencies from the EEG data. Such methods provide a clear spectral view where stimulus frequencies and their harmonics can be identified and quantified. Additionally, Canonical Correlation Analysis (CCA) is frequently used to compare the frequencies observed in the EEG with the expected stimulus frequencies, aiding in confirming the presence and strength of SSVEP responses.

This precise frequency mapping through feature extraction is essential as it directly influences the accuracy and reliability of SSVEP-based BCIs. By accurately identifying which frequency a user is focusing on, the system can infer the user's selection or intention, making it a powerful tool for communication and control in BCIs. The method for SSVEP feature extraction are given below:

- **Power Spectral Density (PSD)**: PSD analysis provides a snapshot of signal power across different frequency bands. For SSVEPs, it's akin to analyzing the intensity of lights flickering at various rates. By focusing on frequencies corresponding to visual stimuli, we can isolate and extract SSVEP signals effectively ([18]).

- **Auto-Regressive (AR) Features**: AR modeling captures the spectral characteristics of SSVEP signals. Imagine creating a mathematical model to mimic the behavior of flickering lights. AR features provide insights into the underlying dynamics of SSVEP responses, aiding in their detection and classification ([18]).

Applications and Implications:

The extracted features from MI, ErrP, and SSVEP are instrumental in the development and enhancement of BCIs. These features allow BCIs to interpret user intentions, detect cognitive errors, and respond to visual stimuli accurately, thereby enabling users, especially those with severe motor disabilities, to interact with their environment in a meaningful way.

Feature extraction is a critical process in the analysis of EEG signals for BCI applications. By employing sophisticated methods like ICA for artifact removal, appropriate filtering techniques, and advanced feature extraction algorithms like CSP, AAR, PSD, and AR, researchers can effectively interpret the brain's electrical activity. These processes not only enhance the performance and accuracy of BCIs but also open new avenues for research in neurotechnology, paving the way for future innovations that could profoundly impact the medical field and beyond.

2.3.3 Integration of Feature Extraction Techniques

In the experiments, a combination of these techniques is employed to extract discriminative features from EEG signals, enabling precise decoding of user intentions and control of robotic systems.

By leveraging advanced signal processing methods such as CSP for MI, AAR parameters for ErrP, and PSD/AR features for SSVEP, the experiments demonstrate effective extraction of meaningful features from EEG signals. These features serve as the building blocks for decoding user intentions and facilitating seamless interaction between humans and machines in BCI applications.

2.4 Brain Signal Classification

Electroencephalography (EEG) signals, captured from the human brain, play a pivotal role in the development of brain-computer interfaces (BCIs) [22]. These interfaces enable direct communication pathways between the brain and external devices, promising revolutionary applications in medical rehabilitation, assistive technology, and interactive computing [3]. This essay explores the detailed methodologies employed in feature extraction and classification of three specific EEG signals: Motor Imagery (MI), Error-related Potentials (ErrP), and Steady-State Visually Evoked Potentials (SSVEP) [2].

Post feature extraction, the classification stage involves assigning signal categories based on the extracted features. Linear Discriminant Analysis (LDA) is a preferred method due to its efficiency in binary and multi-class problems [20].

In the realm of brain-computer interfaces (BCIs), accurate classification of electroencephalography (EEG) signals is critical for the system's effectiveness and user satisfaction [11]. The classification process involves determining which category a new observation belongs to, based on a training set of data containing observations whose category membership is known [11]. This section delves into the classification techniques employed for EEG signals, specifically focusing on Linear Discriminant Analysis (LDA), which is widely used in the analysis of Motor Imagery (MI), Error-related Potentials (ErrP), and Steady-State Visually Evoked Potentials (SSVEP) [11].

Brain signal classification is a fundamental aspect of brain-computer interface (BCI) systems, enabling the interpretation of neural activity into actionable commands [22]. Through sophisticated algorithms and techniques, these systems decode electroencephalography (EEG) signals associated with various brain states, such as motor imagery (MI), error-related potentials (ErrP), and steady-state visually evoked potentials (SSVEP) [4]. Here, we delve into the classification methods utilized in BCI research, drawing insights from the provided references.

1. Training and Test Phases:

- BCI experiments typically involve two main phases: training and testing ([6], [12]). During the training phase, participants engage in specific mental tasks, like imagining limb movements or identifying errors, while their EEG signals are recorded. These signals undergo preprocessing, filtering, and feature extraction to prepare them for subsequent classification. The test phase evaluates the performance of the classification model using new data.

2. Feature Extraction:

- Before classification, relevant features are extracted from EEG signals to characterize different brain states ([13], [14]). Techniques such as Common Spatial Pattern (CSP) analysis, filter-bank approaches, and time-frequency transformations are utilized to capture distinct patterns associated with MI, ErrP, and SSVEP signals.

3. Classification Algorithms:

- Several supervised learning algorithms are employed for brain signal classification, including Linear Discriminant Analysis (LDA), Support Vector Machines (SVM), and neural networks ([11], [18]). These algorithms are trained on labeled EEG data, with the extracted features serving as input for classification.

4. Performance Evaluation:

- Classification accuracy is a crucial metric for assessing BCI system performance ([11], [18]). During training, the classification model's accuracy is measured on labeled training data. The model's generalization ability is then evaluated during testing using unseen data to ensure its effectiveness in real-world scenarios.

5. Technological Advancements:

- Recent progress in BCI research has led to the development of more advanced classification techniques ([16], [20]). These include ensemble methods, deep learning architectures, and hybrid models that combine multiple classifiers. These advancements aim to enhance classification accuracy and robustness, ultimately improving the usability of BCI systems.

6. Comparative Performance Analysis:

- Comparative studies are conducted to assess the performance of different classification techniques ([5], [10]). Metrics such as steady-state error, peak overshoot, settling time, and cognitive load are used to compare the efficacy of proposed methods against existing approaches.

7. Future Directions:

- The field of brain signal classification continues to evolve, driven by advancements in signal processing, machine learning, and neurotechnology ([21]). Future research aims to overcome challenges such as enhancing classification accuracy, improving user experience, and expanding the applicability of BCI systems in various real-world contexts.

Hence, the brain signal classification is essential for enabling communication and control through BCI systems. Leveraging sophisticated algorithms and techniques, researchers strive to accurately decode neural activity, leading to diverse applications in healthcare, assistive technology, and human-computer interaction. In the experiments described, several classification techniques were utilized to interpret brain signals obtained through electroencephalography (EEG). Here's how these techniques were applied and their significance:

1. Linear Discriminant Analysis (LDA):

- LDA was employed as a classification method for decoding MI (Motor Imagery) signals ([16], [17]). In the context of the experiments, LDA likely played a role in distinguishing between different imagined motor tasks based on extracted EEG features. By projecting the high-dimensional feature space onto a lower-dimensional subspace while maximizing class separability, LDA aids in accurately categorizing EEG patterns associated with different motor intentions.

2. Support Vector Machines (SVM):

- SVMs were likely utilized alongside LDA for classifying MI signals ([16], [17]). SVMs are effective in handling nonlinear decision boundaries and are well-suited for binary and multiclass classification tasks. In the experiments, SVMs likely played a complementary role to LDA, offering an alternative approach to classifying EEG signals and enhancing the overall accuracy of the classification system.

3. Wavelet Transforms:

- Wavelet transforms are commonly employed in EEG signal processing to extract both spectral and temporal features from the EEG data ([12], [13]). In the experiments, wavelet transforms likely played a crucial role in capturing the dynamic changes in brain activity during motor imagery tasks. By decomposing the EEG signals into different frequency bands over time, wavelet transforms provide valuable information for distinguishing between different motor tasks and enhancing the discriminative power of the classification system.

4. Common Spatial Pattern (CSP):

- CSP is a technique used for spatial filtering of EEG signals to enhance the signal-to-noise ratio and highlight brain activity patterns relevant to motor imagery tasks ([15], [16]). In the experiments, CSP likely contributed to feature extraction by identifying spatial patterns of brain activity associated with specific motor intentions. By focusing on regions of the brain relevant to motor control, CSP helps improve the accuracy of MI signal classification and enables more precise decoding of motor intentions.

5. Filter-Bank Approach:

- The filter-bank approach involves decomposing EEG signals into different frequency bands using multiple band-pass filters ([15], [16]). This technique allows for the extraction of frequency-specific features from the EEG data, which are then used for classification. In the experiments, the filter-bank approach likely facilitated the extraction of frequency-domain features related to motor imagery, providing additional information for discriminating between different motor tasks.

By integrating these classification techniques into the experimental setup, researchers were able to effectively decode MI signals from EEG data and distinguish between different motor intentions. Each technique contributed unique capabilities to the classification system, enhancing its overall performance and enabling more accurate interpretation of brain signals for real-time control of robotic systems.

2.6 Conclusion

In conclusion, the chapter delved into the intricate realm of brain signal processing and classification, shedding light on the methodologies and advancements driving the field of brain-computer interfaces (BCIs). Through meticulous research and innovation, scientists and engineers have made significant strides in deciphering the complexities of EEG signals and harnessing them for practical applications in healthcare, assistive technology, and human-computer interaction.

The training and test phases emerged as foundational components in BCI experimentation, providing the framework for collecting and evaluating EEG data. By engaging participants in specific mental tasks and recording their brain activity, researchers gain insights into the neural processes underlying motor imagery, error recognition, and visual responses. These phases lay the groundwork for subsequent feature extraction and classification, essential steps in decoding the brain's intricate signals.

Feature extraction techniques, such as Common Spatial Pattern (CSP) analysis and time-frequency transformations, play a pivotal role in characterizing EEG signals associated with different brain states. These techniques enable researchers to identify distinct patterns and extract relevant features for classification. Coupled with advanced signal processing methods, such as filter-bank approaches, researchers can enhance the accuracy and robustness of BCI systems, paving the way for more effective communication and control mechanisms.

Classification algorithms, ranging from Linear Discriminant Analysis (LDA) to deep learning architectures, offer powerful tools for interpreting EEG signals and translating them into actionable commands. These algorithms leverage labeled training data to learn patterns and associations, enabling accurate classification of new observations. As technological advancements continue to evolve, researchers explore novel approaches and hybrid models to further enhance classification accuracy and adaptability across diverse applications.

Comparative performance analysis serves as a critical benchmark for evaluating the efficacy of classification techniques and guiding future research directions. By rigorously assessing metrics such as accuracy, latency, and cognitive load, researchers can identify optimal strategies and refine existing methodologies to meet the evolving needs of BCI users.

Looking ahead, the future of brain signal classification holds immense promise, driven by ongoing advancements in signal processing, machine learning, and neurotechnology. As researchers continue to push the boundaries of innovation, BCI systems are poised to revolutionize healthcare, empower individuals with disabilities, and redefine human-computer interaction. With interdisciplinary collaboration and a commitment to excellence, the journey towards unlocking the full potential of the human brain in the digital age continues unabated.

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CHAPTER 3

Brain-Instructed Controller Designs for BCI-based Position Control

3.1 Introduction

In the Brain-Computer Interface (BCI) Position Control systems employed in neuro-motor prosthetic applications, the main two specific brain signals are: Motor Imagery (MI) and Error-Related Potential (ErrP). MI signals activate the electromechanical motors of robotic arms, while ErrP signals function to cease their movement, effectively serving as a basic binary control mechanism. However, this straightforward approach can lead to positional inaccuracies, that is, overshoots, which manifest as non-zero steady-state errors. Hence, the need for contemporary research in BCI technology that focuses on developing more sophisticated position control methods that can overcome these limitations. A significant challenge in these advancements is the inability of ErrP signals to provide detailed information on the magnitude or direction of the positional errors—they only signal the fact that an error has occurred. [1]-[3]

To improve position control while trying to reduce the cognitive load on users, a novel dual-loop control system has been proposed. This control system consists of an outer loop that manages the motor's position and an inner loop that adjusts the speed of the robotic limb based on dynamic feedback. This setup not only aims to enhance the accuracy of movement but also reduces the cognitive strain associated with operating complex BCI systems.

The aim is to innovate various velocity modulation strategies that are adapted based on precise measurements of positional errors. While traditional two-loop position control systems offer multiple strategies for velocity modulation, experimental limitations in this research prevent their direct implementation. Instead, three new alternative strategies have been formulated, all of which utilize ErrP signal detection to accurately locate the target and make necessary adjustments.

The first strategy introduces a proportional gain, K where $K<1$ applied directly to the signed positional error to tailor the motor's velocity responsively. The second method significantly reduces the speed of the robotic arm by half and implements a direction reversal each time the robotic arm reaches the target, ensuring a steady deceleration for a more precise and accurate stop. The third, more sophisticated method, applies the Takagi-Sugeno fuzzy logic model, which incorporates both the positional error and its rate of change to fine-tune the robotic arm's speed. The fourth method is built upon the previous Takagi-Sugeno fuzzy logic control, wherein the parameters of the Takagi-Sugeno fuzzy logic is determined using a Learning Automaton.

Through a comprehensive stability analysis conducted using the Root Locus technique, it becomes evident that the Learning Automaton induced Takagi-Sugeno fuzzy logic approach delivers the best performance in terms of stability margins. Moreover, all proposed methods are designed to keep cognitive loads on the user consistently low, making the Learning Automaton induced Takagi-Sugeno fuzzy method particularly commendable for its optimal balance of stability, error correction efficacy, and user-friendliness. Therefore, this method not only enhances the precision and responsiveness of BCI-driven robotic arms but also improves the overall user experience by simplifying the cognitive demands during operation.

3.2 System Overview

Existing Brain-Computer Interface (BCI) technology, particularly in the realm of neuro-prosthetic limbs, commonly employs a basic on-off control approach. This approach uses Motor Imagery (MI) signals to activate movement and Error-Related Potential (ErrP) signals to stop it [5],[6]. However, this straightforward strategy can lead to significant positional overshoots, creating a persistent non-zero steady-state error that is particularly problematic for users with neuro-motor impairments.

Current advancements in this research focus on integrating established control theory principles [5],[13] to adjust the velocity of the end-effector on robotic limbs. The objective is to refine the control system to ensure that the limb approaches its target with minimal or no overshoot. This is achieved by configuring the control system to apply a negative adjustment to the speed, which includes reversing the direction whenever the limb overshoots the target, thereby promoting system stabilization.

This chapter introduces three innovative strategies for modulating velocity based on the stated objectives:

1. The initial strategy involves setting a proportional gain on the velocity modulator using the signed positional error as input. Keeping the proportional gain factor below one (a fraction of the initial speed) guarantees that the system moves towards eliminating positional error, thus stabilizing the limb's movements.

2. The second strategy includes both reversing the speed and halving it at every zero crossing of positional error. This predetermined reduction factor, set at two, not only facilitates mathematical ease in designing the system's transfer function but also ensures effective deceleration for stability.

3. The third strategy employs a rule-based system to vary the gain settings of the speed modulator. The Takagi-Sugeno fuzzy reasoning technique is utilized here, which adjusts the variable DC gain based on the positional error and the derivative of the positional error measurements in all cycles after the initial error occurrence. For a given set of error and error derivative, there are specified rules, i.e., there are weights attached to the error and the error derivative. The first cycle of error is crucial as it helps pinpoint the target's position by using the first ErrP signal generated as the limb moves on a set path towards the target. This setup allows users to indirectly choose the target position by generating the ErrP signal when the limb is about to cross the target location.

4. The fourth strategy is a modified version of the previous strategy. Similar to the Takagi-Sugeno fuzzy control strategy, there are weights attached to the positional error and its derivative upon which the variable DC gain of the motor depends. This setup also allows the user to choose the target position by generating an ErrP signal when it approaches the target. The rules of choosing the weights of the positional error and its derivative is however, different and innovative. A Learning Automaton is employed, which is pre-trained, to give accurate prediction of the weights. The initial weights are equally distributed among weight pairs, which is later trained to predict the weights for given error and error-derivative pairs. For accurate prediction, it is rewarded and for inaccurate predictions, it is penalized.

These approaches are designed to enhance the precision of BCI-controlled neuro-prosthetic limbs, reducing overshoot and improving overall functionality for individuals with mobility impairments.

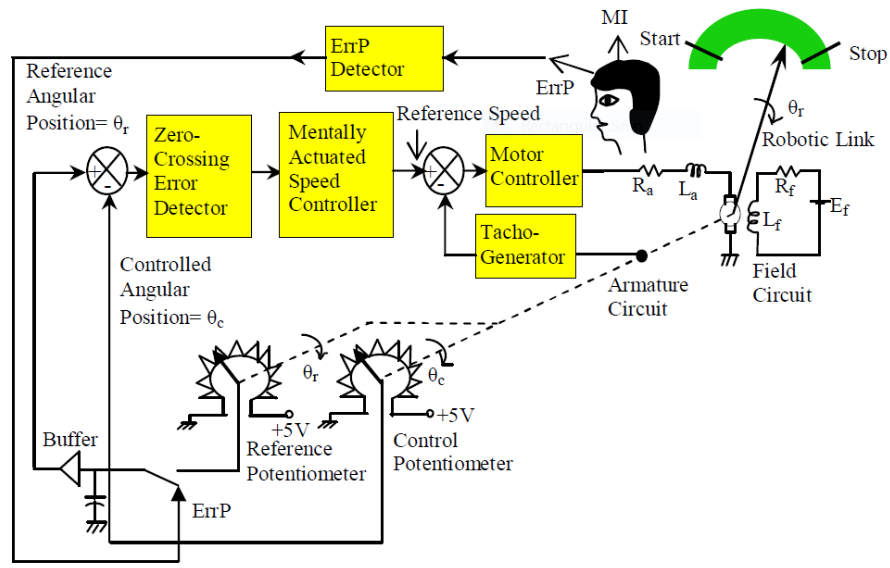

Fig 3.1 Illustrative block diagram of the 2-loop position control system

The proposed system as shown in Fig 3.2 is engineered for a single-dimensional trajectory control of a robotic arm that maneuvers across a pre-established semi-circular path. What distinguishes this setup is its dynamically adjustable endpoint, which is determined online by the user. This feature is particularly beneficial for individuals with neuro-motor impairments, enabling them to interact directly with the robotic arm to select and retrieve desired objects with precision. [13]-[19]

In operational terms, the system adheres to established Brain-Computer Interface (BCI) methodologies by employing Motor Imagery (MI) and Error-Related Potential (ErrP) signals. MI signal facilitates the initiation of the robotic arm's movement, while ErrP signal serves to halt it. The user activates the robotic arm by generating an MI signal, and signals its stop by releasing an ErrP when the robotic arm crosses the intended target position.

However, a notable challenge arises due to the mechanical properties of the motor, such as its inertia, which causes the arm to move beyond the desired point even after receiving the stop command. This overshoot complicates the accurate determination of the target as initially intended by the user.

To overcome this, the design incorporates a unique mechanism using the ErrP signal's onset to accurately define the target position. This process involves a capacitor that begins charging through a potentiometer driven by the motor and continues until the release of the ErrP signal. At the moment the ErrP is detected, a switch mechanism quickly isolates the capacitor from the potentiometer circuit, capturing the exact voltage that correlates with the robotic arm's angular position at that instant. A buffer with a high input impedance is connected across the capacitor to preserve the voltage level, ensuring that the target position is maintained without degradation over time.

This precision allows the user to set the stop position of the robotic arm accurately and autonomously, streamlining the interaction process and significantly reducing cognitive load. The user needs only to determine the target once per operation, allowing them to focus less on the mechanics of control and more on the task at hand.

The control architecture further refines this interaction through a dual-loop control system. The outer loop is responsible for setting the robotic arm's speed based on the positional error detected, and the inner loop uses feedback from a tacho-generator to fine-tune this speed adjustment. This two-tiered approach not only accelerates the response time of the system but also ensures its stability.

At the heart of this system lies the newly introduced Brain Actuated Speed Controller (BASC). This innovative component adjusts the reference speed for the inner control loop by evaluating the positional error. This adjustment is critical for the precise control of the robotic arm, marking a pioneering development in the field of BCI. The integration of BASC enhances the effectiveness of the control strategy, enabling more responsive and stable control of neuro-prosthetic devices.

3.3 Modelling of Proposed Brain-Actuated Position Control Schemes

In this research, we introduce three unique variations of the Brain Actuated Speed Controller (BASC). The BASC's primary function is to transition the control mechanism from a brain-driven activation state to an automatic mode. This is facilitated through a switching mechanism that connects the reference potentiometer to the capacitor, which is triggered by the detection of an Error-Related Potential (ErrP) signal. Once activated, the BASC employs supplementary electronic components, like a comparator circuit, to identify zero crossings in positional error, which are critical for precise control adjustments.[4],[5]

3.3.1 Scheme 1: Brain-Actuated Proportional Type Speed Modulation

In Proportional-type speed control, the angular speed $\dot{\theta}_c$ is set proportional to signed positional error $(\theta_r - \theta_c)$ where θ_r and θ_c respectively denote reference angular position and feedback position of the motor shaft/armature of the control potentiometer as shown in Fig 3.2. [6]

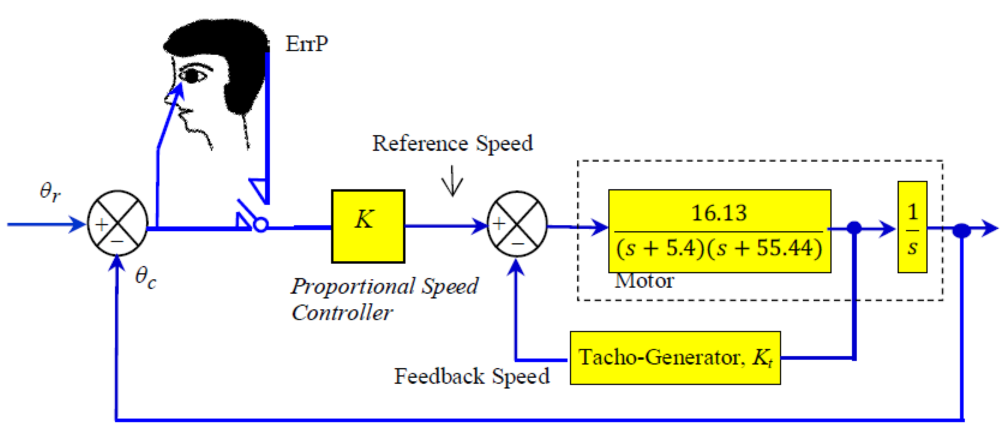

Fig 3.2 Block diagram of the proportional type modulation system

Thus: $$\dot{\theta}_c = K(\theta_r - \theta_c) \quad (1)$$

where in order to maintain stability, it is crucial for K to be less than 1. The stability for the above choice of K is ensured for convergence of $\dot{\theta}_c$approaching zero, when error$(\theta_r - \theta_c)$approaches zero. Equation (1) shows that in the Laplace (s) domain, the transfer function of the proportional type speed controller is expressed as:

$$\frac{s\theta_c(s)}{\theta_r(s)-\theta_c(s)} = K \quad (2)$$

Equation (2) ensures automatic reversal of the speed's sign when there is a reversal in the positional error's sign. It's significant to highlight that the proportional type speed controller, as depicted in Figure 1, operates without the need for a zero-crossing detector, as equation (1) holds at both zero crossing and non-zero values of error as well. The Root Locus plot is given in Fig. 3.9.

3.3.2 Scheme 2: Zero-Crossing Sensitive Brain-Actuated Speed Modulation

The speed modulator sensitive to zero-crossings adjusts the current speed of the robotic link to half of the speed just before each zero-crossing of the error. Speed reversal occurs at every zero-crossing as well. Formally, the current speed $\dot{\theta}_c$ is half of its last speed $(\dot{\theta}_c - 1)$ as shown in Fig 3.3. [4]-[6]

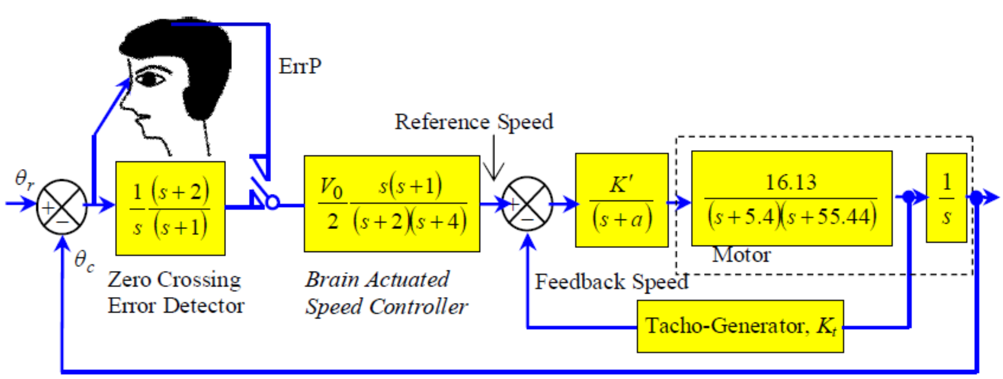

Fig 3.3 Block diagram of the Zero crossing sensitive speed modulation system

Thus: $$\dot{\theta}_c = -\left(\frac{1}{2}\right)(\dot{\theta}_c - 1) \quad (3)$$

The formal approach to modelling (3) is presented graphically in Fig. 3.3. In this figure, it is assumed that each error cycle period, T, is reduced by a certain amount, δ .

$$c(t) = [u(t) - u(t-T)] - [u(t-T) - u(t-(2T-\delta)] + [u(t-(2T-\delta)) - u(t-(3T-2\delta)] - \cdots + u[t-(nT-(n-1)\delta] \quad (4)$$

Simplifying (4), we obtain (5):

$$c(t) = u(t) - 2u(t-1) + 2\,u(t-(2T-\delta)) - \cdots + u[t-(nT-(n-1)\delta] \quad (5)$$

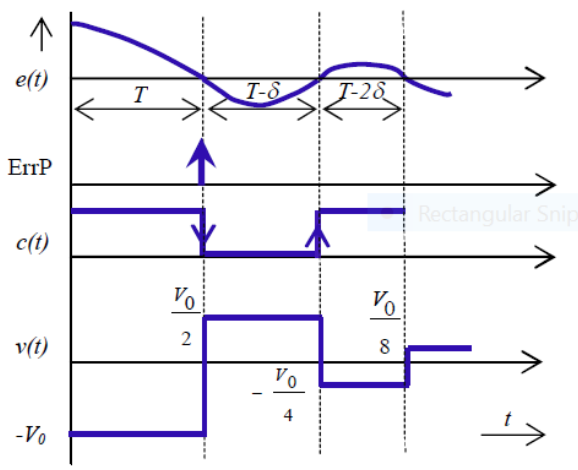

Fig. 4(a) Timing diagram depicts the behavior of the Zero Crossing Sensitive Speed Modulator.

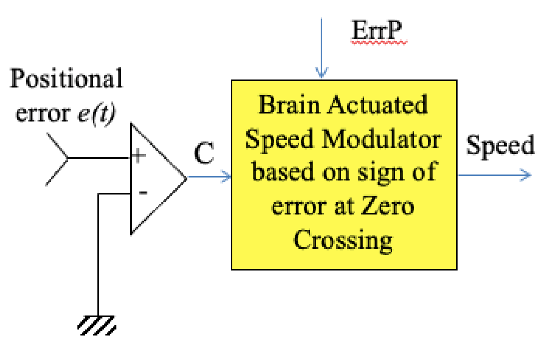

Fig. 4(b) Comparative Circuit of the Zero Crossing Sensitive Speed Modulator

From Fig 3.4 (a) and (b) we can deduce that, every time the robot arm reaches that target position, the error *e(t)* becomes zero and at the first occurrence of that zero-crossing, an ErrP signal is generated from the brain of the subject. This occurrence is registered as an impulse and fed to the comparative circuit. This coincidence of the magnitude of error and the occurrence of the first ErrP signal is hence registered to locate the target position. From now on, the BCI position control system is transferred from manual mode to automatic mode.

Velocity setting of the zero-crossing sensitive speed modulation can be expressed as:

$$v(t) = (\tfrac{v_0}{2})[u(t) - u(t-T)] - (\tfrac{v_0}{4})[u(t-T) - u(t-(2T-\delta)] + \cdots +$$

$$(\tfrac{v_0}{2^n})u[t-(nT-(n-1)\delta] \quad (6)$$

where, v_0 denotes the initial speed of the robotic link.

By applying the Laplace transform to equations (5) and (6), we derive equations (7) and (8) respectively.

$$C(s) = \left(\frac{1}{s}\right)[1 - 2e^{-sT} + 2e^{-s(2T-\delta)} - 2e^{-s(3T-2\delta)} + \cdots + 2e^{-s(nT-(n-1)\delta)}] \quad (7)$$

$$V(s) = \left(\frac{v_0}{s}\right)\left[\frac{1}{2} - \frac{3}{4}e^{-sT} + \frac{3}{8}e^{-s(2T-\delta)} + \cdots + \frac{1}{2^n}e^{-s(nT-(n-1)\delta)}\right] \quad (8)$$

Simplifying equations (7) and (8), $e^{-sT} = 1 - sT$, and T=1.

$$C(s) = \frac{1}{s}\left[\frac{s+2}{s+1}\right] \quad (9)$$

and $V(s) = \frac{v_0}{2}\left[\frac{1}{4s+3}\right]$ (10)

Thus, transfer function is given as:

$$\frac{C(s)}{V(s)} = \frac{v_0}{2}\left[\frac{s(s+1)}{s^2+6s+8}\right] \quad (11)$$

The stability analysis of this system was performed through Root Locus analysis which is shown in Figure 3.10.

3.3.3 Scheme 3: Takagi-Sugeno Fuzzy Model for Speed Adaptation

The Takagi-Sugeno (T-S) type fuzzy controller is chosen for its capacity to manage varying magnitudes and signs of the positional error and its rate of change, which play pivotal roles in adjusting the speed of the robotic arm at each zero-crossing point of the error. This fuzzy logic approach uses predefined linguistic variables such as SMALL POSITIVE, SMALL NEGATIVE, and NEAR ZERO, applying them to the positional error and its derivative.

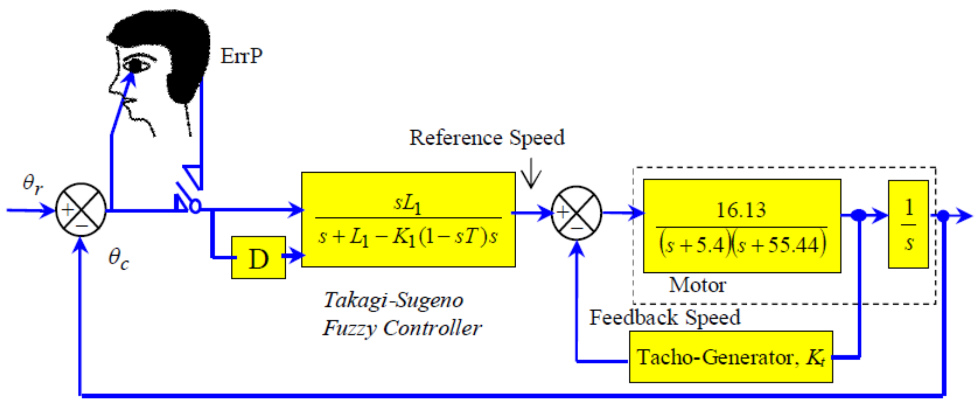

Fig 3.5 Schematic diagram of Takagi-Sugeno fuzzy speed modulation system

These fuzzy quantifiers are employed in sample rules that operate by blending these inputs linearly to calculate the appropriate speed adjustments for the robotic link. This method ensures that the controller can adapt dynamically to changes in the system's behaviour, enhancing the precision of the control mechanism as shown in Fig 3.5. [6]

Rule 1: If error (e) is Small Positive and error derivative ($\dot{e}$) is Small Negative then speed is $(0.1 \times (e) - 10 \times (\dot{e}))$.

Rule 2: If error (e) is Large Positive and error derivative ($\dot{e}$) is Small Negative then speed is $(0.5 \times (e) - 100 \times (\dot{e}))$.

Rule 3: If error (e) is Small Positive and error derivative ($\dot{e}$) is Large Negative then speed is $(0.1 \times (e) - 10 \times (\dot{e}))$.

Rule 4: If error (e) is Large Positive and error derivative ($\dot{e}$) is Small Positive then speed is $(0.5 \times (e) - 100 \times (\dot{e}))$.

Rule 5: If error (e) is Small Positive and error derivative ($\dot{e}$) is Small Positive then speed is $(0.1 \times (e) - 10 \times (\dot{e}))$.

Rule 6: If error (e) is Small Positive and error derivative ($\dot{e}$) is Large Positive then speed is $(0.1 \times (e) - 10 \times (\dot{e}))$.

Rule 7: If error (e) is Large Positive and error derivative ($\dot{e}$) is Large Negative then speed is $(0.5 \times (e) - 100 \times (\dot{e}))$.

Rule 8: If error (e) is Large Positive and error derivative ($\dot{e}$) is Large Negative then speed is $(0.5 \times (e) - 100 \times (\dot{e}))$.

Rule 9: If error (e) is Small Negative and error derivative ($\dot{e}$) is Small Negative then speed is $(0.1 \times (e) - 10 \times (\dot{e}))$.

Rule 10: If error (e) is Small Negative and error derivative ($\dot{e}$) is Small Positive then speed is $(0.1 \times (e) - 10 \times (\dot{e}))$.

Rule 11: If error (e) is Large Negative and error derivative ($\dot{e}$) is Small Negative then speed is $\left(0.5 \times (e) - 100 \times (\dot{e})\right)$.

Rule 12: If error (e) is Near Zero and error derivative ($\dot{e}$) is Small Negative then speed is $(0.04 \times (e) - 0.01 \times (\dot{e}))$.

The coefficients associated with the error and its time derivatives in the mentioned rules are chosen based on intuition. It is apparent from the structure of the fuzzy rules that in Takagi-Sugeno type fuzzy adaptation, that the speed of the robotic controller is determined by the positional error and its derivative [6]. Formally, let the current speed of the controller be $\dot{\theta}_c(t)$ and the positional error is given by$(\theta_r - \theta_c)$. Then the Takagi-Sugeno response of the controller is given by (11).

$$\dot{\theta}_c(t) = K_1\dot{\theta}_c(t-1) + L_1(\theta_r - \theta_c) \tag{11}$$

where, K_1 and L_1 are gain constants of user's choice.

On taking Laplace transform of (11), it is found that the ratio of speed and positional error is given by:

$$\frac{s\theta_c(s)}{\theta_r(s)-\theta_c(s)} = \frac{L_1 s}{[1-(K_1 e^{-sT})+L_1 s]} \tag{12}$$

It is apparent that the above transfer function is stable for all $K_1<1$. The Root Locus plots are given in Fig. 3.11.

3.3.4 Scheme 4: Learning Automaton Induced Brain-Actuated Takagi-Sugeno Speed Modulation

This section introduces an innovative method for automatic speed modulation in robotic arms for neuro-prosthetic use. Due to variations in positional error and its rate of change during the settling period of the manipulator, accurately predicting motor speed can be challenging. The Takagi-Sugeno fuzzy architecture addresses this by using fuzzy set memberships of errors and their derivatives to define the robot arm's speed profile. A typical rule within this framework considers the positional error (e) and its derivative (ė) with fuzzy sets like LARGE POSITIVE (LP) and SMALL NEGATIVE (SN) to modulate speed effectively. [7]-[12]

If e corresponds to fuzzy set A and ė corresponds to fuzzy set B, the resulting speed $\dot{\theta}$ is calculated as$\dot{\theta} = K_1 e + L_1 \dot{e}$, where K_1 and L_1 are constants that relate speed to error $(\dot{\theta}/e)$and speed to error derivative $(\dot{\theta}/\dot{e})$. [20]-[29] Based on the measured values of error and its derivative, and their classification into fuzzy sets like A and B, multiple Takagi-Sugeno fuzzy rules might be triggered simultaneously, leading to fuzzy reasoning. For example, consider two active rules:

Rule 1: If e is A_1 and $\dot{e}$ is B_1, then speed = $K_1 e + L_1 \dot{e}$. (13)

Rule 2: If e is A2 and $\dot{e}$ is B_2, then speed = $K_2 e + L_2 \dot{e}$. (14)

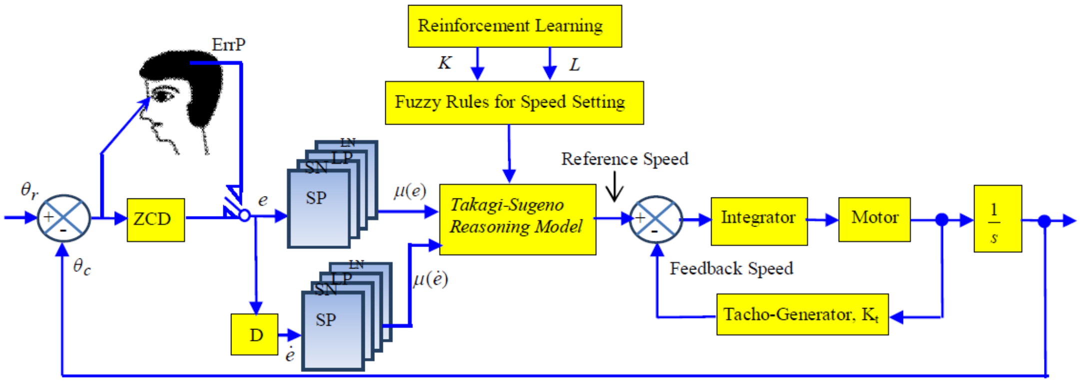

Fig 3.6 Schematic diagram of Learning Automaton Induced Takagi-Sugeno fuzzy speed modulation system

In this scenario, fuzzy inferences are derived by evaluating these rules as illustrated in Fig 3.6. The firing strengths FS_1 and FS_2 for Rule 1 and Rule 2 are calculated based on the membership functions of A_1 and A_2 for e, and B_1 and B_2 for $\dot{e}$, using the following formulas:

$$FS_1 = Min\left(\mu_{A_1}(e), \mu_{B_1}(\dot{e})\right) \tag{15}$$

$$FS_2 = Min\left(\mu_{A_2}(e), \mu_{B_2}(\dot{e})\right) \tag{16}$$

Subsequently, the speed $\dot{\theta}$ is determined based on these firing strengths.

The process of setting coefficients K_i and L_i in each Takagi-Sugeno fuzzy rule is effectively managed through Learning Automaton-based reinforcement learning. Fig 6 outlines this approach, showing how it informs the dynamic adjustment of robot arm speed. To clarify how coefficients are determined within this framework, consider the matrix M. Each row of M correlates with specific combinations of error (e) and its derivative ($\dot{e}$) that hold nonzero memberships in their respective fuzzy sets. This approach selects intervals where the membership functions are positive to define the rows of matrix.

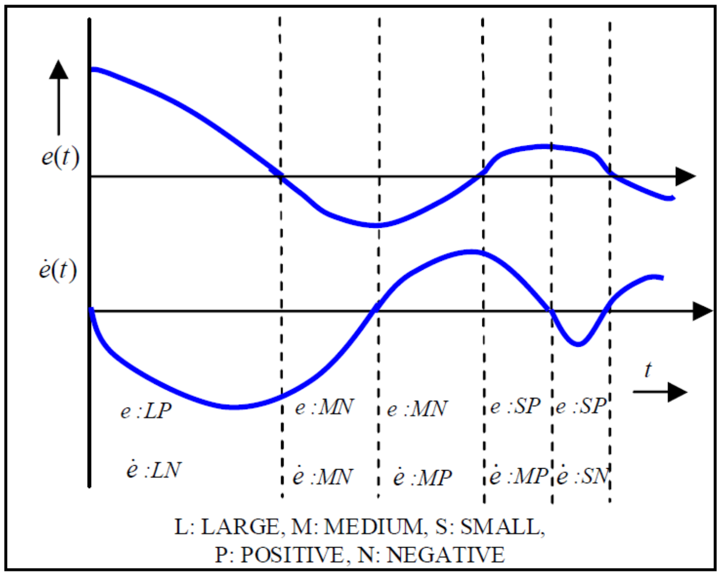

Fig 3.7 Error, Error Derivative and their fuzzy attributes

The columns of M represent different potential values for the rule parameters K_i and L_i. This matrix setup allows the exploration of all viable combinations of K_i and L_i, enhancing the robustness of the speed-setting mechanism. The indices i and j identify particular rows and columns within matrix M, respectively, facilitating systematic exploration and optimization of the control parameters.

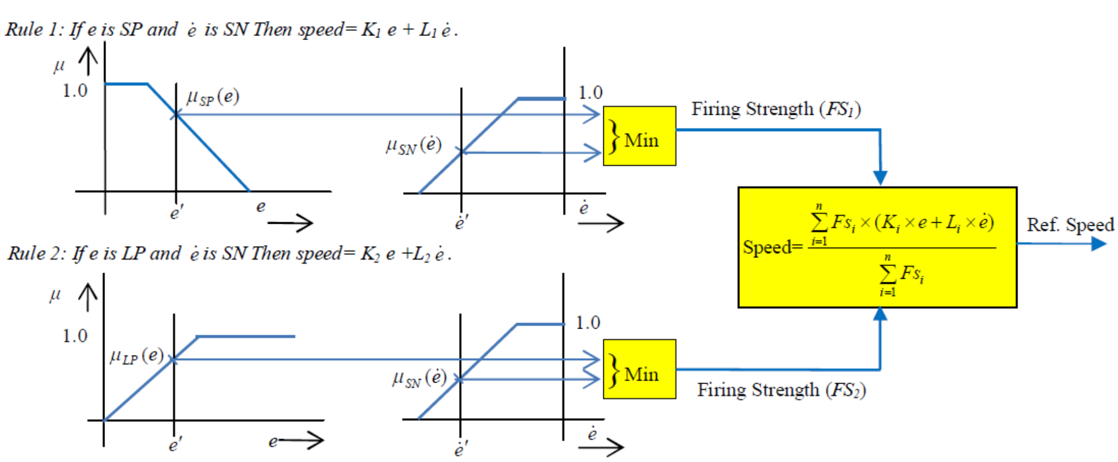

Fig 3.8 Takagi-Sugeno Firing Rule

In the matrix M, the indices i and j respectively correspond to the ith row and jth column. The matrix entries, denoted as mij, represent the likelihood of selecting a specific pair < K_i, L_i> based on the fulfilment of certain criteria related to error and error derivative levels defined in the *ith* row. The probability p_{ij} for each *ith* row must be structured so that the sum of probabilities across all columns in that row equals 1. This is mathematically expressed as:

$$\dot{\theta} = \frac{\sum_{i=1}^{2} FS_i(K_i e + L_i \dot{e})}{\sum_{i=1}^{2} FS_i} \tag{17}$$

for each i, ensuring that for every set of conditions, a selection from the possible < Ki, Li > pairs are definitively made.

$$\dot{\theta} = \frac{\sum_{i=1}^{n} FS_i(K_i e + L_i \dot{e})}{\sum_{i=1}^{n} FS_i} \tag{18}$$

A. Learning of the M matrix

Algorithm-1 is developed for adaptation of the probability matrix M. In step-1 of the Algorithm, the matrix is initialized with equal probability in all feasible columns, so that row- sum=1. The non-feasible elements of the matrix are set to 0. Step-2 of the algorithm is the probability adaptation step.

In this process, measurements of e and $\dot{e}$ determine a specific row in the matrix M, from which a column with a non-zero probability is randomly chosen. The initial probability distribution of the matrix M is shown in Table I. The selected column's K_i and L_i parameters are then applied to the Takagi-Sugeno Controller to adjust the speed of the robotic link as per equation. The control mechanism, as shown in Fig. 1, engages to drive the robotic end-effector to the targeted position, cycling through speed settings determined by selected <K_i, L_i> pairs until the motor halts. In Step 3, if the steady-state error (SSE) falls below a pre-set threshold, the probability values of the selected Ki, Li pairs in the matrix's i^{th} row are increased during the kth learning epoch, while the probabilities of other feasible entries are uniformly decreased, ensuring the total remains 1. Step 4 advances the learning epoch. Step 5 evaluates the convergence of M;

if convergence is achieved, M is printed; otherwise, the process from Step 2 to 5 repeats.

Algorithm-1: Adaptation of M matrix

Step 1: Initialize $m_{i,j}$ for each row i of matrix M in a manner such that for all feasible j=1 to j_{max}, $m_{i,j}$ in the i^{th} row are set equal with $\sum_j m_{ij} = 1$ and non-feasible elements in i^{th} row are set to zero. Set learning epoch k=1.

Step 2: Repeat

(a) Identify the row index that satisfies the given measurement of error (e) and error-derivative ($\dot{e}$) in the respective bounds specified at the row.

(b) Randomly select the j^{th} column of the matrix M in the i^{th} row, such that the selected column lies within feasible space of j in the i^{th} row.

(c) With the suitable K_i and L_i taken from the selected column of M, and measured e and $\dot{e}$, compute $\dot{\theta}$.

(d) Run the position control loop for one error cycle.

Until the motor stops.

Step 3: Measure the steady-state error (SSE) defined by desired (angular) position – terminated (angular) position, and if it is below the user-defined threshold $\dot{\theta}_{Th}$, then reinforce the selected (K_i, L_i) pairs by increasing the probability of the selected actions j of the corresponding ith row by $\delta/2^k$, for small possible δ and penalize all non-selected feasible actions in the same row by decreasing their probability by $\delta/m \times 2^k$, when there exists (m+1) feasible actions in the i^{th} row.

The above steps indicated in Step 3 should be repeated for all selected row i.

Step 4: Increment learning epoch, k=k+1.

Step 5: Repeat steps 2 to 4 until $m_{i,j}$ for all i, j converges, i.e., the difference in $m_{i,j}$ in the last 2 learning epochs is less than a user defined small threshold.

Step 6: Print M matrix.

TABLE I
Example of Learning Matrix M

Error e / Error derivative $\dot{e}$	K_1 L_1 [0.1-0.19] [1-20]	K_2 L_2 [0.2-0.39] [21-40]	K_3 L_3 [0.4-0.59] [41-60]	K_4 L_4 [0.6-0.79] [61-80]	K_5 L_5 [0.8-0.99] [81-100]
SP SN $10^{-2}<e<10^{-1}$ $10^{-2}<\dot{e}<0$	0.5	0.5	0	0	0
SP MP $10^{-2}<e<10^{-1}$ $10^{-2}<\dot{e}<10^{-1}$	0.25	0.25	0.25	0.25	0
MN MP $-10^{-1}<e<-10^{-2}$ $10^{-1}<\dot{e}<10^{-2}$	0	0.25	0.25	0.25	0.25
MN MN $-10^{-1}<e<-10^{-2}$ $-10^{-3}<\dot{e}<-10^{-2}$	0	0.5	0.5	0	0
LP LN $1<e<10$ $-10<\dot{e}<-10$	0	0	0	0.5	0.5

B. Convergence of the Learning Algorithm

Let $p_{i,j}(k)$ be the probability of the k^{th} rewarding action selection on the j^{th} column of i^{th} row in M matrix. Then

$$p_{i,j}(k+1) = p_{i,j}(k) + \frac{\delta}{2^k}$$

Also, $p_{i,j}(k+2) = p_{i,j}(k+1) + \frac{\delta}{2^{k+1}}$

$$=> p_{i,j}(k+2) = p_{i,j}(k) + \frac{\delta}{2^k} + \frac{\delta}{2^{k+1}}$$

Thus, iteratively, we obtain:

$$p_{i,j}(n) = p_{i,j}(0) + \delta\left(1 + \frac{1}{2} + \frac{1}{4} + \cdots + \frac{1}{2^{n-1}}\right)$$

$$p_{i,j}(n)|n \to \infty = p_{i,j}(0) + \delta\left(\frac{1}{1-1/2}\right)$$

$$p_{i,j}(n)|n \to \infty = p_{i,j}(0) + 2\delta \tag{19}$$

Similarly, the probability of the n^{th} penalizing action selection out of m+1 feasible action space at i^{th} row w^{th} column of matrix M is obtained as

$$p_{i,w}(n) = p_{i,w}(0) + \frac{\delta}{m}\left(1 + \frac{1}{2} + \frac{1}{4} + \cdots + \frac{1}{2^{n-1}}\right)$$

$$=> p_{i,w}(n)|n \rightarrow \infty = p_{i,j}(0) + 2\left(\frac{\delta}{m}\right) \tag{20}$$

For convergence, the limit of $p_{i,j}$, $p_{i,w}$ in [0,1],

$$0 < p_{i,j}(0) + 2\delta < 1$$

$$0 < p_{i,w}(0) + 2\left(\frac{\delta}{m}\right) < 1$$

In other words, the bounds on δ can be obtained by satisfying the above inequalities.

C. Speed-setting of the robot arm using converged M matrix

After the M matrix converges i.e., the learning is over, the same matrix can be used to determine K_j and L_j in each error cycle of the control algorithm. The determination of K_j and L_j and $\dot{\theta}$ computation involves two steps as given in Algorithm 2.

Algorithm-2: Determination K_j and L_j
Step 1: For the measurement value of e and $\dot{e}$ identify the row index of matrix M.
Step 2: Identify the feasible column j with the highest probability $p_{i,j}$ in the i^{th} row. Select the action j i.e., K_j, L_j pair and hence evaluate speed $\dot{\theta}$ by computing speed, $\dot{\theta} = K_j + L_j$.

D. Stability Analysis of the Proposed Takagi-Sugeno Based Fuzzy Control System

Let, $\dot{\theta}_c(t)$ be the actual position of the robot arm at time t. From the Fuzzy rules, $\dot{\theta}_c(t)$ can be expressed as:

$$\dot{\theta}_c(t) = K_1\dot{\theta}_c(t-1) + L_1(\theta_r(t) - \theta_c(t))$$

Taking Laplace transform of (17) we obtain (18):

$$s\theta_c(s) = K_1\theta_c(s)e^{-sT} + L_1(\theta_r(s) - \theta_c(s)) \tag{21}$$

Approximating $e^{-sT} = 1 - sT$,

$$s\theta_c(s) = K_1\theta_c(s)(1 - sT) + L_1(\theta_r(s) - \theta_c(s)) \tag{22}$$

Simplifying (22) the transfer function of the Takagi-Sugeno speed controller is obtained as:

$$G_{con}(s) = \frac{s\theta_c(s)}{\theta_r(s)} = \frac{sL_1}{s - K_1(1 - sT)s + L_1} \tag{23}$$

The transfer function of the inner-loop in Fig.1 involving the motor is obtained as:

$$G_{motor}(s) = \frac{16.13}{(s + 5.78)(s + 55.22)}$$

Therefore, the overall transfer function of the system $G_{sys}(s)$ from Fig. 4 is obtained as:

$$G_{sys}(s) = \frac{16.13L_1}{K_1Ts^4 + As^3 + Bs^2 + Cs + 320L_1} \tag{24}$$

where, $A = 61K_1T - K_1$, $B = 320K_1T - 61K_1 - 61 + L_1$, $C = 61L_1 - 320K_1 + 320$.

A Root Locus (RL) analysis is undertaken to examine the performance of the proposed control schemes, that is: the Proportional Type, Zero-Crossing Sensitive Type, Takagi-Sugeno Fuzzy Type and Learning Automaton (LA) induced Takagi-Sugeno Type Brain-Actuated Fuzzy Controller. It is noteworthy that the Takagi-Sugeno type controller includes 2 parameters K_1 and L_1. A thorough investigation into Root Locus construction for all feasible real values of K_1 and L_1 reveals that there exist 4 distinct geometries of Root Locus, as shown in Fig 3.5 (a)-(d). The following observations directly follow from the said RL plots in Fig 3.12 (a), (b), (c), (d).

3.4 Analysis of Stability Margin of the Proposed Controllers

The BCI-based position control system is susceptible to forming limit cycles, which are minor amplitude oscillations occurring around a system's equilibrium point. These limit cycles are generally undesirable because they can place the system on the brink of instability. To address these potential instabilities, it is crucial to perform a stability analysis of the proposed BCI-based control system.

Various techniques for assessing the stability of dynamic systems are documented in existing literature, with the root locus method being one of the more prevalent approaches. This technique involves analyzing the control system's stability by examining the root locus plot, which is derived from the open-loop transfer function, G(s)H(s). Here, G(s) represents the forward path gain, and H(s) denotes the feedback factor. The root locus plot illustrates how the roots of the characteristic equation ($1 + G(s)H(s) = 0$) move as the DC gain K is varied from zero to infinity.

It is crucial to note that the DC gain K, which is located in the forward path of the system, influences the system's stability; a higher value of K may push the system towards instability. Therefore, identifying the maximum permissible DC gain that maintains system stability is a vital component of control system design. The root locus technique efficiently facilitates this by determining the crossover points of the root locus plot with the imaginary axis (jω axis), which help define the maximum DC gain for the system.

The root locus analysis ensures that the system remains stable as long as the roots of the characteristic equation are positioned within the left half of the complex plane (σ + jω). In this research, each of the proposed speed modulation strategies undergoes stability evaluation through the root locus method, allowing for the determination of the maximum allowable DC gain and ensuring the overall stability of the closed-loop system. This analysis is critical in maintaining control precision and preventing the potential onset of limit cycles that could lead to system instability.

A. Root Locus Plot for Scheme 1: Brain-Actuated Proportional Type Speed Modulation (*K=0.3*)

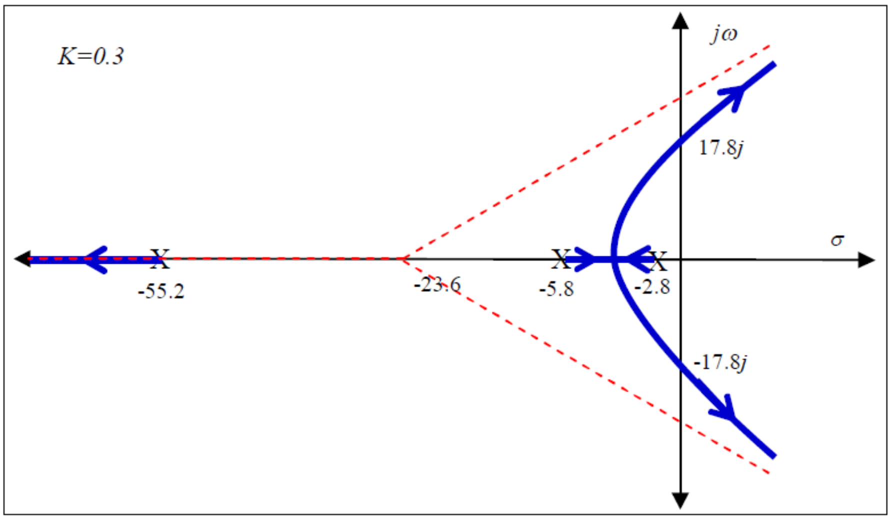

Fig 3.9 Root Locus for Proportional type speed modulation with *K=0.3*.

B. Root Locus for Scheme 2: Zero-Crossing Sensitive Brain-Actuated Speed Modulation

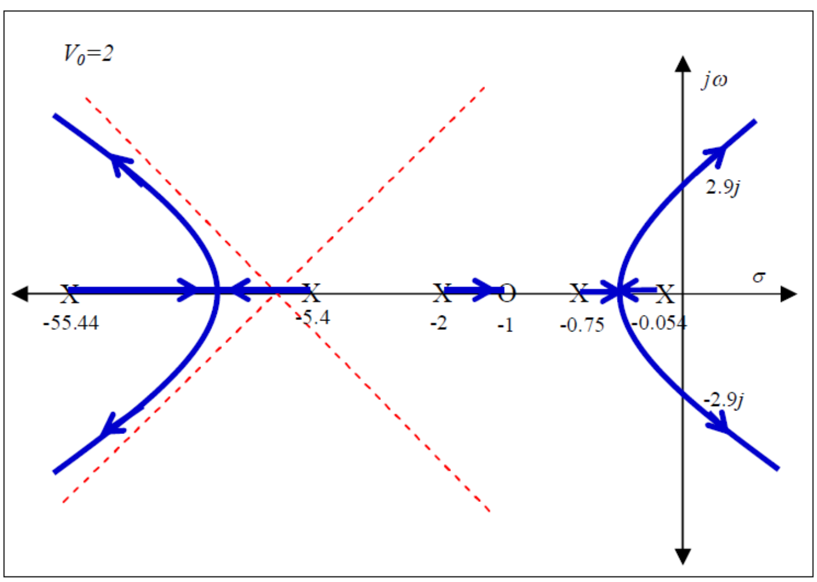

Fig 3.10 Root Locus for Zero crossing sensitive speed modulation system with *V0*=2.

C. Root Locus for Scheme 3: Takagi-Sugeno Fuzzy Model for Speed Adaptation

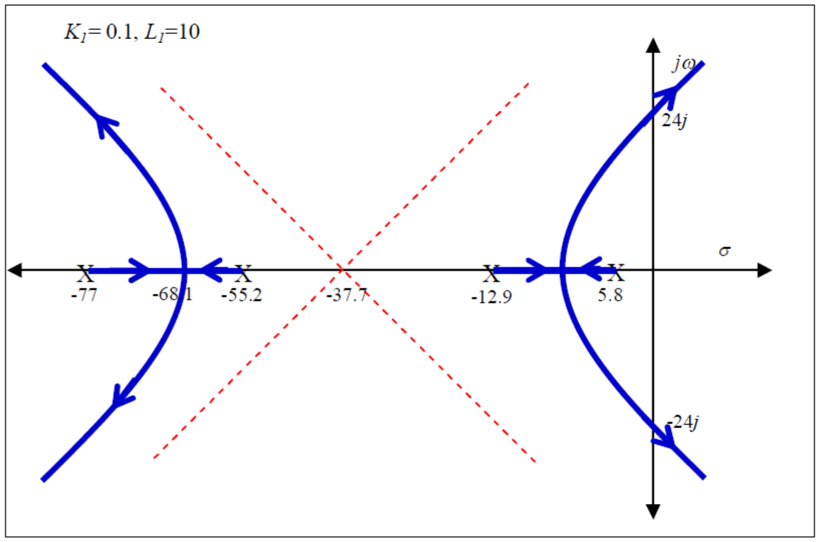

Fig 3.11 (a) Root Locus for Takagi-Sugeno speed modulation with $K1$= 0.1, $L1$=10

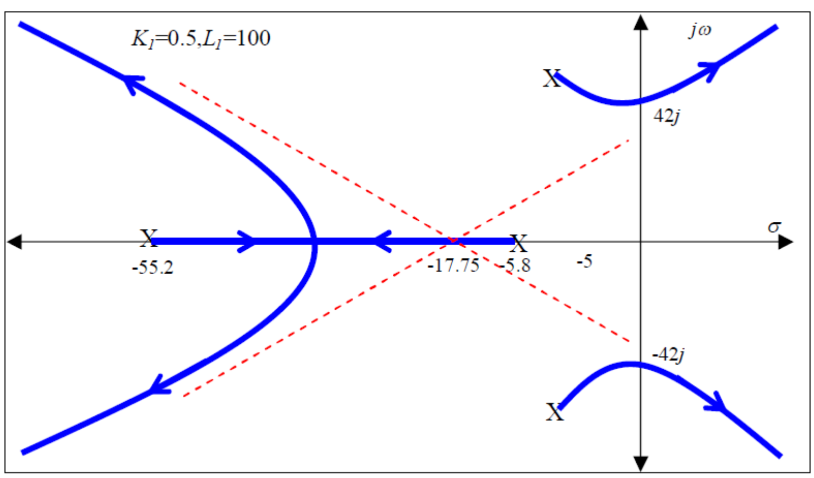

Fig 3.11 (b) Root Locus for Takagi-Sugeno speed modulation with $K1$= 0.5, $L1$=100

D. Root Locus for Scheme 4: Learning Automaton Induced Takagi-Sugeno Fuzzy Model for Speed Adaptation

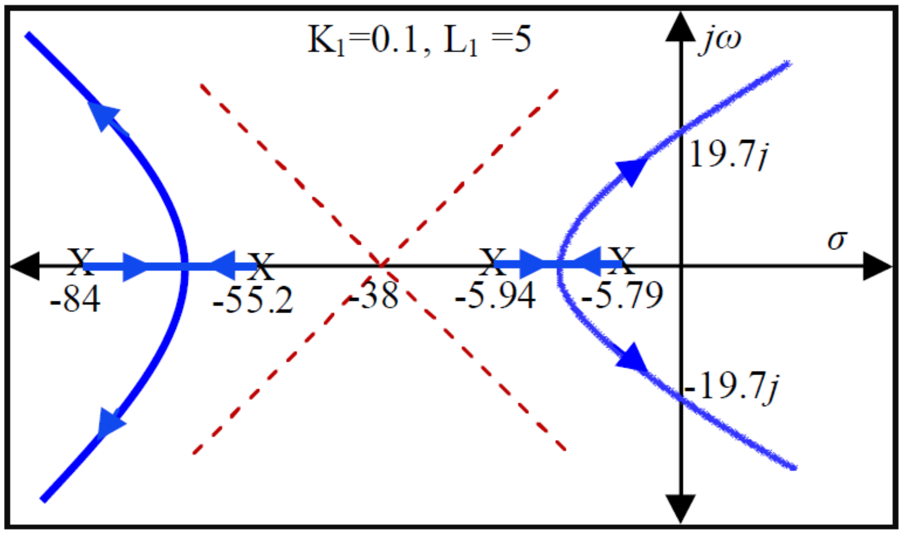

Fig 3.12 (a) Root Locus for LA induced Takagi-Sugeno speed modulation with *K1*= 0.1, *L1*=5

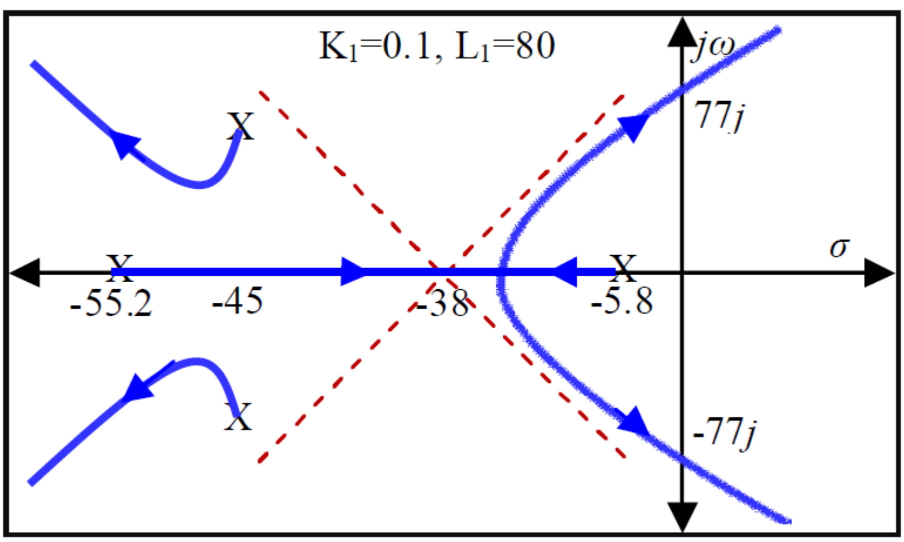

Fig 3.12 (b) Root Locus for LA induced Takagi-Sugeno speed modulation with *K1*= 0.1, *L1*=80

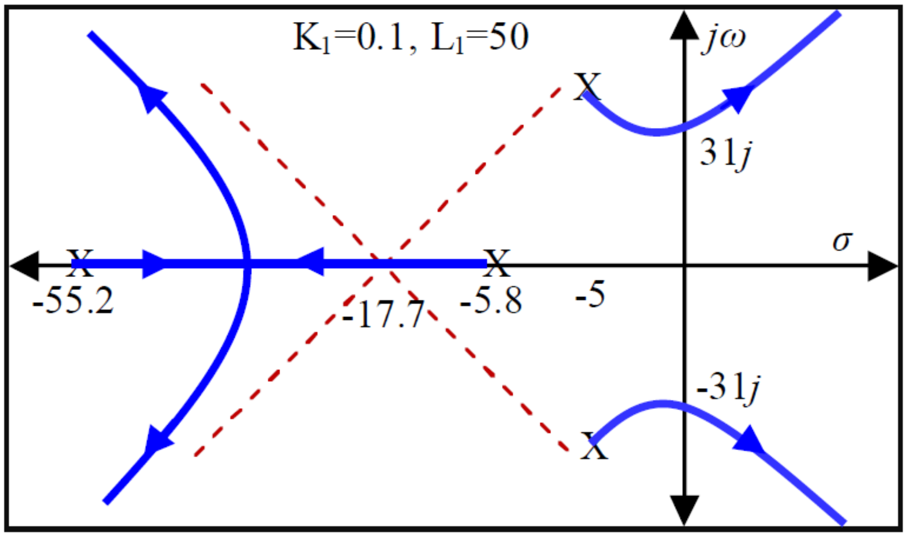

Fig 3.12 (c) Root Locus for LA induced Takagi-Sugeno speed modulation with *K1*= 0.1, *L1*=50

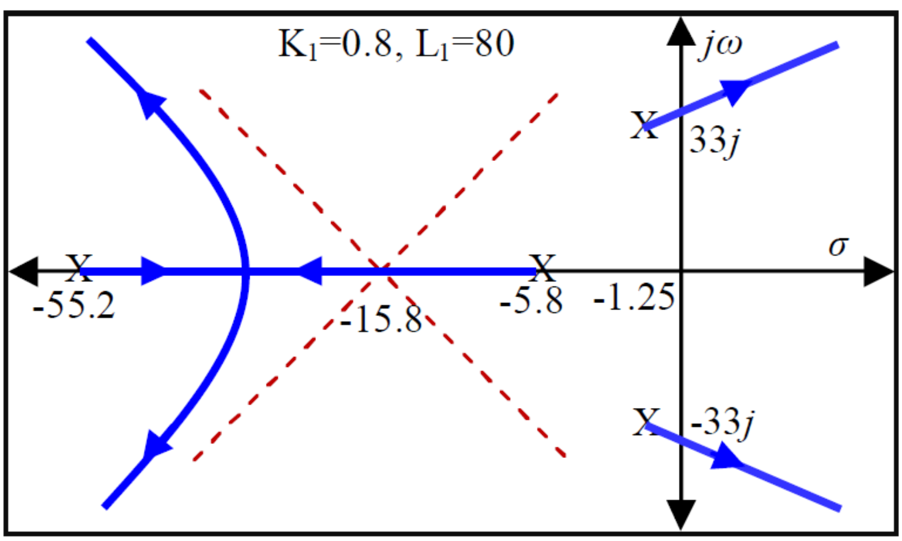

Fig 3.11 (b) Root Locus for Takagi-Sugeno speed modulation with *K1*= 0.8, *L1*=80

From the Root Locus plot the following conclusions can be made:

1. For K_I<1, and L_I>0, the proposed 2-loop LA-induced Takagi-Sugeno fuzzy control system is stable.

2. With increase in K_I from zero towards 1 and any fixed value of L_I>0, the stability margin of the system, obtained by interception of the RL with the $j\omega$ axis gradually decreases.

3. With increase in L_I, keeping K_I fixed in (0, 1), the stability margin of the system increases as the RL plot cuts the $j\omega$ axis at higher y-intercepts.

3.5 Experiment

An advanced experimental setup has been established at the Artificial Intelligence Lab within the Department of Electronics and Tele-Communication Engineering at Jadavpur University. This setup is designed to carry out experiments on BCI-based position control using sophisticated robotic arms. The laboratory has developed a 2-link robotic arm and also utilizes a 6-link Jaco humanoid robot arm produced by Kinova for more complex tasks.

The 2-link robotic arm is equipped with two motors: one motor is responsible for rotating one of the links, while the other motor facilitates the displacement of the second link. In the current series of experiments, only the first motorized link, which is used for rotation, is being tested. The objective of these tests is to maneuver the end-effector from an initial position on the left pad to a desired terminal position on the right pad, following a clockwise path as depicted in Figure 6(b). The performance of the control system, such as steady-state error, peak overshoot, and settling time, will be meticulously evaluated and later summarized in a detailed table.

The study involved 30 healthy participants and 5 individuals with upper limb amputations. In accordance with the Helnisky recommendations [5], all participants provided informed consent before partaking in the study. The experimental setup consisted of both training and testing sessions divided into distinct phases.

Training Sessions

Phase 1: Initially, participants were oriented to the task using a PowerPoint presentation. A fixation cross displayed on the first slide for two seconds was used to capture their attention. Subsequently, participants were instructed to engage in a motor imagery (MI) task aimed at controlling a single robotic arm link. On the third slide, they were to recognize when the robotic link moved past a predefined target position, marked by an image of a cup of tea. At this moment, an Error-Related Potential (ErrP) was typically triggered by the participant noticing the deviation. This ErrP signal allowed the subject to cease active participation as the system then took over automatic control. The phase concluded after capturing EEG data from these activities, which included 126 MI features via filter-bank CSP and 21 AAR features for the ErrP signal. Through 200 trials, we gathered 154 true positive and 46 negative MI instances, and for ErrP, 122 true positive and 78 negative instances.

The techniques that have been used in this paper and tested accuracy on are summarized in Table I.

Table II. List of features extracted from the EEG signals

EEG Signals	Features	No. of features
MI	Common Spatial Pattern (CSP) features (obtained by Filter-bank approach)	126
ErrP	Adaptive Auto Regressive (AAR) parameter	21
SSVEP	Power Spectral Density (PSD) Auto Regressive (AR) features	198 200

The Classification techniques that have been used in this paper and tested accuracy on are summarized in Table II.

Table III Classification accuracy in the Training and the Test Phase

Brain Signal	% Classification Accuracy in	
	Training Phase	Test Phase
SSVEP	99.2	96.2
MI	98.6	96.1
ErrP	98.4	96.3

Phase 2: This phase did not use the PowerPoint and focused on adapting the control matrix (M matrix) after each detected ErrP during the trials. Hardware enhancements detected subsequent zero-crossings in positional error as illustrated in Figure 1. Each zero-crossing prompted the selection and adaptation of a specific <Ki, Li> pair from the M matrix. This adaptation process continued throughout the session, typically encompassing 3-4 adaptations per session, with the motor ceasing upon completion. The M matrix, of specified dimensions, generally reached convergence after approximately 200 sessions, or 600-800 adaptations.

Additional training was carried out on a multi-link Jaco humanoid robot arm for object manipulation in three dimensions, though these details are omitted here due to space constraints.

Testing Sessions

Testing sessions evaluated MI and ErrP-based motion planning for both single and multiple links of the Jaco robot arm. Participants had to plan and initiate link movement and detect errors to stop movement at the target position. The control tasks post-error detection was autonomously handled. Enhanced hardware detected any positional error zero-crossings post-initial ErrP, with a Takagi-Sugeno type controller, modulated by a Learning Automaton, managing speed adjustments.

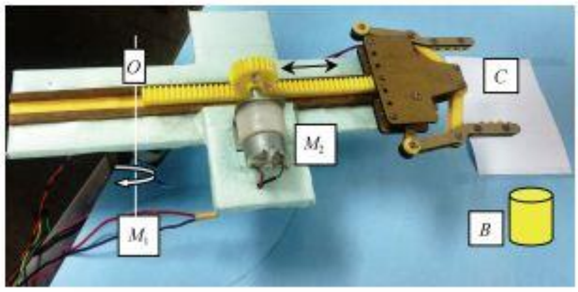

Fig. 3.13 The Lab-developed model of a 2-link robot arm

Fig 3.14 Single link position control using motor M_1 of Fig 3.13

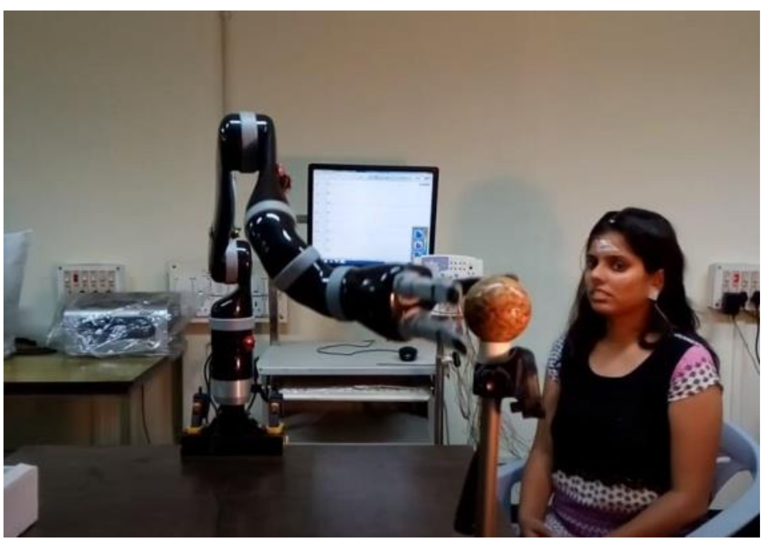

Fig 3.15 Photograph of the experimental set-up for 3-link position control

Performance Evaluation

The effectiveness of the proposed BCI-based control system is analyzed by comparing it against established methodologies in the field. The comparison focuses on four key performance metrics: percentage steady-state error, percentage peak overshoot, settling time, and cognitive load. These metrics are selected for their relevance in assessing the technical and user-centered performance of control systems.

Percentage Steady-State Error and Percentage Peak Overshoot are conventional control theory metrics that evaluate the precision and responsiveness of a system. A lower steady-state error indicates that the system can maintain the target position with minimal deviation, while a lower peak overshoot reflects better control during initial response to a command, reducing the risk of excessive movement beyond the target.

Settling Time measures the duration required for the system to stabilize at the target position after a disturbance or a command change. Faster settling times signify a more agile system that can quickly adapt to changes.

Cognitive Load as adapted from BCI research, quantifies the mental effort required by users to operate the control system. Unlike traditional BCI systems where the user must continually monitor for positional errors, the proposed system simplifies user involvement by utilizing hardware to detect zero-crossings after initial ErrP-based target position identification. This design significantly reduces the cognitive demands on the user, allowing for a more user-friendly and accessible control experience. Table 3 in the paper provides a detailed comparative analysis of these metrics between the proposed system and existing technologies. The results highlight how the proposed system enhances performance not only in technical aspects but also in improving user interaction by reducing cognitive strain. This dual focus on engineering excellence and user experience positions the proposed system as a significant advancement in BCI-based control systems, offering both increased accuracy and ease of use.

TABLE-IV
Comparative Performance of the Proposed Controller with Existing Technique

Technique Used	Performance Metrices			
	Steady-State Error (E_{ss})%	Peak Overshoot (M_p)%	Settling Time (t_s) sec	Cognitive Load
Only MI	7.73	5.4	35	High
MI + ErrP	2.10	4.9	31	High
MI + ErrP +Speed Setting	0.20	4.2	24	Medium
Scheme I	0.18	3.8	22	Low
Scheme II	0.04	1.1	12	Low
Scheme III	0.02	1.05	11	Low
Scheme IV	0.018	1.025	10	Low

Additionally, the setup includes a more complex 6-link Jaco humanoid robot arm, which is used for a different set of experiments involving position control tasks. This robot arm allows for the activation of its links in a non-sequential order based on the specific requirements of the user. For these experiments, only three of the six links are utilized. The user, through a BCI interface, directs the movement of an object from a defined starting point to a predetermined endpoint within the robot's operational space, illustrated in Figure 7. To facilitate user interaction and control over individual links of the robotic arm, Steady-State Visual Evoked Potential (SSVEP) signals are employed. This experimental configuration at Jadavpur University's AI Lab represents a significant contribution to the field of robotics and BCI technology, offering a practical platform for exploring and refining BCI-driven robotic control systems in real-world scenarios.

3.6 Preamble

Light Emitting Diodes (LEDs) that flicker at specific frequencies is integral to the interface of a robotic arm controlled by brain-computer interface (BCI) technology. These LEDs are attached to the different links of the robot arm, each flickering at a unique frequency. When a user intends to activate a particular link, they simply gaze at the LED associated with that link. The frequency of the LED's flicker is then detected by the user's brain waves, and this information is processed by the BCI system to determine which link the user wishes to engage for the task at hand.

Once a link has been selected via Steady-State Visual Evoked Potentials (SSVEP), the user then initiates a motor imagery (MI) signal to command the selected link to move in the desired direction. The direction of movement is controlled by the user's motor imagination: imagining movements with the right-hand results in clockwise motion of the link, while imagining movements with the left-hand results in counterclockwise motion.

As the link begins to move, the user must continuously monitor its position to ensure it stops at the desired target. The target position can vary depending on the control dimensions - it might be a specific point in a one-dimensional setup, a line in a two-dimensional framework, or a plane in a three-dimensional system. When the link approaches and attempts to surpass the target position, an Error-Related Potential (ErrP) is generated by the user's brain, signaling the robot to cease movement. Due to motor inertia, there is often a slight advance past the target position, known as overshoot. To counteract this, one strategy employed is to briefly reverse the direction of the link at a reduced speed, repeating this adjustment until the link aligns precisely with the target position.

The control strategy then transitions to a more autonomous phase. After determining the target position based on the occurrence of the ErrP, the system switches to an automatic, human-independent mode using traditional error-based position control. This phase of the control process is vital as it reduces the need for constant human monitoring and intervention, making the system more efficient and user-friendly.

The paper concludes with a detailed analysis of three distinct speed modulation techniques, which are integral to refining the control policies of the BCI-based robotic system. These methodologies are explored to optimize performance and ensure precise, responsive control of the robotic links.

3.7 Conclusion

The research paper introduces an innovative approach for a BCI-based 2-loop control system tailored for robotic arm manipulation. This system divides its functionality into two critical loops: the outer loop, which is responsible for position control and speed-setting, and the inner loop, which manages the actual speed control of the robotic arm. This dual-loop architecture is designed to enhance precision and responsiveness in robotic movements.

In this novel setup, three different brain-actuated speed-setting models are introduced and evaluated. The stability of these models is rigorously assessed using the Root-locus technique, a classical method in control theory that helps determine the conditions under which a system remains stable. The results from this analysis highlight that the Takagi-Sugeno fuzzy model excels, surpassing both the existing benchmarks and the two other newly proposed models in terms of stability and control effectiveness.

The superior performance of the Takagi-Sugeno model is further corroborated through a detailed control theoretic performance analysis. This examination reveals that the model not only meets but exceeds the performance metrics of previous models, offering enhanced control accuracy and response dynamics.

The practical applicability and effectiveness of the proposed control scheme have been tested through experiments involving both healthy subjects and patients with neuro-motor disabilities. These experiments are crucial as they demonstrate the system's accessibility and ease of use, particularly for users with limited motor functions. The low cognitive load required to operate the system means that even subjects with significant impairments can successfully use the control system without undue stress or difficulty.

Overall, the research delineates a significant advancement in BCI-based control systems for robotic arms, presenting a robust, user-friendly, and highly effective control mechanism that stands out in the field of assistive technologies.

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Chapter 4

Conclusion and Future Direction

4.1 Conclusion

In this study, we introduce an innovative approach to BCI-based control strategies for robot arm rehabilitation, specifically tailored for individuals with damaged upper limbs. Our research focuses on two distinct yet complementary aspects of BCI-based control: the design of a 2-loop controller and the integration of Learning Automaton induced parameter selection within a Takagi-Sugeno type fuzzy controller.

The essence of our novel approach lies in the seamless coordination between the outer position-control loop and the inner speed-control loop. Within this framework, the outer loop employs a Learning Automaton induced mechanism to automatically set reference speeds for the inner loop, enhancing the adaptability and efficiency of the control system. By enabling automatic mode switching based on user input regarding the target position, our approach effectively reduces cognitive load for the user, offering a more intuitive and user-friendly interface compared to conventional methods.

One of the key findings of our study is the superior performance of the proposed system in comparison to existing state-of-the-art algorithms. Through rigorous performance analysis across four critical control parameters, our approach consistently outperforms established methods, highlighting its potential for significantly advancing the field of BCI-based rehabilitation.

Moreover, our experiments extend beyond theoretical analysis to practical validation, involving participation from both healthy subjects and individuals with neuro-motor disabilities. Encouragingly, our findings demonstrate that individuals with upper limb impairments can effectively engage with the BCI system with reduced cognitive burden, underscoring the real-world applicability and impact of our approach.

Overall, our study contributes valuable insights and methodologies to the burgeoning field of BCI-based rehabilitation. By combining innovative control strategies with empirical validation, we pave the way for future research endeavors aimed at enhancing the efficacy and accessibility of assistive technologies for individuals with motor impairments. Through continued exploration and refinement, we envision a future where BCI technologies play a transformative role in improving the quality of life and independence for individuals with upper limb disabilities.

4.2 Merits of the Proposed BCI-based Position Control Schemes

Neuro-prosthetic and robotic control systems offer numerous advantages that have the potential to revolutionize healthcare, rehabilitation, and human-machine interaction. Some of the key advantages include:

1. Restoration of Functionality: Neuro-prosthetic devices and robotic systems enable individuals with disabilities or impairments to regain lost or impaired motor functions. For example, prosthetic limbs controlled by brain-computer interfaces (BCIs) allow amputees to perform activities of daily living with greater independence and autonomy. Similarly, robotic exoskeletons can assist individuals with mobility impairments in walking and navigating their environment.

2. Improved Quality of Life: By restoring mobility and independence, neuro-prosthetic and robotic systems can significantly enhance the quality of life for individuals with disabilities. These technologies enable users to engage in social, vocational, and recreational activities that were previously challenging or impossible. Improved mobility and autonomy contribute to greater self-esteem, confidence, and overall well-being.

3. Enhanced Precision and Control: Neuro-prosthetic and robotic systems offer superior precision and control compared to traditional assistive devices. BCIs enable direct communication between the brain and external devices, allowing users to execute precise movements with fine motor control. Robotic arms and exoskeletons can perform tasks with greater accuracy and consistency, enhancing efficiency and productivity in various domains.

4. Customization and Adaptability: Neuro-prosthetic and robotic systems can be customized to meet the unique needs and preferences of individual users. Advanced control algorithms and machine learning techniques allow for personalized calibration and optimization of device performance based on user-specific characteristics. Additionally, these systems can adapt to changes in user capabilities over time, ensuring continued functionality and usability.

5. Promotion of Neuroplasticity: The use of neuro-prosthetic and robotic systems has been shown to promote neuroplasticity—the brain's ability to reorganize and adapt in response to experience and injury. Through repetitive practice and feedback, users can strengthen neural connections and improve motor skills, leading to long-term functional improvements and rehabilitation outcomes.

6. Facilitation of Rehabilitation: Neuro-prosthetic and robotic systems play a crucial role in rehabilitation and physical therapy programs. These technologies provide interactive and engaging platforms for motor relearning and functional recovery, enabling therapists to deliver targeted interventions and monitor progress more effectively. Additionally, real-time feedback and performance metrics can motivate users and facilitate goal-oriented rehabilitation.

7. Increased Accessibility: Advances in technology and manufacturing have made neuro-prosthetic and robotic systems more accessible and affordable to a broader range of users. Innovations such as 3D printing, open-source hardware, and low-cost sensors have lowered barriers to entry and facilitated greater adoption of these technologies in clinical and home settings. Increased accessibility expands the reach of neuro-prosthetic and robotic solutions to underserved populations and regions with limited healthcare resources.

8. Potential for Augmentation: In addition to assisting individuals with disabilities, neuro-prosthetic and robotic systems have the potential to augment the capabilities of able-bodied individuals. By enhancing strength, endurance, and precision, these technologies can extend human performance in various domains, including healthcare, industry, and sports. Augmented human-machine collaboration opens up new opportunities for innovation and productivity in diverse fields.

9. Reduction of Physical Strain: Neuro-prosthetic and robotic systems can alleviate physical strain and fatigue associated with repetitive or strenuous tasks. By automating or assisting with manual labor, these technologies reduce the risk of musculoskeletal injuries and occupational hazards for workers in various industries, such as manufacturing, construction, and healthcare.

10. Remote Operation and Telepresence: Robotic systems equipped with teleoperation capabilities enable remote control and telepresence, allowing users to interact with distant environments or perform tasks in hazardous or inaccessible locations. Telepresence robots, for example, enable individuals to attend meetings, visit remote locations, or participate in social events virtually, enhancing connectivity and accessibility.

11. Enhanced Surgical Precision: Surgical robots and assistive devices enable surgeons to perform minimally invasive procedures with greater precision and accuracy. By providing magnified visualization, dexterous manipulation, and tremor reduction, these systems improve surgical outcomes, reduce complications, and enhance patient safety in various medical specialties, including orthopedics, neurosurgery, and urology.

12. Research and Innovation: Neuro-prosthetic and robotic control systems serve as valuable research platforms for studying human motor control, brain function, and machine learning algorithms. Insights gained from these studies inform the development of new technologies, therapeutic interventions, and rehabilitation strategies for individuals with neurological disorders or injuries. Additionally, collaboration between researchers and industry partners fosters innovation and drives advancements in the field.

13. Assistance in Elderly Care: Robotic assistants and exoskeletons support elderly individuals in activities of daily living, such as walking, standing, and transferring. These technologies promote independence, safety, and mobility among older adults, enabling them to age in place and maintain a higher quality of life. Robotic companionship and monitoring systems also provide social engagement and assistance with cognitive tasks, reducing isolation and loneliness in aging populations.

14. Training and Education: Neuro-prosthetic and robotic systems serve as educational tools for training healthcare professionals, engineers, and students in robotics, biomechanics, and rehabilitation sciences. Hands-on experience with these technologies facilitates skill development, fosters interdisciplinary collaboration, and prepares the next generation of innovators and practitioners to address complex challenges in healthcare and assistive technology.

15. Economic Benefits: The widespread adoption of neuro-prosthetic and robotic control systems contributes to economic growth and job creation in various sectors, including healthcare, manufacturing, and technology. Investments in research, development, and commercialization stimulate innovation, drive productivity gains, and create opportunities for entrepreneurship and industry expansion. Additionally, cost savings from improved healthcare outcomes and reduced disability-related expenses generate economic value and societal benefits.

In summary, neuro-prosthetic and robotic control systems offer a multitude of advantages across diverse domains, ranging from healthcare and rehabilitation to industry and education. By leveraging technology and innovation, these systems empower individuals, enhance productivity, and promote inclusivity, ultimately contributing to a more accessible, equitable, and sustainable future.

4.3 Demerits of the BCI-based Position Control Schemes

1. Cost: Neuro-prosthetic and robotic systems can be expensive to develop, manufacture, and maintain. The high cost of advanced technology components, specialized hardware, and ongoing technical support may limit accessibility to individuals with limited financial resources or healthcare coverage.

2. Complexity: The design, implementation, and operation of neuro-prosthetic and robotic systems involve intricate technology and specialized expertise. Managing the complexity of these systems, including hardware integration, software development, and user training, requires skilled professionals and resources, which may pose barriers to adoption and deployment.

3. Risk of Malfunction: Neuro-prosthetic and robotic systems are susceptible to technical failures, malfunctions, and software errors, which can compromise their performance and safety. Hardware defects, software bugs, and communication glitches may lead to unintended movements, system errors, or equipment damage, posing risks to users and bystanders.

4. User Dependency: Users of neuro-prosthetic and robotic systems may become overly dependent on the technology, relying on it for daily activities and mobility. Excessive reliance on assistive devices or robotic assistance may reduce users' motivation to engage in physical activity, rehabilitative exercises, or cognitive tasks, potentially hindering their long-term recovery or functional independence.

5. Ethical Considerations: The use of neuro-prosthetic and robotic systems raises ethical concerns related to privacy, autonomy, and informed consent. Collecting, storing, and analyzing sensitive neural data may raise privacy issues and require robust data protection measures. Additionally, decisions made by autonomous or semi-autonomous robotic systems may raise questions about accountability, liability, and human oversight in case of errors or adverse outcomes.

6. Social Stigma: Individuals using neuro-prosthetic and robotic systems may face social stigma, discrimination, or misconceptions about their abilities and limitations. Negative attitudes or stereotypes towards assistive technology users may impact their self-esteem, confidence, and social integration, leading to feelings of isolation or marginalization.

7. Limited Compatibility: Neuro-prosthetic and robotic systems may not be compatible with all users or environments, limiting their applicability and effectiveness. Factors such as anatomical variability, cognitive ability, and environmental constraints may affect the usability and performance of these systems, requiring tailored solutions and adaptive technologies to meet individual needs.

8. Regulatory Challenges: The development and deployment of neuro-prosthetic and robotic systems are subject to regulatory requirements, standards, and approval processes. Obtaining regulatory clearance or certification for medical devices, assistive technologies, or autonomous systems may involve lengthy and costly procedures, delaying market access and innovation.

9. Maintenance and Support: Neuro-prosthetic and robotic systems require regular maintenance, calibration, and technical support to ensure optimal performance and reliability. Access to skilled technicians, replacement parts, and repair services may be limited, particularly in remote or underserved areas, leading to downtime or disruptions in service.

10. Potential for Misuse: The misuse or abuse of neuro-prosthetic and robotic systems, either intentionally or unintentionally, may have negative consequences for users, caregivers, or society as a whole. Security vulnerabilities, hacking threats, or unauthorized access to control systems may compromise user safety, privacy, or autonomy, necessitating robust cybersecurity measures and risk mitigation strategies.

In summary, while neuro-prosthetic and robotic control systems offer numerous benefits, they also present various disadvantages and challenges that must be addressed to ensure safe, ethical, and equitable deployment. By acknowledging and mitigating these drawbacks through research, regulation, and responsible innovation, we can maximize the potential of these technologies to improve human health, well-being, and quality of life.

4.4 Future Scope

Looking into the future, several avenues hold promise for enhancing the efficacy and applicability of BCI-based control schemes for robot arm rehabilitation. Firstly, advancements in signal processing techniques can significantly improve the accuracy and reliability of brain-computer interfaces. By leveraging machine learning algorithms and deep neural networks, researchers can develop more robust signal processing pipelines capable of extracting nuanced neural signals with higher fidelity, thereby enhancing the precision of BCI-based control.

Furthermore, integrating multimodal sensor inputs, such as electromyography (EMG) and inertial measurement units (IMUs), alongside EEG signals can provide complementary information for better understanding user intentions and enhancing control robustness. This multimodal fusion approach can enable more intuitive and natural interaction between users and robotic devices, ultimately leading to improved rehabilitation outcomes.

In addition to signal processing advancements, there is a growing need for the development of adaptive and personalized control algorithms. By leveraging adaptive control techniques and reinforcement learning algorithms, BCI-based control systems can dynamically adjust their parameters and strategies based on user feedback and performance metrics. This adaptive approach not only enhances system adaptability to user variability but also enables personalized rehabilitation protocols tailored to individual needs and capabilities.

Moreover, the integration of virtual reality (VR) and augmented reality (AR) technologies holds immense potential for enhancing user engagement and rehabilitation outcomes. By immersing users in virtual environments and providing real-time feedback on their motor performance, VR and AR systems can enhance motivation, facilitate motor learning, and promote neuroplasticity, thereby accelerating the rehabilitation process.

Another area ripe for exploration is the development of collaborative robotic systems that seamlessly integrate with BCI-based control schemes. Collaborative robots, or co-bots, can assist users in performing rehabilitation exercises, providing physical support and guidance while simultaneously adapting to user intentions and preferences through BCI inputs. This human-robot collaboration paradigm not only enhances safety and efficiency but also fosters a sense of partnership and empowerment for users during the rehabilitation process.

Furthermore, there is a growing interest in the integration of neuromodulation techniques, such as transcranial magnetic stimulation (TMS) and transcranial direct current stimulation (tDCS), with BCI-based control systems. Neuromodulation techniques can modulate neural activity in targeted brain regions, potentially enhancing motor learning, recovery, and neuroplasticity in individuals with neurological disorders.

Lastly, efforts to promote interoperability and standardization across BCI platforms and robotic devices can facilitate broader adoption and integration of BCI-based control schemes into clinical practice. By establishing common data formats, communication protocols, and performance metrics, researchers and clinicians can more effectively collaborate, share resources, and benchmark the effectiveness of BCI-based rehabilitation interventions.

In summary, the future of BCI-based control schemes for robot arm rehabilitation holds tremendous promise, driven by advancements in signal processing, adaptive control algorithms, multimodal sensor integration, virtual reality technologies, collaborative robotics, neuromodulation techniques, and efforts towards interoperability and standardization. By leveraging these interdisciplinary approaches and technologies, researchers can unlock new frontiers in neurorehabilitation, ultimately improving the quality of life and independence for individuals with upper limb impairments.

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