PREDICTING HAND GRASPING ORIENTATION FOR PROSTHETIC HAND CONTROL USING MULTIMODAL SENSOR DATA (EEG, EMG, AND IMU) WITH MACHINE LEARNING APPROACH

By

Nafiseh Ghaffar Nia

Dr. Erkan Kaplanuglu
Associate Professor of Engineering
Management and Technology Department
(Chair)

Dr. Ahad Nasab
Professor of Engineering Management
and Technology Department
(Committee Member)

Dr. Yu Liang
Professor of Computer Science and
Engineering Department
(Committee Member)

Dr. Gokhan Erdemir
Associate Professor of Engineering
Management and Technology Department
(Committee Member)

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Nafiseh Ghaffar Nia

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ABSTRACT

Enhancing the control of prosthetic hands is a crucial challenge that directly impacts the daily functionality of individuals with limb loss. Our research delves into advanced machine learning (ML) methodologies to accurately predict hand-grasping orientations, thereby improving the precision of prosthetic control. We present a comprehensive framework that amalgamates inputs from multiple sensors. This includes electroencephalography (EEG) to discern user intentions, electromyography (EMG) to evaluate muscle activity, and inertial measurement units (IMU) to track features of hand movement. By harmoniously integrating these varied data streams, our ML model strives to provide predictions of hand orientation that are more accurate and intuitive than those achievable with single-sensor systems. This innovative approach has the potential to significantly elevate prosthetic functionality and user experience, enabling more precise and effortless execution of grasping tasks. Integrating these sensors within a singular, cohesive ML framework allows for the dynamic assessment of various physical and neurological cues. This methodological synergy enhances the prosthetic's adaptability to each user's unique movement patterns and neural commands. Applying deep learning techniques, particularly through a combination of ML models, we proposed a new model called AutoMerNet. This model further enhances our system's ability to learn from complex, multi-modal sensor data, continually improving its predictive capabilities over time.

This research contributes to the technological advancement of prosthetic hands and opens avenues for personalized prosthetic adjustments based on individual physiological and biomechanical characteristics. The enhanced control provided by our ML model holds promise for significantly improving the quality of life for prosthetic users, facilitating more natural and effective interaction with their environment.

DEDICATION

I wholeheartedly dedicate this research to the cherished memory of my two late maternal uncles, whose enduring inspiration and support have profoundly shaped my journey.

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LIST OF SYMBOLS

x, Input data

z, Latent representation

$f_{encoder}$, Encoding function

$g_{decoder}$, Decoding function

$\hat{x}$, Reconstructed output

L, Loss function

Q, Query

K, Key

V, Value

d_k, Dimension of keys

P, Position

σ, Activation function

w_i, weights

b, Bias

H, Learning rate

LIST OF ABBREVIATIONS

ML, Machine Learning

EEG, Electroencephalography

EMG, Electromyography

IMU, Inertial Measurement Unit

BCI, Brain Computer Interface

VR, Virtual Reality

AR, Augmented Reality

CHAPTER 1

INTRODUCTION

The control of a prosthetic hand is one great stride in advancing assistive technology and robotics toward enhancing the quality of life for individuals with limb loss. Integrating advanced technologies, especially within the domains of processing biological signals and brain-machine interface (BCI), has enabled prosthetic hands to be controlled naturally and intuitively [1]. Prosthetic hand technology has come a long way in the past few decades, from just a simple mechanical device to a highly sophisticated, sensor-driven system attempting to mimic the intricacies of human hand actions. The early prosthetic devices were relatively primitive and usually body-powered or controlled by simple myoelectric signals. Although these permitted basic grasp functionality, they could not perform tasks that demanded great dexterity and responsiveness [2].

Recent advances have allowed myoelectric prostheses to be developed, which use electrical signals created by muscle contractions in one's residual limb to control the movements of the prosthetic hand [3]. Given multiple sensors and microprocessors, such devices offer finer control and movement patterns closer to the natural ones. Innovations in materials science and miniaturization of electronic components support the functionality and aesthetics of prosthetic hands.

The advent of the BCIs has revolutionized this field of prosthetics by opening a pathway of direct communications between the brain and the prosthetic. BCIs decode the neural activity and then translate those signals into commands for action, which can control the prosthetic hand, hence letting users do tasks in a more accurate and intuitively natural way [4]. It has a huge potential, especially for subjects who have lost limbs or have high-level amputations where traditional myoelectric controls are poor. In fact, most BCI systems use non-invasive techniques through electroencephalography or more invasive methods using implanted electrodes to pick up brain activity. Artificial Intelligence (AI) and Machine Learning (ML) algorithms are crucial in decoding these neural signals and converting them into actionable commands for the prosthetic hand [5]. Integrating BCIs with prosthetic devices is still an emerging field, with ongoing research aimed at improving the accuracy, reliability, and user-friendliness of these systems. Recent assistive robotics encompasses various technologies designed to support individuals with disabilities in performing daily activities. Within this domain, prosthetic hands represent a critical area of development. Modern prosthetic hands do much more than merely act like a grasp or holding device; rather, they have been made to replicate the intricate dexterity which a natural hand encompasses. This includes the ability to perform tasks that require fine motor skills, such as typing or handling delicate objects. Using AI and ML in assistive robotics has significantly enhanced the adaptability and functionality of prosthetic hands [6]. These technologies enable the prosthetic hand to learn and adapt to the user's specific needs and preferences, providing a more personalized and effective solution.

1.1 Using Biological Signals for Prosthetic Hand Control

The control of prosthetic hands using biological signals involves the interpretation of various physiological signals, such as EEG, electromyography (EMG), and inertial measurement units (IMU). EMG signals, generated by the electrical activity of muscles, are commonly used to control myoelectric prostheses [7]. These signals are captured at the surface of the skin by electrodes and then processed to determine what movements the user intends to perform. In the context of BCI applications, however, EEG signals are of the most relevance since they capture brain activity [8]. In such a case, the use of EEG in the control of prosthetic hands offers a more direct and intuitive way of device control for subjects with limited residual muscle activity. This is also possible to be completed by including the IMU sensors in the prosthetic device, providing useful information on limb orientation or movement, hence controlling better feedback about the position and movement of the hand.

1.2 The Impact of AI and ML Techniques on Prosthetic Hand Control

AI and ML have revolutionized the concept of prosthetic hand control and driven outstanding improvements in functionality, adaptability, and user experience. These technologies support the development of intelligent prosthetic devices that learn from and adapt to the user in view of their individual needs, thus giving an almost seamless interface between the prosthetic hand and the user.

One of the core challenges in the control of a prosthetic hand lies in the biological signals themselves that have to be accurately interpreted, like EMG and EEG [9]. AI and ML algorithms excel at processing complex and often noisy signals to meaningful patterns corresponding to the user's intended movements [10]. Advanced ML techniques, such as deep learning, allow modeling nonlinear relationships between input signals and the desired output. This considerably improves the accuracy and reliability of prosthetic control systems. AI and ML make prosthetic hands capable of being tailored to suit particular users through their salient features and preferences. Learning from the user's movements and interactions, these systems can prioritize output based on natural and intuitive control. This adaptability will, in particular, benefit the users under different levels of their muscle activity or when changes occur with their residual limb. Individualized ML models permit adjustment in sensitivity and responsiveness of the prosthetic hand to have the best performance in various situations. Artificial intelligence within prosthetic hands allows for real-time feedback and predictive control, enhancing the user experience. It's through current and historical data that AI algorithms can infer the intentions of users' actions to provide smoother, more anticipatory movements. For example, if it detects that you are about to grasp an object, it could preemptively adjust the grasp strength and finger positioning. This predictive capability reduces the cognitive load on the user, making the prosthetic hand feel like a natural extension of their body.

AI-driven prosthetic hands execute highly complex tasks involving fine motor activity and control. In that situation, the algorithms of ML make possible multi-degree-of-freedom movements for a prosthetic hand, including wrist rotation, finger flexure, and execution of part of their coordinated actions [11]. This level of dexterity can be required while carrying out normal daily activities like typing, cooking, or manipulating small objects. It refines movements for greater precision and fluidity over time, due to the continuous learning process of the prosthetic hand [11]. These AI and ML techniques also carry out fault detection and maintenance of prosthetic hands. By continuously monitoring the device's performance and usage pattern, AI systems can detect possible faults or failures and even forecast maintenance needs, well before they become critical [12]. The proactive maintenance approach will ensure longtime reliability and the life of a prosthetic hand while reducing any downtime and improving user confidence.

AI-powered prosthetic hands can make rehabilitation easier and train new users. The ML algorithms adjust device behavior according to users' progress and provide personalized support during a user's learning process. Virtual Reality (VR) and Augmented Reality (AR) environments with AI enhancements help create different scenarios where the user can exercise and polish his skills safely and controlled [13]. Such training significantly shortens the time required for adaptation to the device.

1.3 Limitations and Challenges in Prosthetic Hand Control

While the field of prosthetic hand control has made remarkable strides with the integration of advanced technologies such as AI and ML, several limitations and challenges persist. Addressing these issues is crucial for further advancements and the widespread adoption of sophisticated prosthetic solutions.

One of the primary challenges in prosthetic hand control is the complexity of processing biological signals, such as EMG and EEG. These signals are often noisy and vary significantly between users and even within the same user over time. Developing robust algorithms that can consistently interpret these signals accurately remains a significant hurdle. Additionally, real-time processing of these signals requires substantial computational resources, which can be difficult to integrate into a portable prosthetic device.

ML models used in prosthetic hand control require extensive training data to perform accurately. However, collecting large datasets of high-quality biological signals paired with precise movement labels is challenging [14]. The variability in signal quality and movement execution among different users further complicates the creation of comprehensive training datasets. This limitation can lead to models that perform well in controlled environments but struggle in real-world scenarios.

Integrating advanced AI and ML techniques into existing prosthetic devices can be challenging due to hardware and software limitations [14]. Many current prosthetic devices may not have the necessary processing power or sensor capabilities to support sophisticated ML algorithms. Upgrading or retrofitting these devices to incorporate advanced control systems can be costly and complex. Besides, the computational demands of AI and ML algorithms, along with the need for continuous signal processing and sensor data acquisition, result in high power consumption [15]. Ensuring that prosthetic devices have sufficient battery life to function throughout the day without frequent recharging is a significant challenge. Developing energy-efficient algorithms and optimizing hardware components for low power consumption are essential to addressing this issue.

Also, using AI and ML in prosthetic hand control raises ethical and privacy concerns, particularly regarding the collection and use of biological data [16]. Protecting users' data by securely storing and processing it is essential to protect their privacy. Additionally, there are ethical considerations around the potential for AI systems to make decisions that affect users' autonomy and safety. Developing transparent, explainable AI models and establishing clear guidelines for data usage are critical to addressing these concerns.

1.4 Potential Solutions for Prosthetic Hand Control Challenges

Researchers and developers can leverage various technological advancements and innovative approaches to overcome the numerous challenges in controlling prosthetic hands. Implementing sophisticated AI and ML algorithms, such as deep learning and recurrent neural networks (RNNs), can help accurately interpret noisy biological signals like EMG and EEG. These models can learn to filter out noise and extract meaningful patterns. Combining data from multiple sensors (e.g., EMG, EEG, IMU) can provide a more comprehensive understanding of user intentions, improving the accuracy of signal interpretation and control.

Using techniques like data augmentation and generative adversarial networks (GANs) to create synthetic training data can help overcome the scarcity of high-quality datasets [17]. This approach can enhance the robustness and generalizability of ML models. Applying transfer learning allows models trained on large, diverse datasets to be fine-tuned for specific users with limited additional data, reducing the amount of personalized training required.

Developing adaptive AI systems that continuously learn from the user's interactions can personalize the control of the prosthetic hand, making it more intuitive and reducing the learning curve [18]. Designing user-friendly interfaces and providing real-time feedback can help users adapt quickly. VR and AR training environments can also facilitate user adaptation.

Creating modular prosthetic devices with interchangeable components can make it easier to upgrade existing hardware to support advanced AI and ML algorithms without replacing the entire device. Implementing edge computing techniques can enable real-time processing on the device itself, reducing the need for powerful external processors and making the system more portable [19].

Implementing robust encryption and anonymization techniques to ensure the secure storage and processing of users' biological data can address privacy concerns. Developing explainable AI models that provide clear insights into their decision-making processes can help address ethical concerns about autonomy and safety [20]. Establishing clear guidelines and regulations for data usage is also essential.

Utilizing 3D printing and other advanced manufacturing techniques to create customizable prosthetic components can ensure a better fit for individual users, addressing the variability in physiological and anatomical characteristics [21]. Developing control systems that can be easily adapted and fine-tuned to meet the specific needs and preferences of different users can enhance the usability and effectiveness of prosthetic hands.

1.5 Importance of Predicting Hand Grasping Orientation

Predicting hand-grasping orientation is a critical aspect of controlling prosthetic hands, particularly for individuals who rely on these devices for daily activities. The orientation of the hand and fingers must be precisely controlled to successfully grasp and manipulate objects of varying shapes, sizes, and textures. Accurate prediction of hand grasping orientation allows prosthetic hands to perform tasks that require fine motor skills, such as picking up small objects, using tools, or handling delicate items. This capability is crucial for users to perform daily activities independently. Correct orientation ensures that tasks are performed more efficiently and effectively, reducing the time and effort required [22]. This leads to greater user satisfaction and confidence in using the prosthetic hand.

Proper orientation helps secure objects firmly in the prosthetic hand, preventing them from slipping or dropping. This is particularly important for tasks involving fragile or valuable items. Accurate grasping reduces the need for users to make multiple adjustments or exert excessive force, which can lead to fatigue and discomfort over time.

Different objects require different grasping techniques. For example, grasping a cylindrical object like a bottle requires a different orientation than grasping a flat object like a book. Predicting the correct orientation allows the prosthetic hand to adapt to various objects seamlessly. The ability to adjust grasping orientation for different objects enhances the versatility of the prosthetic hand, enabling users to engage in a broader range of activities, from writing to personal care.

Accurately predicting hand orientation enhances fine motor control, allowing for precise manipulation of objects. This is particularly important for activities that require delicate handling, such as threading a needle or assembling small components. Accurate prediction ensures that the prosthetic hand's movements are coordinated with the user's natural movements, creating a more intuitive and seamless user experience.

By accurately predicting and automatically adjusting the hand's orientation, the prosthetic hand reduces the user's cognitive load [23]. This allows users to focus more on the task rather than the mechanics of controlling the prosthetic hand. Reduced cognitive effort and increased ease of use encourage users to engage more actively with their prosthetic hand, promoting better device integration into their daily lives.

Accurate grasp prediction can be used in rehabilitation settings to train users on how to use their prosthetic hands effectively. Data from grasping orientation predictions can inform personalized training programs tailored to individual users' specific needs and progress.

Predicting hand-grasping orientation involves sophisticated AI and ML algorithms that analyze sensor data in real-time. This integration drives technological innovation and the development of more advanced, intuitive prosthetic devices. User feedback and data analysis can continuously improve grasp prediction models, leading to iterative enhancements in prosthetic hand design and functionality.

1.6 Research Objective and Proposed Approach

The primary goal of this work is to propose a sophisticated machine-learning model named AutoMerNet that can accurately predict hand-grasping orientation using biological signals, including EEG, EMG, and IMU. AutoMerNet integrates the strengths of three powerful machine learning architectures, including an Autoencoder for feature extraction, a Transformer for sequence analysis, and an Artificial Neural Network (ANN) for classification and final prediction. By leveraging and combining these advanced techniques, the aim is to enhance the control of prosthetic hands, making them more intuitive, responsive, and adaptable to the diverse needs of users.

The development of AutoMerNet addresses several key challenges in the control of prosthetic hands. One of them is robustness in feature extraction. The Autoencoder component of AutoMerNet excels at extracting meaningful features from noisy and complex biological signals. This improves the accuracy of interpreting EEG, EMG, and IMU data, leading to more reliable control of prosthetic hands. The efficient design of the model enables real-time signal processing, which is crucial for seamless and natural control of the prosthetic device. AutoMerNet's architecture maximizes the use of available training data. The Autoencoder reduces the dimensionality of the input data, making it easier to train the subsequent Transformer and ANN models. Transformers excel at capturing long-range dependencies within data sequences. This particularly benefits EEG, EMG, and IMU data processing, where patterns can unfold over extended periods. Besides, by utilizing advanced feature extraction and sequence analysis techniques, AutoMerNet can potentially incorporate synthetic data augmentation methods to enhance the training process, thereby mitigating the issue of limited real-world data. AutoMerNet can continuously learn and adapt to individual users' signal patterns, making the prosthetic hand more intuitive and reducing the time required for users to adapt to the device. The model's ability to provide accurate and real-time predictions can be integrated with user-friendly interfaces, facilitating a smoother learning curve and quicker user adaptation.

1.7 Dissertation Structure

This dissertation is divided into seven chapters, each crafted to explore a specific aspect of this domain. Chapter 1 provides a comprehensive overview of prosthetic hand control methodologies, highlighting existing limitations and the potential of AI to address them. It also clearly outlines the research objectives and the overall goal of the dissertation.

Chapter 2 delves into the historical development of prosthetic hand control mechanisms, encompassing both traditional methods and contemporary advancements. It critically analyzes the strengths and weaknesses of existing control strategies and establishes the foundation for understanding the rationale behind the proposed AI-based approach.

Chapter 3 explores the role of biological signals, such as EEG, EMG, and IMU data, in prosthetic hand control and provides a detailed explanation of each biological signal's characteristics and functionalities relevant to hand movement prediction. It discusses the potential advantages and challenges of utilizing these signals for AI-powered control.

Chapter 4 meticulously details the data collection methodology, including selecting appropriate sensors, experimental protocols, and data recording procedures. It provides a clear description of the experimental setup, outlining the hardware and software components involved in data acquisition. Also, emphasizes the importance of ensuring data quality and consistency for successful AI model development.

Chapter 5 introduces the proposed AI-based methodology for predicting hand orientation grasping, including the chosen AI model architecture and its training process. It also presents a novel algorithm designed to predict hand orientation based on the acquired biological signals. Furthermore, it provides a rigorous evaluation of the proposed algorithm's performance, including the metrics used and the obtained results.

Chapter 6 offers a comprehensive discussion of the findings presented in Chapter 5. It analyzes the effectiveness of the proposed algorithm, compares the proposed approach with existing methods, highlights its advantages and limitations, and discusses the implications of the research findings for the advancement of AI-powered prosthetic hand control.

Chapter 7 summarizes the dissertation's key contributions to the field of prosthetic hand control with AI. It also suggests potential works for future research and concludes by emphasizing the significance of AI in revolutionizing prosthetic hand control and improving the quality of life for amputees.

CHAPTER 2

CONTROLLING PROSTHETIC HANDS: BACKGROUND

2.1 Introduction

Research toward the creation of functional and intuitive prosthetic hands reaches a long history. The early devices that were developed focused on the restoration of basic hand function, often by using simple mechanical systems that provided limited dexterity and were cumbersome for the user. Early prosthetics were designed to help perform activities like holding and grasping an object, therefore offering the user some rudimentary functionality of the hand [24]. However, with technological progress, so did the potential of prosthetic hands. Recent developments aim for almost natural control and sensory feedback by using sophisticated electronics, sensors, and algorithms [25]. Modern prosthetic hands now feature myoelectric control, where sensors detect electrical signals from the user's muscles to control the prosthetic, allowing for more precise and varied movements. Researchers are trying to introduce mechanisms for sensory feedback, particularly haptic feedback, which would allow users to feel touch and pressure. This would fall directly into both increasing the applicability and intuitiveness of working with such devices in the first place. Also, researchers are working on prosthetics that can simulate one's natural hand, not only in appearance and move but by returning a great deal of functionality and sensation, hence hugely improving the quality of life for amputees.

2.2 Early Days: Mechanical Marvels (Pre-1900s)

Evidence of the earliest prosthetic hands dates back to ancient Egypt, where rudimentary devices were crafted from wood and bronze [26]. These early prosthetics were primarily cosmetic, aimed at restoring outward appearance after amputations. However, some designs, like the prosthetic toe dating back to 950-710 BC, hinted at the potential for functionality [26].

Following the basic designs of the ancient world, the Middle Ages saw a renewed focus on prosthetics for soldiers returning from battle. Knights who lost limbs often used simple wooden prosthetics to aid in horseback riding or wielding weapons [26].

The Renaissance period (14th-17th centuries) marked a turning point in prosthetic hand design [27]. Advancements in metalworking and engineering led European artisans to create more intricate and functional devices. Iron, copper, and leather became the materials of choice, allowing for the construction of articulated joints and harnesses [28]. The most iconic example from this era is the prosthetic hand of German knight Götz von Berlichingen (1480-1562) [27]; see Figure 2.1.

Figure 2.1 The prosthetic hand of German knight Götz von Berlichingen [27]

This engineering marvel featured complex joints and a harness system, allowing for some degree of movement. However, control remained challenging, requiring manual manipulation of the device with the remaining hand.

While Götz von Berlichingen's hand garnered significant attention, it wasn't the only innovation of the time. Artisans from France and Switzerland also pioneered using cables, gears, cranks, and springs to create prosthetic limbs with a wider range of motion, including grasping mechanisms in some hand designs [26]. These "steampunk" creations, while requiring external controls, laid the groundwork for future advancements in prosthetic technology.

2.3 Harnessing Electricity (1900s)

The 20th century witnessed a revolutionary shift in prosthetic hand control with the introduction of myoelectric control. This technology utilizes the residual limb's electrical signals generated by muscle contractions (EMG).

The first myoelectric prosthetics were rudimentary, featuring basic movements like opening and closing a single grasp invented by Russian scientist Alexander Kobrinski in 1960 [29]. However, they represented a significant leap forward, offering amputees a more intuitive way to interact with the world. These early devices often relied on bulky amplifiers to process the EMG signals, limiting their practicality.

2.4 EMG Takes Center Stage (Mid-20th Century)

As the field of prosthetics advanced, researchers focused on improving myoelectric control. The role of EMG became crucial for several reasons. Advancements in microprocessors and miniaturization allowed for more sophisticated EMG signal processing. This enabled the development of prosthetic hands capable of performing multiple grasp patterns and functions [30]. Furthermore, comprehensive research on EMG control and pattern recognition laid the groundwork for developing more sophisticated prosthetic hands [9, 31].

2.5 Modern Advancements (Late 20th Century - Present)

The late 20th century saw an explosion of innovation in prosthetic hand control. Researchers developed multi-function prosthetic hands with numerous degrees of freedom, allowing for a wider range of movements and improved dexterity [32]. Advancements in materials science led to the creation of lighter and more durable prosthetics. While EMG remained the primary control method, researchers began exploring additional modalities.

EEG measures electrical activity in the brain. Though not directly used in prosthetic control, some studies explore its potential to understand user intent and supplement EMG signals [33].

IMUs track movement and orientation. Integration of IMUs in prosthetic hands allows for more natural control based on the user's arm and hand position [34].

Researchers are exploring how deep learning can be used to analyze surface electromyography (sEMG) signals, which detect muscle activity. This can lead to more intuitive and responsive prosthetic hands controlled by the user's own muscles. Another area of research focuses on mimicking the natural way the brain controls the hand. This could involve things like using brain-computer interfaces (BCIs) to directly control the prosthetic hand [35]. Researchers are also considering reducing the mental and physical effort required to control a prosthetic hand. This could involve things like developing better control interfaces or using machine learning to anticipate the user's needs [36].

2.6 The Future: Brain-Computer Interfaces (Present - Ongoing)

The significant achievement of prosthetic control lies in Brain-Computer Interfaces (BCIs). BCIs bypass the need for muscle signals and directly translate brain signals into commands for the prosthetic hand. This approach promises unparalleled control and a more natural feel for amputees [37]. Researchers actively explore using BCIs in prosthetic hand control. Early trials have shown promising results, with amputees achieving remarkable control over prosthetic limbs using their thoughts [38]. While some studies involve implants, significant progress is being made in non-invasive BCIs using EEG headsets. This offers a safer and more accessible option for applications like stroke rehabilitation with exoskeletons [39]. Advancements in electrode technology are crucial for BCIs. Recent developments include flexible, ultra-thin electrodes that minimize brain tissue damage and improve signal quality [40]; see Figure 2.2.

Figure 2.2 Advanced prosthetic hand (DARPA)

Machine learning algorithms play a key role in deciphering complex brain signals. Machine learning techniques lead to more precise and faster control of prosthetic limbs and other BCI applications, see Figure 2.3.

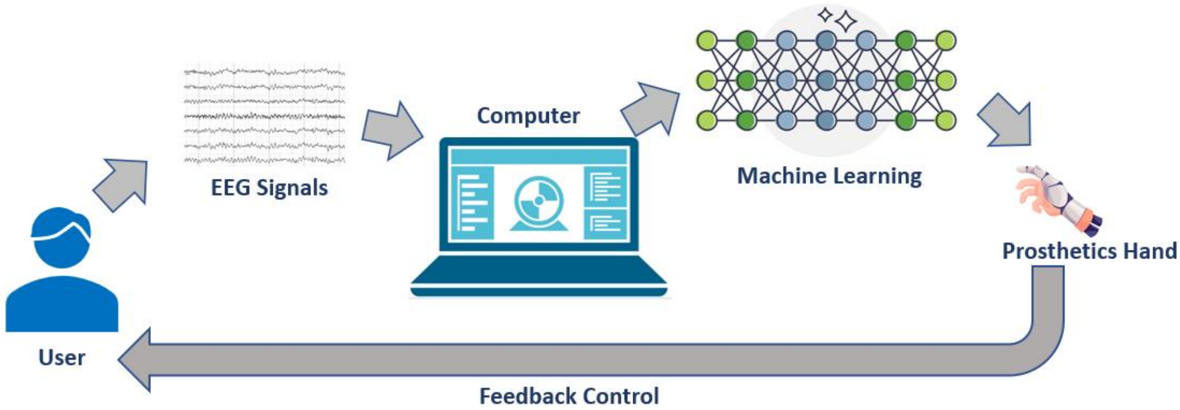

Figure 2.3 BCI translates brain signal to control prosthetics hand using ML algorithms

These advancements are just the beginning. The future holds very impressive potential for BCIs with enhanced prosthetic control; some researchers even foresee the restoration of near-natural sensation and control to amputees. BCI could be combined with AR systems that made interaction with virtual objects frictionless by issuing brain commands to them. The potential for direct thought exchange between people represents a view into a possible future application of BCIs, which requires critical thinking and, above all, ethics.

While there are still some challenges to long-term stability, safety, and ethics, the research on BCI is undergoing rapid development. It gives us a vision that the mind will be able to directly act on technology, opening doors to a new age of BCI.

2.7 Summary

The history of prosthetic hands is the enthralling narrative of the outstanding progress of human ingenuity and technological innovation. This journey, which began hundreds of years ago, has evolved from what was rudimentary and simplistic in its earliest past to the highly sophisticated, technologically advanced prosthetics of today. Prosthetic hands did exist in the past, although very basic and often terribly limited in their function, providing a semblance of normality rather than actual utility. Over time, with advancements in materials science, engineering, and biomedical technology, prosthetic hands have undergone a dramatic transformation. Modern prosthetic hands now offer a range of movements and capabilities, including intricate finger movements, grasp strength adjustment, and even sensory feedback, allowing amputees to perform various daily tasks with greater ease and precision. Researchers and engineers continuously strive to enhance the functionality, comfort, and aesthetic appeal of these devices, aiming to restore not only physical capability but also a sense of normalcy and confidence to the lives of amputees.

The future of prosthetic hands holds immense promise, particularly with the advent of BCIs. BCIs represent a groundbreaking leap forward, potentially enabling a more intuitive and natural connection between the brain and the prosthetic hand. This technology could allow users to control their prosthetic hand with their thoughts alone, resulting in movements that are more fluid and natural. Furthermore, ongoing research in neural integration and advanced robotics suggests that future prosthetic hands could provide even more sophisticated sensory feedback, closely mimicking the sensations of a natural hand. As we look ahead, the intersection of neuroscience, robotics, and artificial intelligence continues to pave the way for revolutionary advancements in prosthetic hand technology. These innovations not only aim to enhance the physical capabilities of amputees but also strive to improve their overall quality of life, offering new levels of independence and self-assurance. The journey of prosthetic hands is indeed a testament to human perseverance and the relentless pursuit of excellence in the field of medical technology. A summary of the evolution of prosthetic hands can be seen in Table 2.1.

Table 2.1 The evolution of prosthetic hands; further details are elaborated in this chapter

Year	Control Method	Functionality	Materials
Pre-1900s	Mechanical (Cosmetic)	Rudimentary grasping	Wood, bronze
14th-17th centuries	Mechanical (Harnesses)	Articulated joints for some movement	Iron, copper, leather
1480-1562	Mechanical (Harnesses)	Complex movements require manual control	Iron, leather
1900s	Myoelectric (EMG)	Basic opening and closing grasp	Early electronics
Mid-20th Century	Myoelectric (EMG)	Multiple grasp patterns and functions	Advanced microprocessors
Late 20th Century – Present	Myoelectric (EMG)	Numerous degrees of freedom improved dexterity	Lighter, more durable materials
Present – Ongoing	Myoelectric (EMG) or Electroencephalography (EEG)	More intuitive and responsive control, Unparalleled control, natural feel, minimized brain tissue damage, improved signal quality	Advanced microprocessors, EEG technology, advanced algorithms

CHAPTER 3

CONTROLLING THE ASSISTIVE DEVICES WITH BIOLOGICAL SIGNALS

3.1 Introduction

In robotics, an exoskeleton or prosthetics limb is an assistive device consisting of a structure exterior to the user having passive or motor-driven operation. Deployed devices consist of joints and links corresponding to those in the human body and, therefore, are categorized by the part of the body supported: upper extremity, lower extremity, or whole body. Some upper limb exoskeletons are very important in helping those with no functional upper limb. The human upper limb usually has seven degrees of freedom (DOF). However, some designs aim to provide all these DOFs in the exoskeleton also some may use less than seven DOFs. The design of these systems with considerations of biomechanics, safety, acquisition types, power sources, materials and weight are very complicated. Control of upper-limb exoskeletons based on human intention is a challenge. Proper selection of a control input signal, which allows understanding the user's motion intention, is crucial for the accuracy of the approach [41]. A great amount of research has been conducted on various biological signals. Specifically, this was done for EMG, the electrical potential generated by muscle cells in the case of muscle contraction or rest. EMG signals seem very promising for control approaches since they directly reflect the motion intention. Brain signal monitoring has advanced and, in turn, brought to the fore electroencephalography as another feasible control technique for upper-limb exoskeletons. Another exoskeleton control method includes inertial Measurement Units. IMUs provide data relating to orientation, acceleration, and angular velocity, which can be important in carrying out motion analysis and control. Through the integration of data obtained from IMUs, exoskeletons can achieve precise and responsive control, enhancing their effectiveness in assisting and augmenting human movement. The combination of the EMG, EEG, and IMU signals can provide a comprehensive way for developing intuitive and effective control systems for an exoskeleton, as presented in this research.

3.2 Controlling the Prosthetics Hands with Biological Signals

For centuries, researchers have dreamed of creating a prosthetic hand that seamlessly integrates with the human body. The key to achieving this is harnessing the body's natural control system using biological signals. This chapter explores how these signals have revolutionized prosthetic hand control and the exciting possibilities they hold for the future.

3.2.1 Electrical Language of the Body

Our muscles communicate with the brain using a complex language of electrical signals. When we think about moving a limb, the brain sends signals down the spinal cord, triggering electrical impulses in the muscles. These electrical impulses, called EMG signals, cause the muscles to contract and produce movement, see Figure 3.1. Pioneering researchers in the field of neuromuscular physiology, such as Luigi Galvani in the 18th century, laid the groundwork for understanding these electrical signals [42].

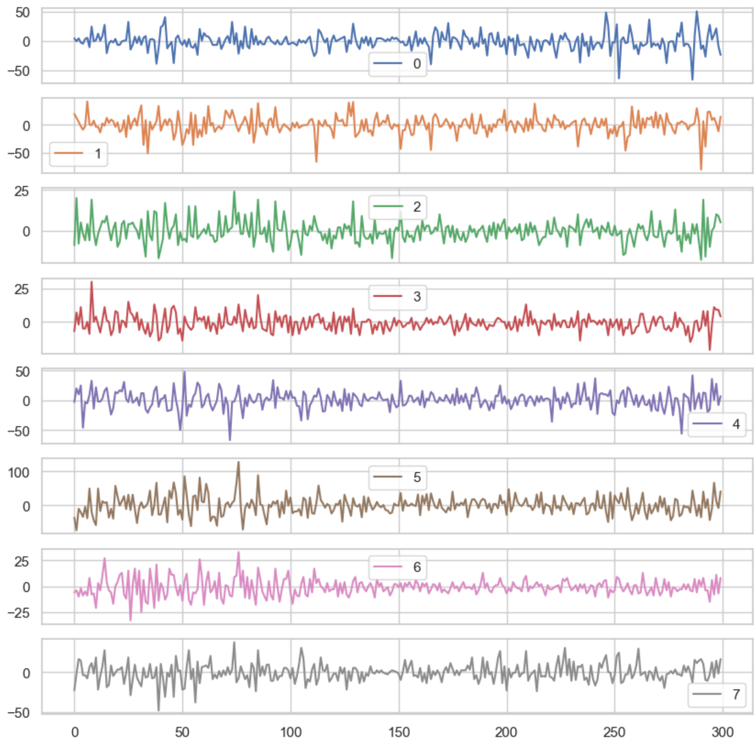

Figure 3.1 Muscle signals (EMG) from eight parts of muscle during activities

3.2.2 Characteristics of EMG Signals

EMG offers a window into the intricate world of neuromuscular communication. EMG signals provide valuable insights into muscle function, fatigue levels, and even neurological disorders by measuring the electrical activity generated by muscle fibers during contraction. However, interpreting these signals effectively requires a deep understanding of their inherent characteristics and the factors influencing their variability.

One key characteristic of EMG signals is their stochastic nature. The amplitude, representing the voltage fluctuations, exhibits a random variation that can be approximated by a Gaussian distribution. This inherent randomness necessitates statistical analysis techniques for robust interpretation. Typically, the peak-to-peak amplitude of these signals falls within a range of 0 to 10 millivolts (mV) [43]. However, this value is not the sole indicator of muscle force; it requires careful consideration alongside other EMG features.

The frequency content of EMG signals holds crucial information about muscle activation patterns. The usable energy resides within a frequency band ranging from 0 to 500 Hz [44]. However, the most dominant portion of this energy spectrum is concentrated between 50 and 150 Hz [44]. This specific frequency range reflects the firing rates of motor units, the fundamental building blocks of muscle control. Analyzing these frequency components allows researchers and clinicians to differentiate between various muscle activation states, such as isometric contractions (holding a weight) versus dynamic movements (lifting a weight).

EMG signals are not static entities. They exhibit a high degree of inter- and intra-individual variability. This means that EMG patterns can differ significantly not only between different people performing the same movement but also for the same individual performing the action repeatedly. Factors such as muscle fatigue, tiredness, and even sleep deprivation can demonstrably alter EMG characteristics. Additionally, psychological states like stress can introduce further variability, influencing muscle recruitment patterns. These inherent variations in EMG signals pose a significant challenge when developing control systems for assistive technologies. For instance, exoskeletons that rely on EMG for user intent recognition must be able to adapt to individual variability and account for the influence of fatigue or stress on the user's EMG patterns. By meticulously considering these characteristics and their underlying physiological mechanisms, researchers can design robust and user-centric control algorithms that optimize the performance and user experience of such assistive technologies.

3.2.3 The Birth of Myoelectric Control

The 1940s saw the realization that these EMG signals could be harnessed to control prosthetic limbs [44]. Pioneering researchers envisioned a future where amputees could control their prosthetics intuitively, using their own muscle power [45]. Their work focused on developing basic myoelectric systems for controlling simple movements in prosthetic hands.

Electrodes placed on the residual limb picked up EMG signals, and rudimentary control systems translated these signals into simple on/off commands for the prosthetic hand [46]. These early devices, while limited in functionality, laid the groundwork for future advancements.

3.2.4 The Power of Pattern Recognition

As technology advanced, researchers focused on refining myoelectric control. Introducing microprocessors and miniaturization allowed for sophisticated signal processing and pattern recognition algorithms. Pioneering work played a crucial role in developing these algorithms [47]. These algorithms could analyze the complex patterns of EMG signals generated by different muscle contractions. This enabled the development of prosthetic hands capable of performing multiple grasp patterns and functions, mimicking a wider range of natural hand movements.

3.2.5 Benefits of EMG Signals

EMG signals offer several advantages for controlling prosthetic hands. One key benefit is their intuitive nature. Myoelectric control utilizes existing neural pathways for hand movement, creating a more natural feel for amputees than mechanical controls [48]. Studies have shown that this can significantly improve dexterity and task completion. For instance, research demonstrated that myoelectric control yielded better results than other methods.

Furthermore, EMG signals allow for improved dexterity in prosthetic hands. Advanced pattern recognition algorithms can translate these signals into complex movements, enabling users to control individual fingers or perform specific grasp patterns. This enhances the functionality and allows for a more natural interaction with objects. Studies have achieved near-natural grasp patterns in advanced prosthetic hands using myoelectric control [49].

Finally, EMG signals hold promise for incorporating biofeedback into future prosthetics. By analyzing these signals, the prosthetic hand could provide feedback on grasp strength and hand position. This information can improve the user's control and coordination.

3.2.6 Challenges and Limitations of EMGs in Controlling Prosthetics

While EMG signals offer exciting possibilities for prosthetic control, there are still challenges to overcome. One key hurdle lies in discerning complex signals. Differentiating between the subtle EMG signals from various muscle groups can be tricky. This limits the level of control amputees have over individual fingers and finer movements. Some researchers are actively exploring solutions [50]. Their work focuses on developing advanced signal-processing techniques and machine-learning algorithms to improve the ability to interpret these intricate signals.

Another challenge is phantom limb pain. Some amputees experience this phenomenon, which can disrupt the generation of clear EMG signals. This, in turn, can significantly affect their ability to control their prosthetic hand. Studies by [51] are investigating alternative control methods for amputees facing this challenge. Their research explores the use of noninvasive brain-computer interfaces (BCIs) as a potential solution for those experiencing phantom limb pain.

3.3 Electroencephalogram (EEG) for Prosthetic Control

Electroencephalography (EEG) is a sophisticated, non-invasive technique for measuring the brain's electrical activity. By placing electrodes on the scalp, EEG captures the minute voltage fluctuations produced by neuronal activity. This method provides critical insights into brain function and is increasingly being explored for its potential in controlling prosthetic limbs.

3.3.1 The Motor Cortex and Movement Control

The motor cortex, located in the frontal lobe of the brain, is primarily responsible for planning, controlling, and executing voluntary movements [52]; see Figure 3.2. It consists of several regions, including the primary motor cortex (M1), the premotor cortex, and the supplementary motor area. The primary motor cortex, situated on the precentral gyrus, is critical in generating neural impulses that control movement execution.

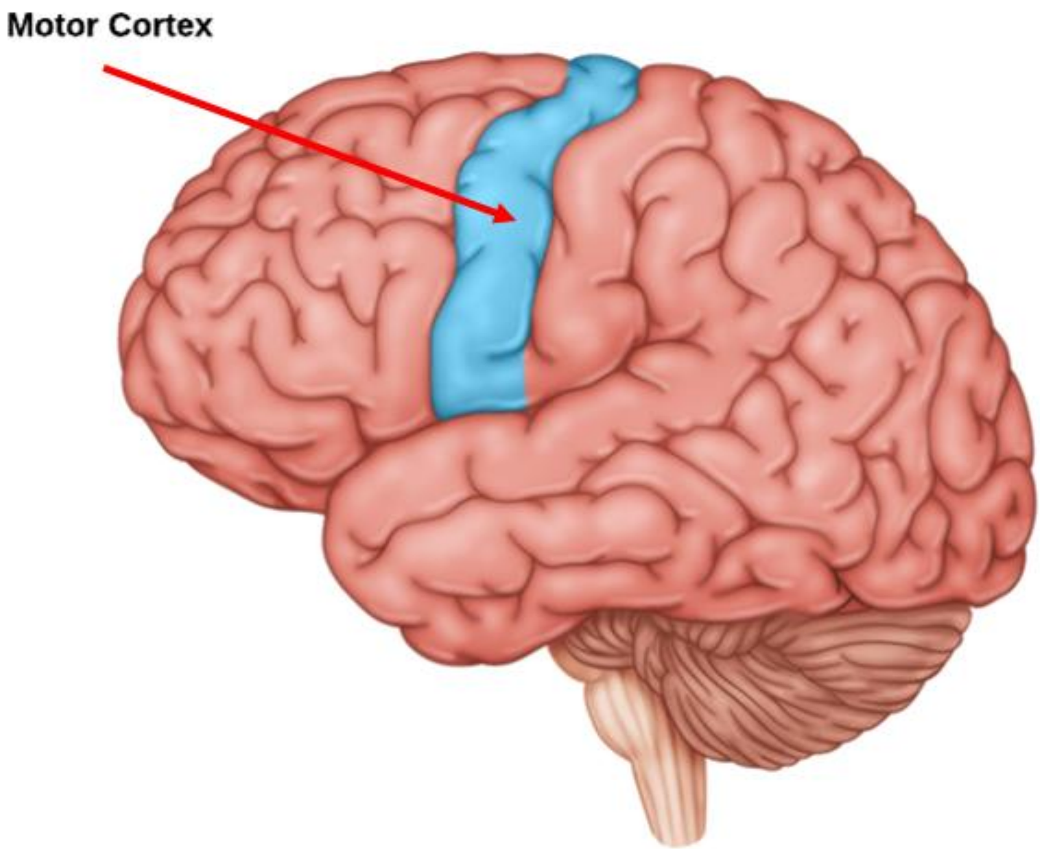

Figure 3.2 The motor cortex is located in the frontal lobe of the brain

EEG electrodes placed over the motor cortex can capture the electrical activity associated with movement planning and execution. The recorded EEG signals from this region reflect the brain's motor commands and can be analyzed to infer the user's intended movements. This information is crucial for developing brain-computer interfaces (BCIs) for prosthetic control.

3.3.2 Structural Dynamics and Characteristics of EEG

The human brain comprises billions of neurons that communicate via electrical impulses. EEG signals are like a complex symphony characterized by three key features: amplitude, frequency, and phase. Amplitude is measured in microvolts (µV) and reflects the strength of the electrical activity. Higher amplitudes generally indicate greater synchronization of neuronal activity within a specific brain region. EEG captures the aggregate electrical activity of these neurons, particularly within the cerebral cortex, the brain's outermost layer. The resulting EEG signal is a complex waveform segmented into various frequency bands, each correlating with distinct brain states. By analyzing the dominant frequencies in the EEG signal, researchers can infer the user's brain state and use this information for various purposes, such as controlling external devices. EEG waves can be classified with different frequencies [53]. For example: Delta waves (0.5-4 Hz): Deep sleep or unconsciousness. Theta waves (4-7 Hz): Drowsiness, meditation, or daydreaming. Alpha waves (8-13 Hz): Relaxed wakefulness with eyes closed. Beta waves (13-30 Hz): Alertness, focused attention, or problem-solving. Gamma waves (above 30 Hz): Higher cognitive functions and information processing. See Figure 3.3.

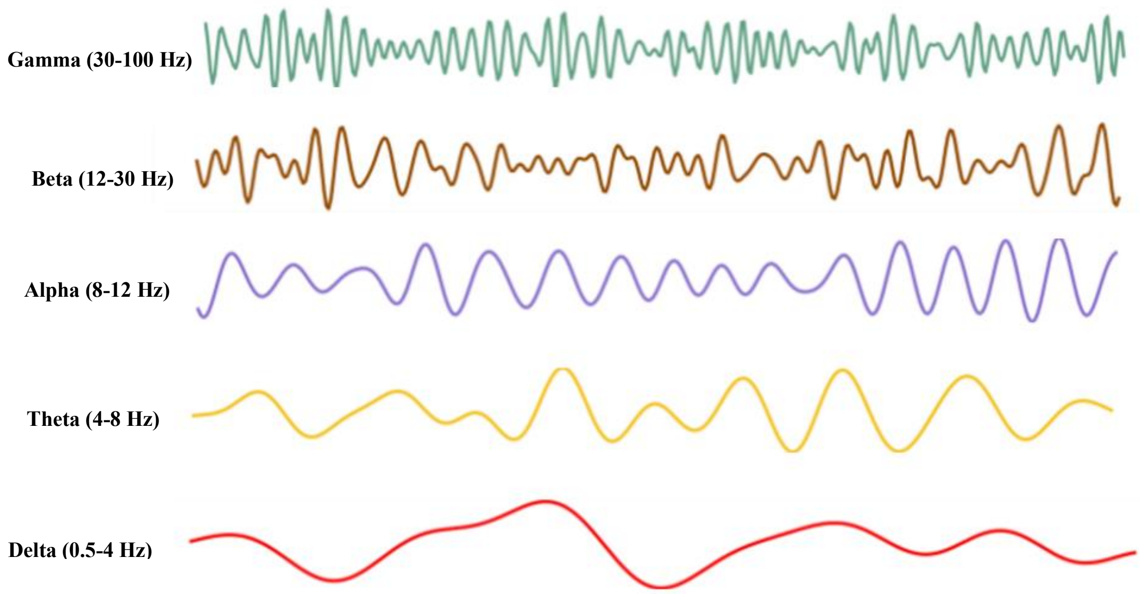

Figure 3.3 EEG waves with different frequencies

The phase of an EEG signal refers to the position of its waveform cycle at a specific point in time. The relative phase between different brain regions can provide information about their functional connectivity, revealing how various parts of the brain communicate.

EEG also presents inherent trade-offs in its ability to capture spatial and temporal details of brain activity. Compared to other imaging techniques like fMRI, EEG has a relatively low spatial resolution [54]. This means it cannot pinpoint the exact source of brain activity with high precision. The recorded signal reflects the combined activity from a group of neurons beneath the electrode.

On the other hand, EEG excels in its temporal resolution. It can capture rapid changes in brain activity with high fidelity, making it ideal for real-time applications. This allows researchers to study the dynamic fluctuations in brain activity that occur during thought or movement, which is crucial for applications like brain-computer interfaces.

Understanding these characteristics is essential for effectively interpreting EEG signals and unlocking their potential for various applications, particularly in prosthetic control. The ability to decode user intent and translate it into action holds immense promise for improving the lives of amputees.

3.3.3 Advantages of EEG in Prosthetic Control

EEG offers several advantages over traditional methods for controlling prosthetic limbs. Firstly, EEG boasts intent-based control [55]. It detects brain activity associated with the intention to move a limb, even before any muscle activation occurs. This distinction makes EEG a more intuitive and natural control mechanism, potentially leading to smoother and more precise prosthetic control. Another key benefit of EEG is its ability to mitigate phantom limb pain. Amputees often experience discomfort and pain sensations originating from the missing limb [56]. This pain can hamper EMG control systems, which depend on muscle signals. EEG, however, bypasses the need for muscle activation, offering a significant advantage for those struggling with phantom limb pain.

Also, EEG presents exciting possibilities for developing enhanced multimodal control systems. Combining EEG with EMG allows for a more nuanced and sophisticated approach. EEG can be used to decode high-level commands, such as opening or closing the hand. EMG can then be employed to fine-tune individual finger movements. This synergy between the two technologies has the potential to unlock a new level of control and functionality for prosthetic limbs.

3.3.4 Challenges and Limitations of EEG in Controlling Prosthetics Hand

Electroencephalography (EEG) holds immense promise for the future of prosthetics. However, several technical hurdles must be addressed to realize its full potential. The first major challenge lies in the inherent complexity of EEG signals [57]. These signals are faint and intricate, requiring advanced processing techniques to decipher the user's intended movements. Decoding these signals with accuracy hinges on sophisticated algorithms and machine-learning models. Without these advancements, translating subtle brain activity into precise control commands remains a significant obstacle.

Another limiting factor is the restricted spatial resolution of EEG [58]. Unlike imaging techniques that provide detailed anatomical information, EEG struggles to pinpoint the exact origin of brain activity within the skull. This limitation makes distinguishing between closely spaced neural signals difficult, potentially leading to misinterpretations of complex control intentions. Overcoming this hurdle is crucial for enabling users to send nuanced commands and achieve a wider range of finer motor control with their prosthetics.

Furthermore, successfully implementing EEG-based prosthetics requires a high degree of personalization [59]. Each individual's brain activity patterns are unique. To ensure optimal control, extensive calibration and training sessions are necessary. This personalization process allows the system to adapt to the user's specific EEG signature and translate it into accurate commands for the prosthetic limb. While personalization offers a significant benefit in the long run, it creates an initial barrier that needs to be smoothened for wider adoption of this technology.

3.3.5 Combining EEG and EMG for Enhanced Prosthetic Control

The field of prosthetic control is constantly evolving, with researchers seeking solutions that offer greater intuitiveness, precision, and reliability. One promising approach lies in the synergistic combination of EEG and EMG signals [60]. By leveraging the unique strengths of each modality, this hybrid system paves the way for a more robust and nuanced control experience for prosthetic hand users. The cornerstone of this approach lies in the complementary nature of EEG and EMG data. EEG excels at capturing high-level information about the user's intent to move, decoding brain activity even before any physical muscle activation occurs. EMG, on the other hand, shines in its ability to detect electrical signals from muscle contractions, enabling precise control over individual finger movements. This synergy ensures that both the planning (intention) and execution (movement) phases of limb control are accurately represented within the control system.

This combined approach translates to several key advantages. Firstly, the control system can achieve significantly higher accuracy and responsiveness by utilizing EEG to initiate movements and then employing EMG to fine-tune the details [61]. This allows for a more natural and intuitive prosthetic control experience, closely mimicking how biological limbs function. Additionally, EEG signals offer a significant benefit as they are not influenced by factors like muscle fatigue or phantom limb pain, which can degrade EMG control. Conversely, EMG can address the limitations of EEG's spatial resolution by providing more precise control over individual finger movements. This creates a robust system where each modality compensates for the limitations of the other. Finally, combining EEG and EMG opens doors for developing adaptive control strategies. Over time, the system can learn and adjust to each user's specific neural and muscular patterns. This continuous learning process can lead to significant improvements in functionality and user experience over the long term. As the system becomes more attuned to the individual, prosthetic control becomes increasingly intuitive and seamless.

3.4 Inertial Measurement Units (IMUs) for Prosthetic Control

Inertial Measurement Units (IMUs) are advanced sensors essential for capturing motion and orientation data [61]. They are crucial in various applications, including the control of prosthetic limbs, where they provide real-time feedback on movement and positioning, Figure 3.4.

Figure 3.4 IMU device is used to record data in three dimensions: X, Y, and Z

3.4.1 Characteristics and Components of IMUs

IMUs capture motion and orientation in three-dimensional space, providing a comprehensive understanding of linear and rotational movements [62]. IMUs typically consist of three primary components, each playing a vital role in capturing different aspects of motion:

- Accelerometers:

Function: Measure linear acceleration along three orthogonal axes (x, y, z).

Characteristics: Provide data on the rate of change in velocity, indicating how fast an object moves in a particular direction. They are sensitive to both static (e.g., gravity) and dynamic (e.g., sudden movement) forces. It is used for detecting tilts, vibrations, and motion, which are essential for understanding the precise movements of a prosthetic limb.

- Gyroscopes:

Function: Measure rotational velocity around three axes.

Characteristics: Capture the rotation rate, helping to determine how an object is turning or spinning. They are crucial for tracking orientation and angular changes over time. It provides critical data for stabilizing and controlling the orientation of the prosthetic limb, ensuring smooth and accurate movements.

- Magnetometers:

Function: Measure the strength and direction of the magnetic field in three dimensions.

Characteristics: They offer absolute orientation by detecting the Earth's magnetic field. They often correct drift in gyroscope data and provide a stable heading reference. They enhance the accuracy of orientation measurements, especially useful in environments where precise directional data is required.

3.4.2 The Role of IMU Signals in Controlling Prosthetic Hands

IMUs provide critical data on the movement and orientation of prosthetic limbs, which can be used to refine control algorithms and improve the functionality of the prosthetic hand. When placed on different parts of the prosthetic limb, IMUs capture detailed motion data that can be analyzed to understand the user's intended movements and provide precise control over the prosthetic hand. IMUs have emerged as valuable tools for enhancing functionality and user experience in prosthetic control. These compact sensors pack a powerful punch, offering a unique set of advantages that contribute to more intuitive and effective prosthetic control.

The first key benefit of IMUs lies in their ability to provide real-time feedback. Unlike some other sensors, IMUs deliver immediate data on the motion and orientation of the prosthetic limb. This allows the control system to adjust on the fly, ensuring the prosthetic hand accurately reflects the user's intended movements. Furthermore, IMUs boast exceptional enhanced motion tracking capabilities. They typically integrate both accelerometers and gyroscopes. Accelerometers measure linear acceleration, detecting changes in speed and direction. Gyroscopes, on the other hand, track rotational movements. This combined functionality allows the system to comprehensively understand the user's limb movements, encompassing both linear actions like reaching and rotational movements like wrist rotation. This comprehensive data stream empowers the control system to translate the user's intentions into more natural and nuanced prosthetic movements.

Beyond real-time feedback and motion tracking, IMUs offer the advantage of robust performance. They are designed to function effectively in various environments and conditions. Unlike some sensors that might be susceptible to environmental factors, IMUs can operate reliably regardless of lighting conditions, temperature fluctuations, or even mild moisture exposure. This ensures consistent and dependable data for prosthetic control, allowing users to confidently interact with their surroundings without worrying about sensor malfunction.

Besides, IMUs demonstrate remarkable versatility. To create a more comprehensive control system, they can be seamlessly integrated with other sensor modalities, such as EEG and EMG. EEG can decode the user's intent to move, while EMG can detect muscle activation for fine-tuning individual finger movements. IMUs, with their real-time motion data, bridge the gap between intent and execution, providing valuable information about the limb's position and orientation. This synergy between different sensors unlocks a new level of control, allowing users to achieve a wider range of movements and interact with the world in a more natural and intuitive way.

3.4.3 Combining IMUs, EEG, and EMG for Advanced Prosthetics Control

The research for ever-more intuitive and natural control of prosthetic hands has led us to a powerful approach which is integrating data from IMUs, EEG, and EMG. This new synergistic combination leverages the strengths of each modality, creating a robust and comprehensive control system that unlocks a new level of functionality for prosthetic users. The cornerstone of this approach lies in the complementary nature of the data provided by each sensor. IMUs excel at capturing real-time information about the prosthetic hand's motion and orientation. EEG offers a unique window into the user's brain activity, decoding their intent to move even before any physical muscle activation occurs. Finally, EMG masters its ability to detect electrical signals from muscle contractions, enabling precise control over individual finger movements. By combining this data, the control system gains a holistic understanding of the user's intended movements, encompassing both planning (through EEG) and execution (through IMU and EMG).

This multi-sensor approach can leverage IMU data to refine the control signals derived from EEG and EMG. For instance, EEG might indicate the user's desire to grasp an object, but IMU data can help determine the precise hand orientation and trajectory needed for a successful grasp. This refinement leads to more precise and responsive prosthetic hand movements, mimicking natural limb function more closely. Additionally, by incorporating multiple data sources, the system becomes less reliant on any single sensor. If one sensor experiences signal degradation or malfunction, the others can compensate, ensuring enhanced reliability and robustness of the overall control system.

Combining IMU, EEG, and EMG data opens doors for developing truly adaptive control strategies. As the user interacts with the prosthetic hand, the system can continuously learn and adjust to their specific patterns of movement and muscle activation. Over time, this ongoing learning process can significantly improve functionality and user experience. Also, this continuous adaptation personalizes the prosthetic control experience, allowing users to interact with the world with greater confidence and dexterity. The future of prosthetic control lies in the seamless integration of these diverse data sources, providing users with more natural, intuitive, and responsive control over their prosthetic limbs.

CHAPTER 4

DATA COLLECTION, EXPERIMENT, AND TOOLS

4.1 Introduction

Human biological data, represented by EEG, EMG, and IMU, is key to further development in prosthetic hand control. These three flows of data provide different but complementary information regarding the neural, muscular, and movement dynamics of the user and, accordingly, help in the development of more responsive and intuitive prosthetic devices. We can thus exploit these different data sets in driving sophisticated algorithms to finally translate the complex interplay between neural signals, muscle activity, and limb movements into strict commands for prosthetic devices.

4.1.1 EEG Insights

EEG data capture the electrical activity of the brain, including neural processes related to motor intentions. The motor cortex is at the core of this issue. It is in charge of monitoring, controlling, and executing all voluntary movements during planned actions. It provides direct access to the activity from the brain, which helps in decoding the intention behind the different movements that the hand can make. This information is essential in creating a seamless interface between the user's brain and the prosthetic hand.

From EEG signals, we can decode specific brainwave patterns that accompany different hand movements in the motor cortex. This ability may enable neural interfaces by which it will be possible for users to control prosthetic hands by thought. Such interfaces could especially benefit people with high-level amputations or spinal injuries since they could work directly routing to prosthetic control bypassing residual limb muscle signals. My translation of motor cortex activity and movements can enhance usability and functionality in prosthetic devices.

4.1.2 EMG Insights

EMG data provide information regarding the detailed muscle contractions and electrical activities of muscles involved in hand movements. This kind of information is critical in trying to understand how the user's residual muscles intend to move a missing limb. With such EMG signals, fluid control is achieved and thus natural movement of the prosthetic hand is possible in real time. It is further supported by the fact that data from an EMG can be used to estimate muscle fatigue and regulate the prosthetic's response to ensure user comfort and usability. Two major player muscles are involved in hand movements and functionality, especially in grasping: flexor and extensor muscles. These are antagonist muscles that lie on opposite sides of the forearm to facilitate hand movements. The flexor muscles lie primarily on the anterior aspect of the forearm and flex the fingers and the wrist. Major flexor muscles involved in hand actions are the flexor digitorum superficialis and flexor digitorum profundus. These muscles contract to bend the fingers, hence enabling the hand to grasp and hold objects. Flexor EMG signals provide a key carrier of information about force levels and timing, which, during grasp or pinching activities, is necessary to control the exact functioning of a prosthetic hand. On the other hand, extensor muscles are located on the posterior or back side of the forearm. In relation to hand movements, extensor digitorum and extensor carpi radialis are major extensor muscles. They are responsible for extending the fingers and the wrist, which enable the hand to release an object and to open the fingers. EMG signals from the extensor muscles become equally important since they provide information on the relaxation and extension phases of hand movements.

The type and nature of the tasks performed in the exercises have a great similarity in affecting the EMG signal of both flexor and extensor muscles. Activities containing fine actions, such as writing or picking up small objects, created different signal patterns compared with gross motor activities. High-frequency low-amplitude signals may appear in the flexor muscles owing to fine control. In contrast, tasks that require a strong grasp, such as holding a heavy weight, result in large-amplitude and low-frequency EMG signals from flexor muscles due to the chronic and powerful contractions. Understanding the detailed EMG profiles of flexor and extensor muscles is paramount for designing advanced prosthetic hands. These profiles help develop algorithms to accurately interpret muscle signals and translate them into precise prosthetic movements. By monitoring and analyzing the EMG data from these muscles, it is possible to create prosthetic devices that can adjust their response based on the detected muscle activity, enhancing their functionality and user experience.

4.1.3 IMU Insights

IMUs can provide valuable data about limb orientation and movement manifests, such as three-dimensional acceleration readings, rotation readings, and angular velocity readings along the x, y, and z axes. These are salient features that describe spatial dimensions of hand movements.

The IMU sensors are quite critical to prosthetic hands, as they enhance their capabilities. Various data are captured by these sensors, giving valuable information about hand movements and their orientation in three-dimensional space. One of the major kinds of data captured is acceleration data. In a simple way, this data measures changes in the speed of the hand and is, therefore, very helpful in determining the speed and even direction of hand movements. If data were analyzed, then the same kind of feats to be achieved by users of prosthetic hands would be: detect rapid motion that would snap the fingers or measure precisely hand steadiness for delicate tasks.

IMU sensors further capture information on rotation, which is the orientation of the hand with respect to the arm in space. This information is valuable in ascertaining the exact orientation of the hand. This will include hand-orientation estimation for tools, rotation tracking for more complex manipulation actions like turning a doorknob.

Finally, the IMU sensor component provides data on angular velocity, that is, the quickness of change in rotational position of the hand. This is crucial in capturing smooth rotations for the natural look of movements and in tasks requiring timing of rotational speed and precision; for example, the pouring of liquids.

4.1.4 Comprehensive Motion Analysis

Attaching EEG sensors to the scalp over the motor cortex and EMG sensors to the extensor and flexor muscles of the forearm provides valuable information from neural and muscular activity during the grasping process of different objects. However, to gain complete knowledge of hand movement, we have also placed IMU sensors on the hand at three different locations: the palm, forearm, and upper arm. This is the optimal sensor setting for capturing motion dynamics with high precision and therefore shall be combined with the source signals from EEG and EMG to attain high control over and accuracy in prosthetic hand movements. This robust approach can help the prosthetic device to simulate movements of the natural hand effectively and provide precision functionality in the user experience. This multisensory approach paints a rich picture and offers crucial advantages in prosthetic hand control, offering key insights into hand movements.

Spatial and temporal information extracted from IMU combined with neural activity recorded by EEG and muscular activation obtained by EMG allowed for a much more accurate prediction of intended hand motion. Further, real-time feedback from IMUs on hand position and movement can allow a user to correct the actions of the prosthetic hand into considerably smoother and more natural control. These combined data in the control algorithms design can adapt to each user's individual movement patterns, providing an enhanced response time to the prosthetic hand and making the whole reaching process much more intuitive and less effortful, reducing the user's cognitive load.

4.2 Set Up and Devices

4.2.1 OpenBCI for Recording EEG and EMG Data

We selected the OpenBCI system to collect EEG and EMG data. OpenBCI was chosen for its versatility, affordability, and high-quality data acquisition capabilities. The system is compatible with various sensors and offers customizable options, making it ideal for our research needs. It has a board named Cyton biosensing, which is an Arduino-compatible, 8-channel neural interface with a 32-bit processor that can sample EEG and EMG. Also, a dongle that is required to use the Ganglion board with a Mac, Windows, or Linux computer. It features Bluetooth 4.0 standards, a high-speed transfer rate, and simple pairing. OpenBCI's open-source nature allows for extensive customization and integration with other systems, which is crucial for our multi-modal data collection approach. Figure 4.1 shows the OpenBCI GUI while recording EEG and EMG data.

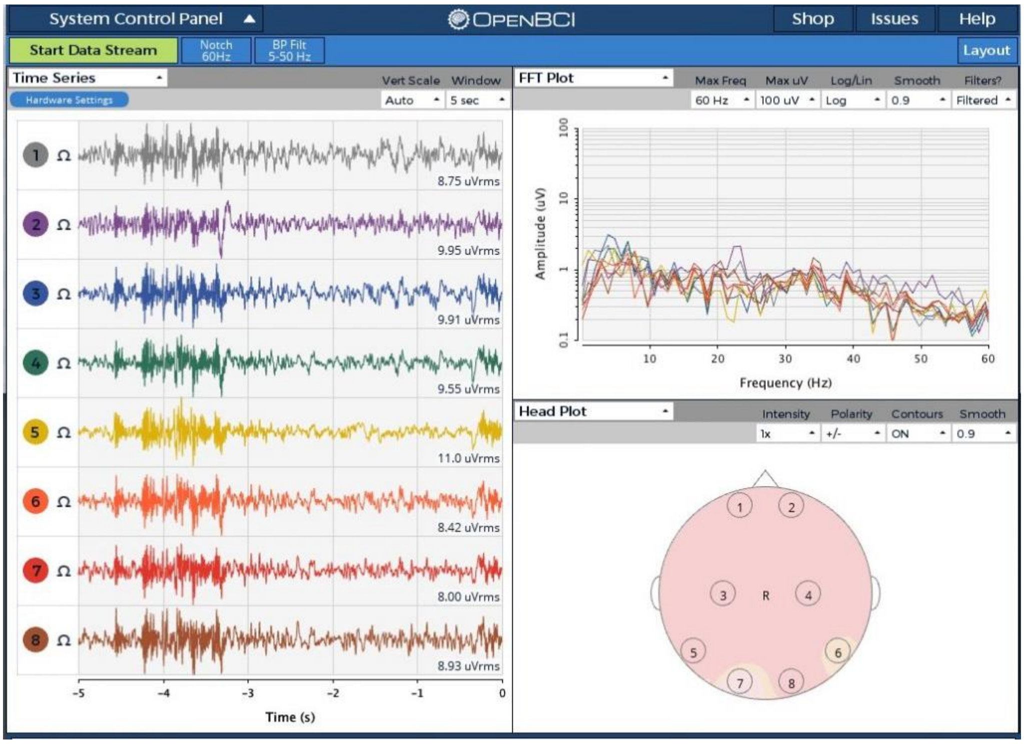

Figure 4.1 OpenBCI GUI for eight channel setups to record EEG and EMG siganls

The EEG signals were recorded using an Ultracortex-mark-IV EEG headset. The device is powered with several features to improve performance and usability. It has some place for sensors that are actually strategically located in a place in the motor cortex to pick up what might constitute relevant brain activity during a hand movement. The motor cortex is one critical area for motor control, and placing sensors there ensures that the most relevant signals will be picked. We recorded detailed high-resolution EEG data using an eight-channel setting. The use of multiple channels picks up a large part of neural activity, thereby enabling us to examine the details of the operation of the brain in overseeing hand movements in great detail. The headgear is designed to be comfortable, allowing subjects to wear it continuously without experiencing unease. This is particularly important for maintaining data quality over long recording sessions. (Figure 4.2)

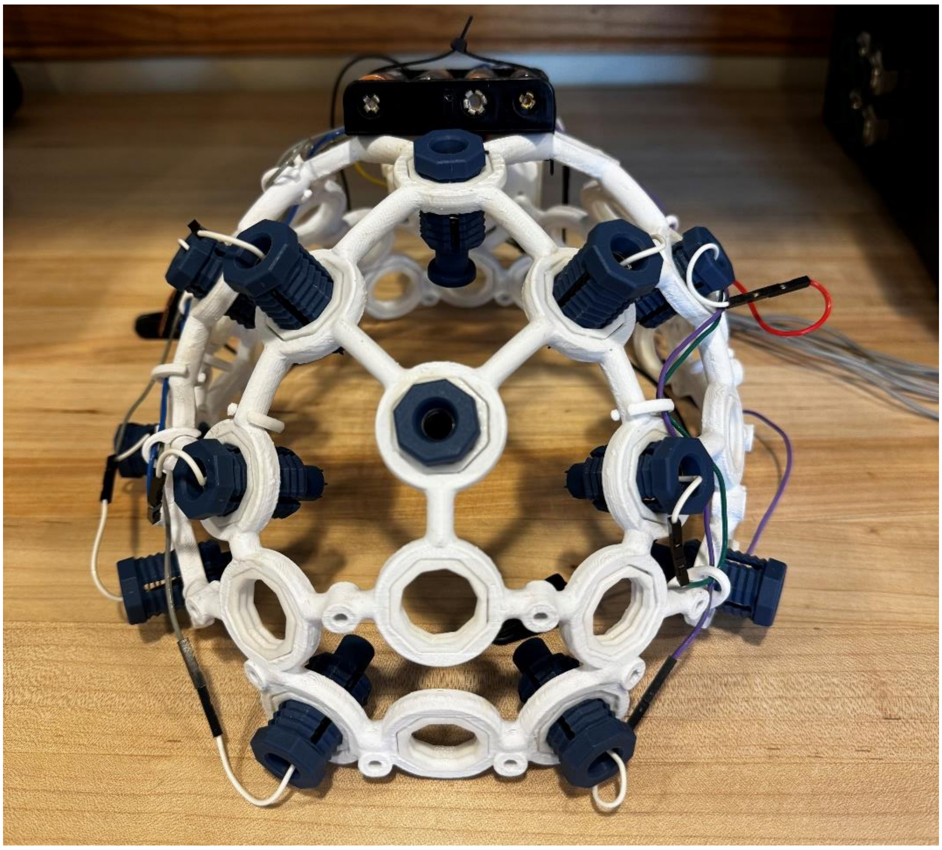

Figure 4.2 Ultracortex Mark IV EEG headset with EEG recording sensors

We recorded the EMG signals from the extensor and flexor muscles of the forearm through sensors using the OpenBCI system. The exact and reliable data taken from these muscles are critical to the analysis of the activities of muscles during several hand grasps. OpenBCI features a flexible implementation of EMG sensors, which simplifies the process of integrating and working with these sensors, Figure 4.3 demonstrates sensors placement for recording EMG signals, here elbow is the reference.

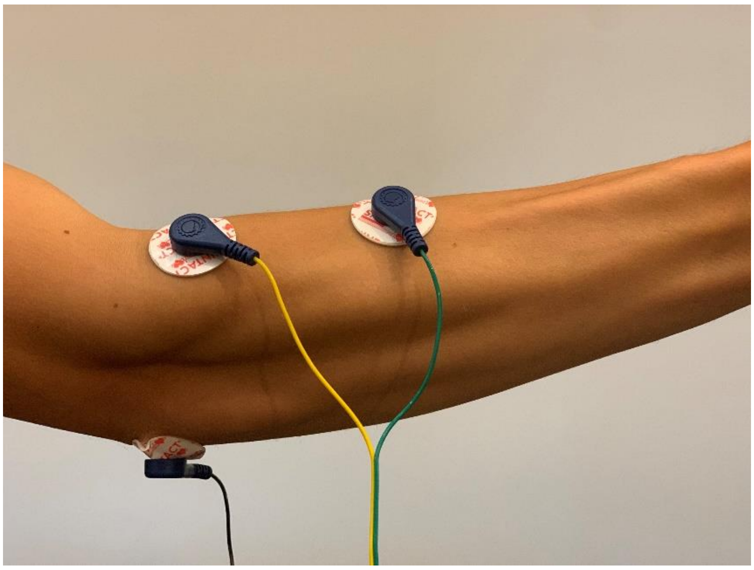

Figure 4.3 EMG sensors placement for recording muscle signals through OpenBCI setup [63]

This adaptability allows seamless customization to fit various research and application needs, ensuring that users can efficiently capture and analyze muscle activity data without encountering significant technical obstacles.

4.2.2 Witmotion Bluetooth IMU Sensors

IMU data were acquired by the Witmotion Bluetooth IMU sensors, providing angular velocity, angles, and acceleration data in three dimensions. The adopted IMU devices are embedded with a three-axis accelerometer and gyroscope, which makes it possible to gain high-resolution information on orientation and movement. The accelerometer is a device that measures linear acceleration, whereas a gyroscope captures rotational movement; thus, these two provide information on hand motion. Witmotion IMUs have Bluetooth connectivity, thus facilitating smooth data transmission and synchronization with other recording devices; this setup is thus not too complicated to reduce chances of data loss and interference. Besides, these inertial sensors are small, lightweight, and attach conveniently to parts of the body without interfering with the movement.

We chose three key locations on the hand: the palm, forearm, and upper arm. The reason for choosing these parts is that they show the dynamics of the hand while performing any task comprehensively. The palm sensor captures fine motor movements and subtle shifts in hand orientation. The forearm sensor provides information on the overall direction and velocity of the hand. The upper arm sensor captures broader motion patterns and contributes to understanding the relationship between upper and lower arm movements. By strategically placing sensors on these three locations, we ensure the collection of detailed and comprehensive motion data, enhancing the control and accuracy of prosthetic hand movements while grasping different objects in experiments.

Figure 4.4 illustrates the placement of IMU sensors and EMG sensors on a participant for data recording. The IMU sensors are positioned at three specific locations: the back of the hand, the forearm, and the upper arm. EMG sensors are placed on the extensor and flexor muscles of the forearm. This setup ensures comprehensive data collection, capturing the necessary information from multiple points to analyze muscle activity and movement accurately during various tasks.

Figure 4.4 IMU sensors and EMG sensors placements for recording data

4.2.3 Custom Graphical User Interface (GUI)

A custom-made graphical user interface was designed in order to be able to exactly coordinate and synchronize collection of EEG, EMG, and IMU data. We were able to start and pause the recording of all data streams with creating this interface, as it was an integral part of our experimental setting. This GUI allowed us to define the recording process in such a way that during the performance of tasks, all data was correctly synchronized and perfectly aligned during recording. This was a very critical component in preserving data integrity and improving the efficiency of our data collection exercise, Figure 4.5.

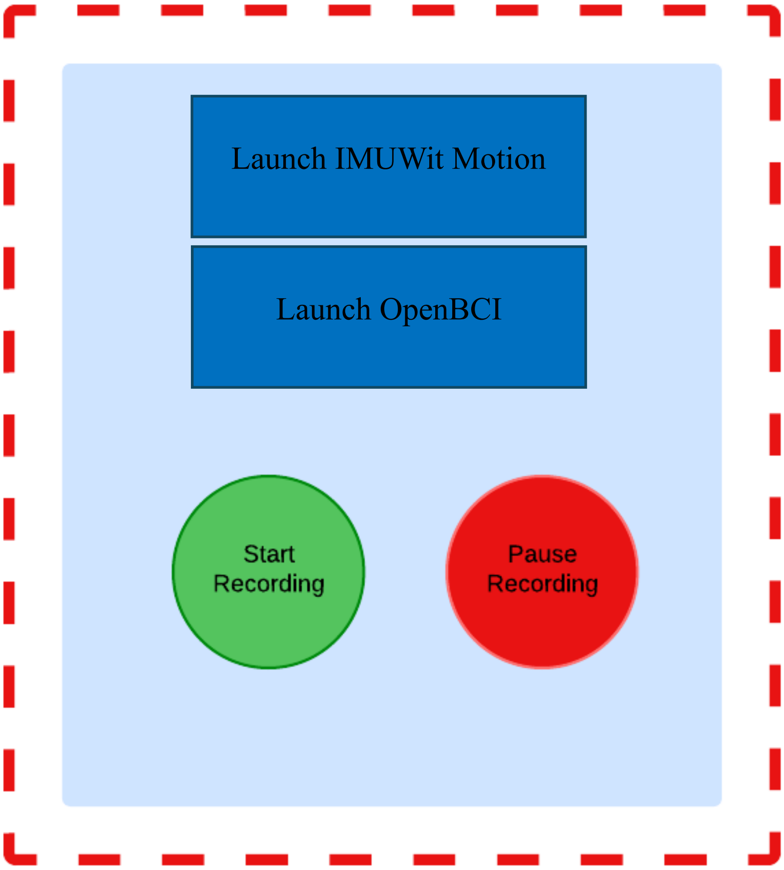

Figure 4.5 Proposed GUI for launching devices simultaneously

Our custom GUI served as a central point, alleviating the challenge of individually operating all devices that record data: EEG, EMG, and IMU. In this way, we were able to start, monitor, and stop recordings for all of these devices from a single, unified interface. This reduced the data collection procedure to the minimum possible complexity with minimal possible human error in the crucial moments of recording. The GUI offered an exact synchronizing of data acquisition on all three recording devices. It provided sending start and stop commands simultaneously, which guaranteed that data collection for EEG, EMG, and IMU for each subject started and stopped at the same moment. This is a very high level of precision in synchronization that was very important to achieve because we had to analyze and compare data from all three sources for each exact moment of the execution of a certain task by each participant.

This synchronized data collection process further allowed us to see possible relationships between these various data streams. For example, the GUI will allow us to see if there is a spike in EEG activity when a subject is performing some task and whether this spike is combined with a change in the EMG data or how the IMU sensor readings behave at that same moment. Such connections could be unearthed by carefully examining the synchronized data to understand in depth how these physiological and motion-related signals interplayed with one another.

4.2.4 Data Collecting Protocol

The Institutional Review Board of the University of Tennessee at Chattanooga (FWA00004149) has approved this research project #23-111. All participants freely volunteered to participate and signed a consent form.

In this work, we conducted a study on 13 participants, each performing seven different grasping tasks in varied scenarios. The range of tasks was chosen to represent the most common hand grasps in daily activities. To ensure realism and practicality, specific objects were used that closely approximate real-world scenarios. Figure 4.6 demonstrates all seven objects for the experiments. The chosen tasks included:

- Power Grasp: Holding a hammer tightly and firmly to hit an object. This type of grasp requires significant force and coordination, primarily engaging the forearm muscles.
- Precision Grasp: Holding a pen for highly precise, fine motor actions. This grasp engages fine motor skills and coordination between the thumb and fingers, essential for tasks such as writing and detailed work.
- Lateral Grasp: Grasping a key in a way that simulates inserting and turning it. This grasp involves the thumb and the side of the index finger, representing an action that requires lateral pinch strength.
- Hook Grasp: Carrying a suitcase to simulate a grasp where the fingers form a hook, excluding the thumb. This type of grasp is suitable for carrying heavy weights for extended periods, engaging the flexor muscles of the fingers.

- Pinch Grasp: Holding a small cube to describe the handling of small items between the thumb and one or more fingers. This grasp is crucial for tasks that require fine precision and control, typically when holding small objects.
- Cylindrical Grasp: Holding a bottle to simulate the grasp of cylindrical objects. This is common in everyday life, such as when holding a drink, and it engages coordination and strength in all fingers and forearm muscles.
- Spherical Grasp: Grasping a ball to represent the grasp of spherical objects. This type of grasp involves the whole hand and is useful for various activities that require encompassing and holding round objects securely.

These tasks were selected to provide a comprehensive representation of hand movements and grasps, capturing the variability in human hand use in daily life. We aim to accommodate a wide array of functional demands by including tasks that differ in complexity and required grasp type.

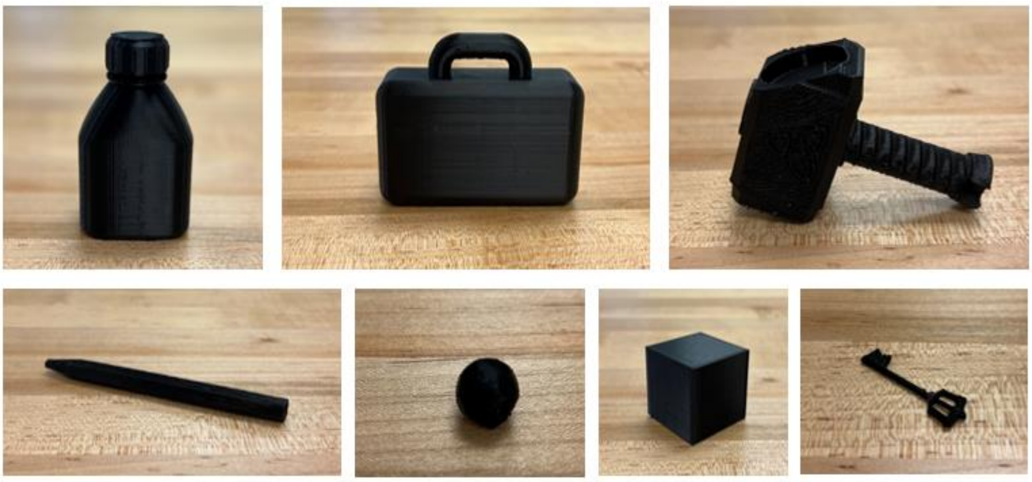

Figure 4.6 Objects used in the biomechatronic lab to generate hand-grasping UTC dataset

We attached the EEG headset to the participant's scalp, the EMG sensor to the participant's forearm muscle, and the IMU sensors to the palm, forearm, and arm, see Figure 4.7. The task protocol involved 5 seconds of grasping followed by 5 seconds of release, repeated continuously for the duration of one minute. We asked each participant to perform each grasping task for one minute. This protocol ensured consistent and repeatable data collection across all participants and tasks. The repetition of the grasp and release cycle provided a rich dataset for analyzing the dynamics of hand movements and muscle activity.

Figure 4.7 Placement of EEG, EMG, and IMU sensors for collecting data from participant

We recorded EEG, EMG, and IMU data simultaneously during the tasks. By implementing this custom GUI, we ensured that all data streams were initiated and terminated precisely simultaneously, maintaining perfect temporal alignment. This level of synchronization was crucial for our analysis, as it allowed us to correlate neural, muscular, and motion data accurately, leading to more robust and reliable findings in our study of hand grasping orientation for prosthetic hand control. The GUI enhanced the efficiency of our data collection process and significantly improved the quality and reliability of the collected data.

The collected data were then processed and analyzed to develop and fine-tune our proposed predictive models for hand-grasping orientation, ultimately enhancing the control strategies for prosthetic hands. The synchronized data collection and comprehensive feature extraction were critical for the accuracy and reliability of our models. The comprehensive collection of EEG, EMG, and IMU data using advanced devices like the OpenBCI system and Witmotion IMU sensors provided a robust dataset for our research. This meticulous approach to data collection and the use of sophisticated tools were pivotal in achieving the goals of our study on predicting hand-grasping orientation for prosthetic hand control. Integrating multiple data sources allowed us to capture the full complexity of hand movements, leading to more accurate and responsive prosthetic control systems.

CHAPTER 5

METHODOLOGY

5.1 The Transformative Role of AI and ML in Prosthetic Hand Control

Artificial Intelligence (AI) and Machine Learning (ML) have brought groundbreaking advancements to prosthetics, particularly in developing and controlling prosthetic hands. By integrating AI and ML, researchers and engineers are creating intelligent prosthetic devices that can seamlessly interpret and respond to the user's neural and muscular signals. This integration results in a more natural and intuitive user experience, allowing individuals to regain functionality and independence. AI and ML algorithms play a pivotal role in personalizing prosthetic control. These algorithms can learn and adapt to users' unique neural and muscular signal patterns. Over time, this adaptive learning process enhances the precision and efficiency of the prosthetic hand's movements, making it more responsive to the user's intentions. Such personalization is crucial for prosthetics to effectively assist users in various daily activities, from simple tasks like grasping objects to more complex actions requiring fine motor skills.

The adaptability of AI and ML in prosthetic devices improves the prosthetic hands' functionality and significantly enhances the user's quality of life. By providing a prosthetic hand that responds accurately and swiftly to the user's commands, AI and ML technologies help users perform everyday tasks with greater ease and confidence. This technological advancement leads to increased independence and a better overall experience for individuals relying on prosthetic hands. Incorporating AI and ML in prosthetic hands represents a significant technological leap forward. These advanced systems not only mimic natural hand movements but also adapt to the user's specific needs, ensuring a higher level of precision and control. As AI and ML continue to evolve, their role in prosthetic hand control will undoubtedly expand, offering even more sophisticated solutions to enhance the lives of individuals with limb loss.

5.2 Data Collection and Preprocessing

5.2.1 Data Collection

In this work, we focus on the collection of three kinds of data: EEG, EMG, and IMU signals. The data were recorded simultaneously from 13 subjects while executing seven different grasping tasks with specific objects. This includes power Grasp executed with a hammer, precision grasp executed with a pen, lateral grasp performed with a key, hook grasp executed with a suitcase, pinch grasp performed with a small cube, cylindrical grasp performed with a bottle, and spherical grasp performed with a ball. Each gesture was performed for 1 minute and included 5 seconds of grasp, followed by 5 seconds of release, in a continuous cycle.

We engineered a custom-made GUI, which provided a means of sending the start and stop commands to all devices simultaneously so that all data streams would be precisely aligned. We have used this GUI, as key to keeping the temporal alignment of EEG, EMG, and IMU data for later analysis and interpretation. Chapter 4 provides more details.

5.2.2 Data Preprocessing

Some preprocessing steps are essential to optimizing our ML model's performance before feeding it data.

- Average Filtering

Noise or random fluctuations in real-world data often hide the real patterns, hence affecting the ability of ML to learn meaningful features. One such technique in eliminating noise from the data to reveal underlying trends is average filtering, also referred to as moving average filtering. It does this by determining the average of various specified data points within a sliding window moving across the whole data sequence. This averaging process helps to suppress the process of averaging over these random fluctuations and gives a clearer view of the core information in the data.

- Normalization

Normalization scales the data to a specific range between 0 and 1. This ensures that all features in our dataset contribute equally to the training process. Larger-scale features could dominate the learning process without normalization, leading to suboptimal results. The ML model can effectively focus on learning the underlying relationships between all features by scaling everything to a similar range.

- Data Cleaning

One of the critical steps is data cleaning, which guarantees the quality and reliability of our analysis. Such a step involves the detection of errors, inconsistencies, or irrelevant data points within our dataset. Among the most critical cleaning tasks are those on missing values, which arise when data points were not recorded or collected, and on handling artifacts, which are spurious elements regarding the phenomenon under study. These views can result from technical errors or data collection or processing failures. Artifacts like these are removed after identification to ensure the accuracy and integrity of our data.

By performing these preprocessing steps, we significantly improve our data quality and prepare it for effective feature extraction using our proposed model.

5.3 Brief Overview of Basic Machine Learning Methods Used in Proposed Model

5.3.1 Autoencoder Model

The auto-encoders are neural networks designed for efficient learning in representations, usually for the purpose of reducing dimensionality or de-noising. Their main advantage in the extraction of features via auto-encoders is that students can learn nonlinear transformations by capturing the underlying structure of the data. This will be done through a two-part structure comprising an encoder and a decoder.

The first network is called an encoder, which takes in input data and progressively compresses it through a lower dimensional representation known as the latent space. Such compression often happens via multiple slated artificial neurons. Every layer of this encoder transforms the data while it captures all the most essential features and passes on less important information. It does this by progressively reducing the dimensionality to capture a compressed version of the input data that contains the essential characteristics necessary for reconstruction.

The decoder picks up where the encoder left off, performing the opposite operation. In most cases, it receives latent space representation and later tries to reconstruct this input. The architecture of this decoder usually mirrors the structure of the encoder but in reverse. It uses multiple layers of neurons to gradually increase the dimensionality of the data until it is fully restored. By comparing this reconstructed output with the initial input, an autoencoder learns and self-modifies the internal parameters for better accuracy of the latent space representation. Figure 5.1 demonstrates the architecture of the basic autoencoder.

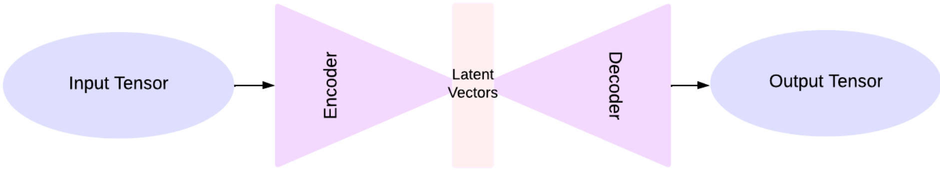

Figure 5.1 Basic Autoencoder architecture, including encoder and decoder

The encoder takes the input data x, and maps it to a latent representation, z, through a series of transformations. Mathematically, this can be expressed as:

$$z = f_{encoder}(x) \tag{5-1}$$

Where $f_{encoder}$ represents the encoding function, typically composed of linear transformations followed by non-linear activation functions.

The decoder takes the latent representation z and attempts to reconstruct the original input $\hat{x}$:

$$\hat{x} = g_{decoder}(z) \tag{5-2}$$

where $g_{decoder}$ represents the decoding function.

Training: The autoencoder is trained to minimize the reconstruction error, which measures the difference between the input x and the reconstructed output $\hat{x}$. Common loss functions include mean squared error (MSE) and binary cross-entropy:

$$L(x,\hat{x}) = \|x - \hat{x}\|^2 \tag{5-3}$$

The training process involves adjusting the weights of the encoder and decoder to minimize this loss.

- Feature Extraction Using Autoencoders

In feature extraction, the primary goal of using an autoencoder is to obtain a compressed representation z that captures the most important features of the input data. This latent representation can be used for feeding our next step of our proposed model.

- Advantages of Autoencoder-Based Feature Extraction

Autoencoders offer several advantages over traditional methods of feature extraction from data. Most real-world datasets indicate complex relationships that are pretty hard to capture by linear methods like PCA. In contrast, autoencoders can learn nonlinear relationships in the data. This speeds up the process of compressing data into a lower-dimensional representation while keeping central information required for procedures such as classification or clustering. These nonlinearities are very well-captured by the autoencoder method, resulting in a more expressive and informative set of features for our model.

Real-world data is often full of noise or irrelevant information. An autoencoder is readily trainable to act as a denoising filter. The training process puts pressure on the autoencoder to develop representations in which essential information is captured, and then it discards noise from the input data. During feature extraction, the autoencoder acts as a pre-processing step that makes available cleaner and more robust features for our main model.

5.3.2 Transformer Model

The Transformer model, introduced by Vaswani et al. in their paper "Attention is All You Need" in 2017, has already made many changes in the area of natural language processing (NLP), becoming broadly applicable for many varied tasks with sequential data. Unlike traditional recurrent neural networks (RNNs) and long short-term memory networks (LSTMs), the Transformer relies entirely on attention mechanisms in its core of sequence handling and thus makes it parallelizable without pitfalls such as long-term dependences and vanishing gradients.

- Transformer Architecture

The Transformer architecture consists of an encoder and a decoder, each composed of a stack of identical layers. The encoder processes the input sequence and generates a set of continuous representations, while the decoder uses these representations to produce the output sequence, see Figure 5.2.

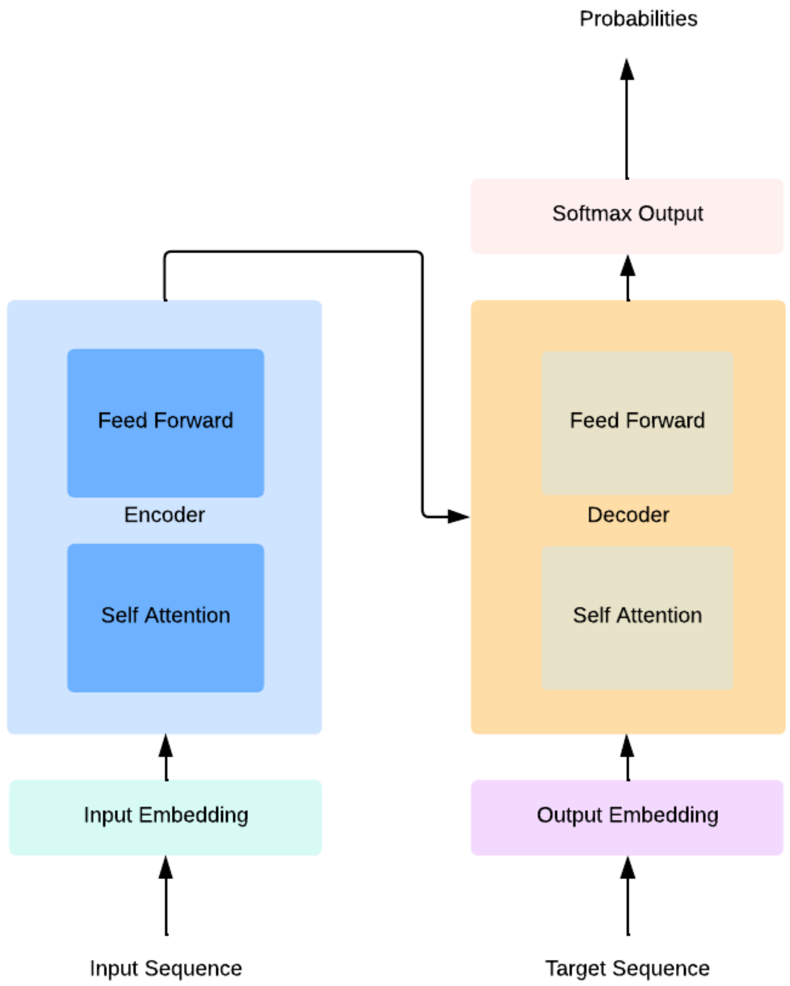

Figure 5.2 The main architecture of the Transformer model

- Encoder

The encoder transforms an input sequence into a sequence of continuous representations. Each encoder layer consists of two main components: multi-head self-attention and a feed-forward neural network, with residual connections and layer normalization applied to both. The self-attention mechanism allows each position in the input sequence to attend to all other positions, providing context for each word. Scaled dot-product attention is the fundamental building block of the attention mechanism. For a given input sequence, it computes attention scores mathematically as follows:

$$\text{Attention}(Q, K, V) = \text{softmax}\left(\frac{QK^T}{\sqrt{d_k}}\right)V \tag{5-4}$$

- Computing the dot products of the query (Q) with all keys (K).

- Scaling the dot products by ($\sqrt{d_k}$) (the dimension of the keys) to prevent the gradient from becoming too small for large (d_k).

- Applying a softmax function to obtain attention weights.

- Multiplying the attention weights with the value vectors (V) to get the final output.

Instead of performing a single attention function, multi-head attention splits the queries, keys, and values into multiple heads, performs scaled dot-product attention in parallel, and concatenates the results. This allows the model to focus on different parts of the sequence simultaneously. So, mathematically:

$$\text{MultiHead}(Q, K, V) = \text{Concat}(\text{head}_1, \text{head}_2, \dots, \text{head}_h)W^O \tag{5-5}$$

where each head is computed as:

$$\text{head}_i = \text{Attention}\left(QW_i^Q, KW_i^K, VW_i^V\right) \tag{5-6}$$

Each sub-layer is followed by a residual connection and layer normalization to stabilize training. This means that the input to the sub-layer is added to its output before normalization:

$$\text{Output} = \text{LayerNorm}\left(X + \text{SubLayer}(X)\right) \tag{5-7}$$

Each position in the sequence is passed through a fully connected feed-forward network independently and identically. This network consists of two linear transformations with a ReLU activation in between:

$$\text{FFN}(x) = \max(0, xW_1 + b_1)\, W_2 + b_2 \tag{5-8}$$

- Decoder

The decoder generates the output sequence one token at a time, using the encoder's continuous representations and previously generated tokens. The decoder has several mechanisms. The multi-head self-attention mechanism is similar to the encoder's but with a mask applied to prevent attending to future tokens. This ensures that the prediction for each position depends only on known outputs. Also, multi-head attention over encoder's output allows the decoder to attend to all positions of the encoder's output, providing the necessary context for generating the next token in the sequence. Feed-forward neural network is identical to the one used in the encoder, it is applied to each position independently. Residual connection and layer normalization are as in the encoder, each sub-layer in the decoder is followed by a residual connection and layer normalization.

- Attention Mechanism

The attention mechanism is the core innovation of the Transformer, allowing the model to weigh the importance of different parts of the input sequence dynamically.

- Queries, Keys, and Values

The input sequence is linearly transformed into three matrices: (Q) (queries), (K) (keys), and (V) (values).

- Scaled Dot-Product Attention

For each position in the sequence, attention scores are computed by taking the dot product of the query with all keys, scaling by $(\sqrt{d_k})$, applying the softmax function, and multiplying by the value vectors.

- Positional Encoding

Since the Transformer does not inherently capture sequence order, positional encodings are added to the input embeddings to provide information about the position of each token. Positional encodings are generated using sine and cosine functions of different frequencies:

$$\mathrm{PE}(pos, 2i) = \sin\left(\frac{pos}{10000^{2i/d_{model}}}\right) \quad (5\text{-}9)$$

$$\mathrm{PE}(pos, 2i+1) = \cos\left(\frac{pos}{10000^{2i/d_{model}}}\right) \quad (5\text{-}10)$$

where (pos) is the position and (i) is the dimension.

The Transformer architecture has been game-changing in the field of NLP and beyond. One of the greatest strengths of Transformers is their parallelization ability. Unlike RNNs, which process data sequentially, there are no recurrent connections within Transformers. This feature enables the whole sequence to be processed in parallel, dramatically increasing the speed of training and inference. Compare this to a Transformer, which can process all the words together and dramatically reduces processing time. It makes the Transformer very suitable for large-scale NLP tasks where processing speed matters.

It has the key strength of easily handling long-range dependencies in a single sequence. For this very capability, it leverages a mechanism called self-attention. While RNNs and

LSTMs have to bear the overhead of learning the behavior of relationships of distant words in a sequence, Transformers are capable of relating all positions to one another. It enables the model to understand how different words relate to one another, even if they are far apart in the sequence. This long-range relationship understanding capability empowers the transformers to maintain a deeper understanding of the context and meaning within a sequence.

On top of this, the transformers model not only speed and long-term dependency but are highly scalable. Their architecture makes them scale well with an increased amount of data and computational resources. This puts the transformer in a special position with respect to large-scale NLP applications such as Machine Translation, which involves dealing with vast texts to develop effective models, and being deeply computational resource-hungry, will soon, with the ever-increasing computation at hand, kick off into more complex NLP tasks.

Though developed originally for natural language processing, transformers have shown great promise in handling sequential data since they are very effective at catching long-range dependencies and context. These traits make the transformer very appropriate to process EEG, EMG, and IMU data containing complex temporal sequences.

Transformers use what is called self-attention, a mechanism that works in a self-directed way to weigh the importance of parts of the input sequence. This allows the model to focus on relevant parts of the data, no matter their position in the sequence. In this respect, transformers in EEG data analysis could model these long-range dependencies between brain signals, which would provide a much more holistic view of brain activity and thus an enhanced ability to decode with higher accuracy the user's intent. Similarly, muscle activation patterns vary a lot over time in the case of EMG data. In this respect, transformers can handle these variations and provide better accuracy in muscle activity recognition. For IMU data, containing sequences of motion and orientation data, transformers can track these long-range dependencies to sustain more precise motion analysis and control.

EEG signals themselves are highly dynamic and possess complex temporal patterns. Since transformers can attend to those most relevant parts in the sequence, they process these complicated patterns and thus better interpret brain states. In a similar vein, the timing and intensity of muscle contractions in the EMG data are very variable. With transformers that can process complex temporal sequences, they can easily and justly process the signal of the muscles. Similarly, IMU signals contain complex movement and rotation patterns. These sequences are effectively parsed by a transformer and enable an exact understanding of motion dynamics. There is an ease of contamination of noise in EEG signals that emanates from many sources, which often causes considerable interference during data analysis. The transformer, being essentially a self-attention mechanism, selectively pays attention to the major part of the signal and thereby reduces the effect of noise on the results. EMG can also be contaminated with electrical noise or cross-talk between different muscles. The self-attention mechanism provides some inherent features that help isolate relevant signals from noise. Not to say that the IMU signals are completely immune to noise, most of those could originate from many environmental and sensor drift-related factors. Such properties, which emphasize key data points in the cases, increase their strength with respect to motion analysis.

Traditional sequential models process the data one step at a time; this may be slow if the length of the sequences in question is large. In contrast to this, one of the main differences is that a Transformer processes the whole sequence in a single go. This shall gain an upper hand by getting faster computation, hence setting a foundation for real-time analysis in sensor data applicable to EEG, EMG, and IMU data processing.

One of the main advantages of transformers is that they are highly scalable, and their performance improves as long as they are trained on large enough datasets. Intrinsic scalability is a critical virtue for the creation of robust models with good generalizability to different subjects or conditions, which is very important in EEG, EMG, and IMU data processing applications. Besides, integration inside the processing pipeline of EEG, EMG, and IMU data opens further perspectives toward prosthetic control by these developments.

Transformers demonstrate exceptional ability in modeling long-range sensor dependencies and complex temporal patterns. Improved understanding translates into more accurate decoding, hence improved control of user intents. Prosthetic control will then be more accurate and responsive, letting users interact more naturally with the world.

In reasoning, however, the conventional modes of processing cannot meet the real-time demands, while with parallelization enshrined in Transformers, it is faster in analysis. This makes the control for prosthetics much smoother and responsive to user input, thereby significantly enhancing the user experience.

5.3.3 Artificial Neural Network in Classification

Artificial Neural Networks (ANNs) have become a cornerstone in machine learning, particularly excelling in classification tasks. Their ability to learn complex patterns and relationships from data makes them ideal for predictive analytics and classifications.

- Structure of an Artificial Neural Network

An ANN is essentially a network of interconnected nodes or 'neurons' arranged in layers. These include the input layer, one or more hidden layers, and finally, the output layer, see Figure 5.3. Each neuron thus acts like a biological neuron and processes the signals and passes them on in the network.

Initial data is fed into the input layer. Each neuron of this layer relates to an attribute or feature in the dataset. Hidden layers are between the input and output layers; they introduce nonlinearity into a network and nonlinearly transform inputs. Two important parameters, depth (number of layers) and width (number of neurons in each layer), have much to do with the learning ability of the network. The output layer is the last layer, which produces the result of classification. It mostly includes one neuron with a sigmoid activation function for binary classification. For multi-class classification, it contains several neurons with a softmax activation function to give probabilities for each class.

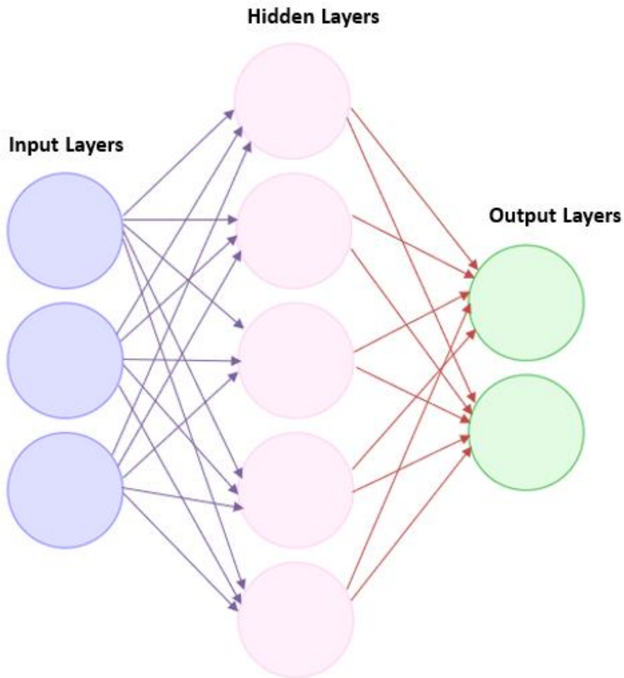

Figure 5.3 The main architecture of Artificial Neural Network (ANN)

- ANN Working Mechanism

The working mechanism of an ANN in classification involves three main processes: forward propagation, loss calculation, and backpropagation.

- Forward Propagation

1. Activation Function: Each neuron applies an activation function to its input to introduce nonlinearity, enabling the network to learn complex patterns. Common activation functions include ReLU (Rectified Linear Unit), sigmoid, and tanh.

2. Weighted Sum: Each neuron computes a weighted sum of its inputs, adds a bias term, and applies the activation function:

$$z = \sum_i w_i x_i + b \tag{5-11}$$

$$a = \sigma(z) \tag{5-12}$$

where (z) is the weighted sum,(w_i) are the weights, (x_i) are the inputs, (b) is the bias, and (σ) is the activation function.

3. Layer-wise Processing: The output of each neuron in a layer becomes the input for neurons in the subsequent layer, propagating the signal forward through the network until the output layer.

- Loss Calculation

The loss function measures the difference between the predicted output and the actual target. Common loss functions for classification include cross-entropy loss for binary and multi-class classification:

$$L(y, \hat{y}) = -\frac{1}{N}\sum_{i=1}^{N}[y_i \log(\hat{y}_i) + (1 - y_i)\log(1 - \hat{y}_i)] \tag{5-13}$$

where (y) is the true label, ($\hat{y}$) is the predicted probability, and (N) is the number of samples.

- Backpropagation

1. Gradient Descent: The network uses gradient descent to minimize the loss function. It calculates the gradient of the loss function with respect to each weight and bias by applying the chain rule of calculus backward through the network.

2. Weight Update: Weights and biases are updated using the gradients to reduce the loss:

$$w \leftarrow w - \eta \frac{\partial L}{\partial w} \tag{5-14}$$

$$b \leftarrow b - \eta \frac{\partial L}{\partial b} \tag{5-15}$$

where (η) is the learning rate, controlling the step size in the optimization process.

3. Epochs and Iterations: The process of forward propagation, loss calculation, and backpropagation is repeated over multiple epochs and iterations until the network converges to a minimal loss value.

ANNs dominate the world of classification tasks, since their key feature of learning complex patterns and relationships between data elements makes them very efficient for numerous applications.

What sets ANNs apart from much simpler statistical models is the ability to model nonlinear relationships between input data and the desired outputs. This is a result of nonlinear activation functions within a network's hidden layers. Nonlinear activation functions introduce nonlinearity into the network, so it can capture the more subtle patterns and interactions among inputs that have a chance of getting missed by linear models.

Another of the main advantages of ANNs is that they are capable of learning relevant features from raw data with little intervention. On the other hand, ANNs learn such features inherently from the training data. This obviates the need to use predefined features and frees the network from finding the most relevant patterns for any given classification task.

One of the main strengths is flexibility in the type and structure of data. Successful developed applications range from numeric analysis to image and text processing, which makes it very versatile and helpful in many other fields. For instance, one ANN classifies emails as spam or not according to its textual content, while another ANN classifies images of flowers based on their visual appearance under different types of flowers.

One of the important viewpoints about classification models is to have the ability to generalize well on new and unseen data. A common pitfall here is overfitting, when the model learns the noise, that is, it memorizes specific details of the training data but fails on new data. In this regard, ANNs can inherently handle this type of problem by using regularization techniques either through dropout or L2 regularization. These techniques prevent the model from turning overly complex and focus on learning generalizable patterns that hold true for a broader range of data. ANNs offer omnipotent and versatile approaches toward classification tasks. They model complex relationships, learn features automatically, and handle very diverse data types, generalizing well. Thus, ANNs are transforming various industries and shaping the future for data-driven decision-making.

5.4 Proposed Model

In this experiment, we consider the datasets obtained from three modalities: EEG, EMG, and IMU. Since all these modalities result in highly dimensional and complex datasets, it becomes very challenging to predict the hand grasping orientation. Figure 5.4 to Figure 5.10 present examples of EEG and EMG signals, while Figure 5.11 and Figure 5.12 display IMU data signals recorded from participants, highlighting the complex nature of these signals during various tasks.

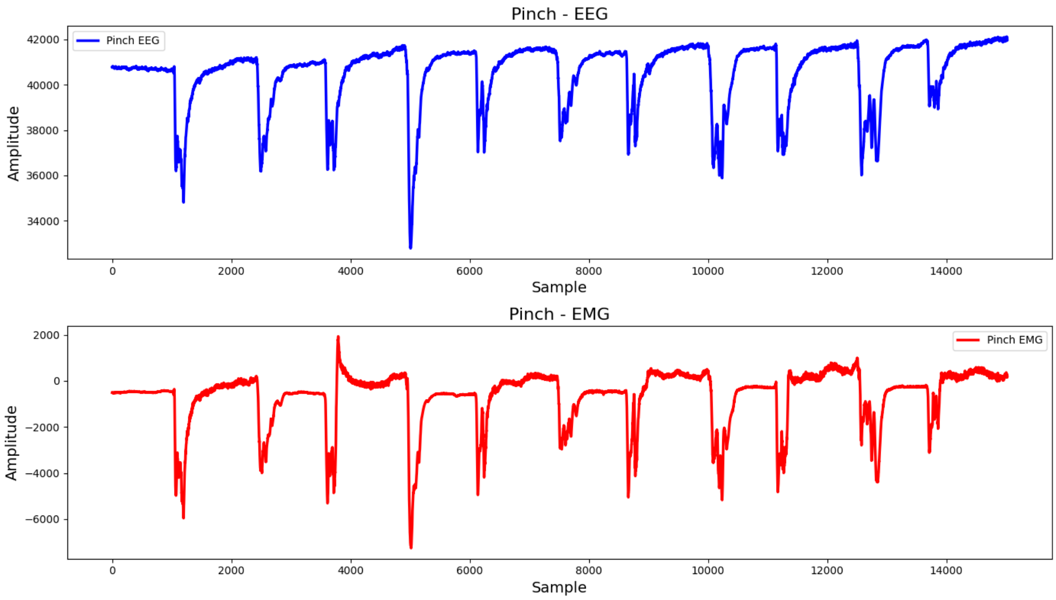

Figure 5.4 Sample of EEG and EMG signals of pinch grasping

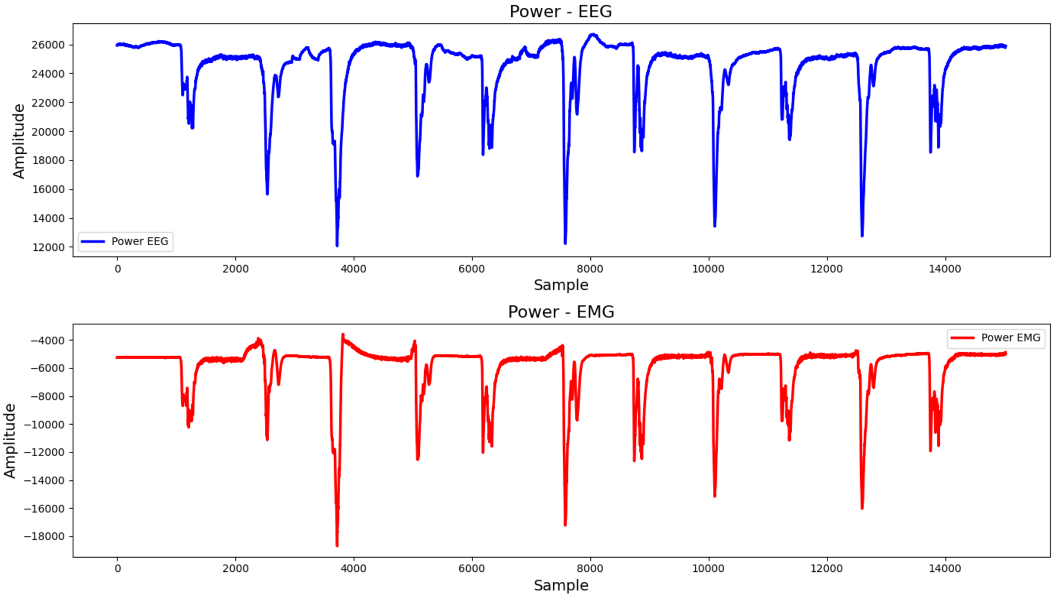

Figure 5.5 Sample of EEG and EMG signals of power grasping

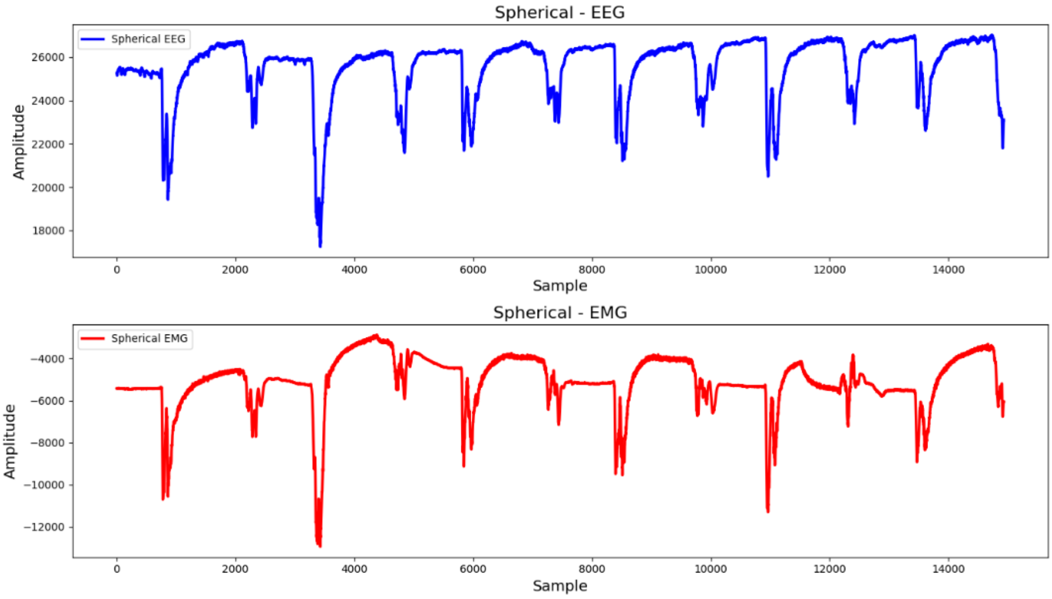

Figure 5.6 Sample of EEG and EMG signal of spherical grasping

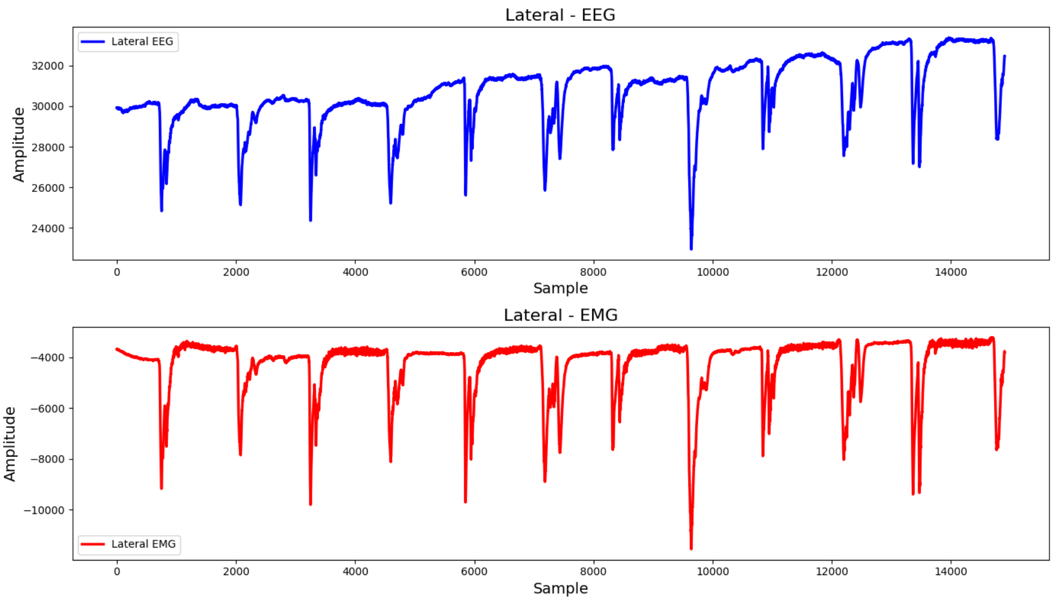

Figure 5.7 Sample of EEG and EMG signals of lateral grasping

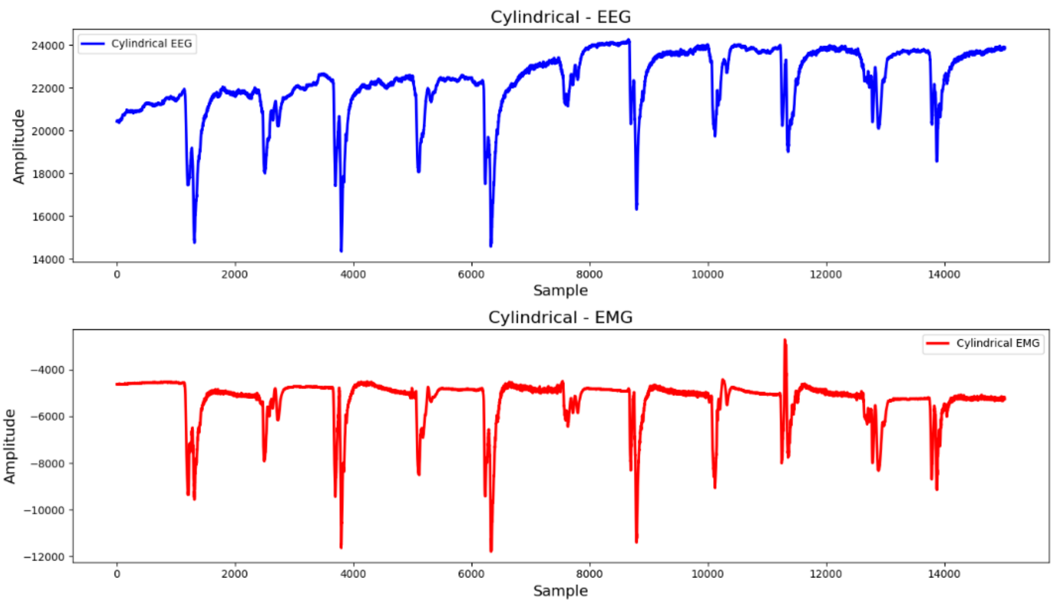

Figure 5.8 Sample of EEG and EMG signals of cylindrical grasping

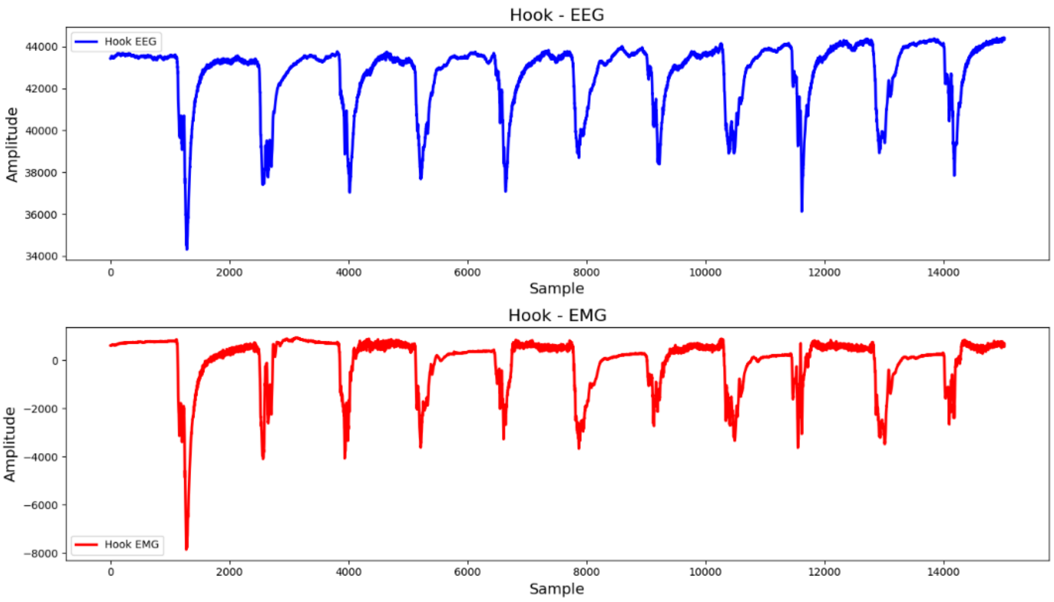

Figure 5.9 Sample of EEG and EMG signals of hook grasping

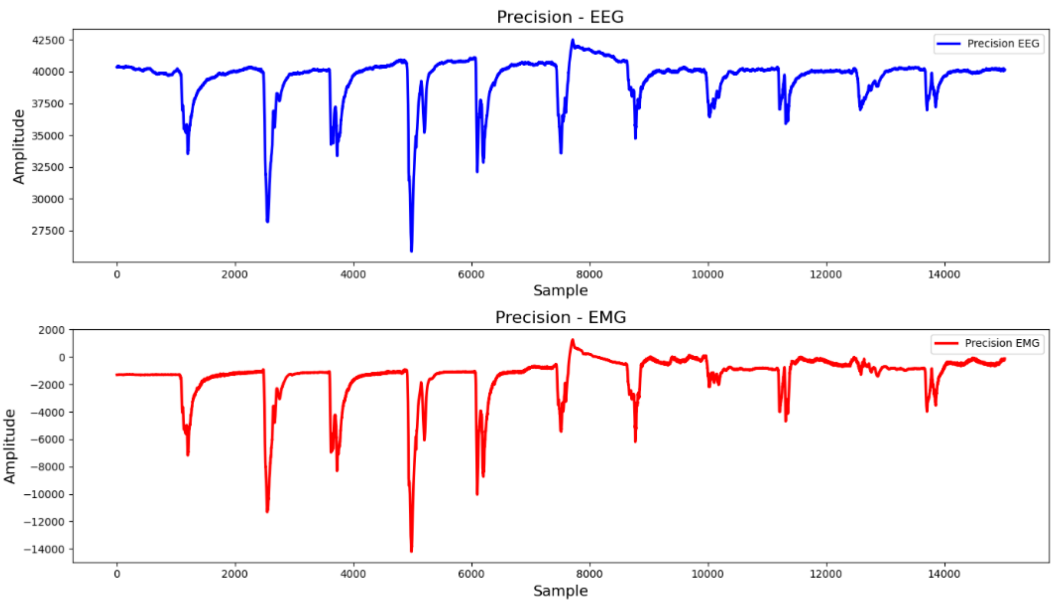

Figure 5.10 Sample of EEG and EMG signals of precision grasping

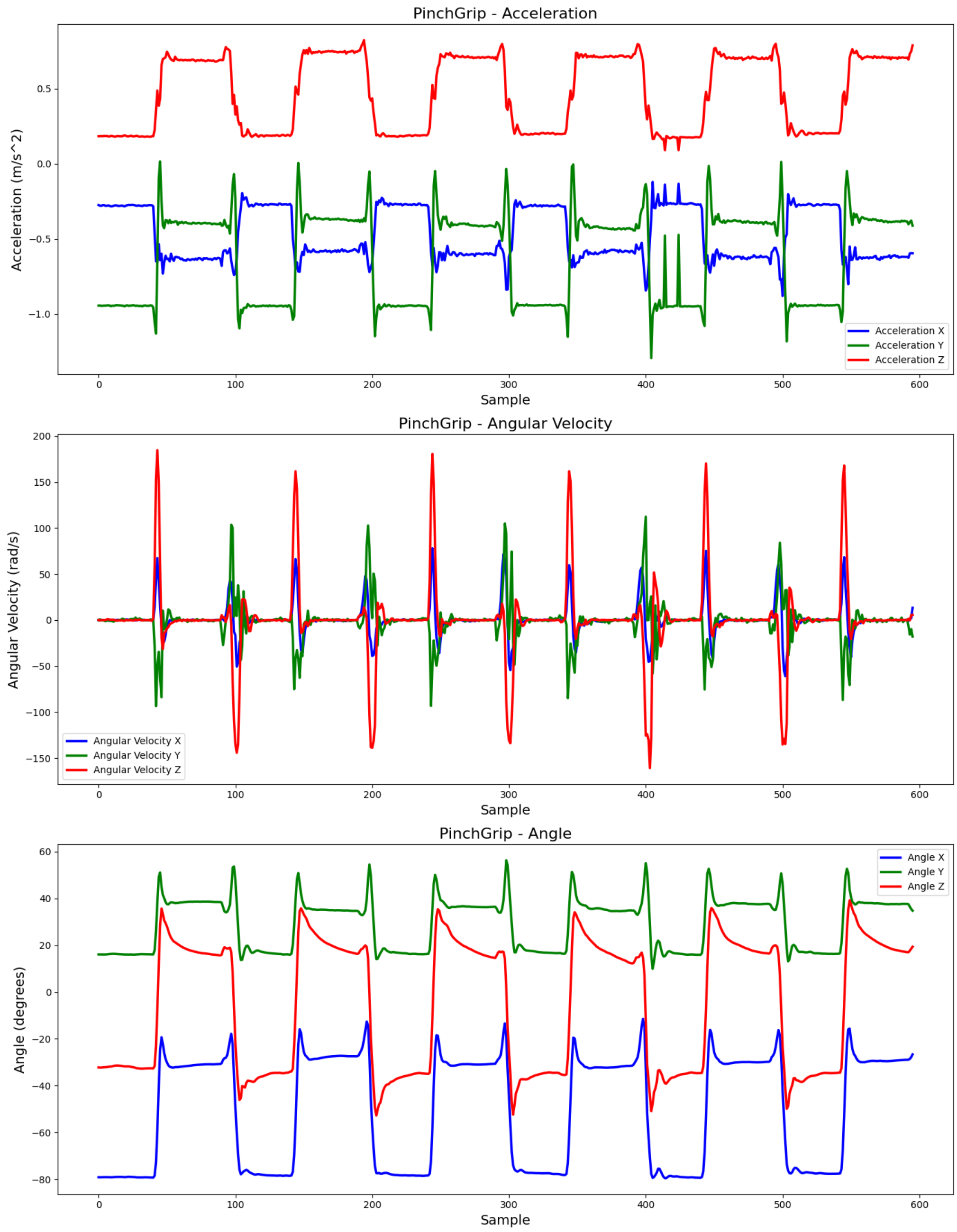

Figure 5.11 Acceleration, angular velocity, and angle in IMU signals for pinch grasping

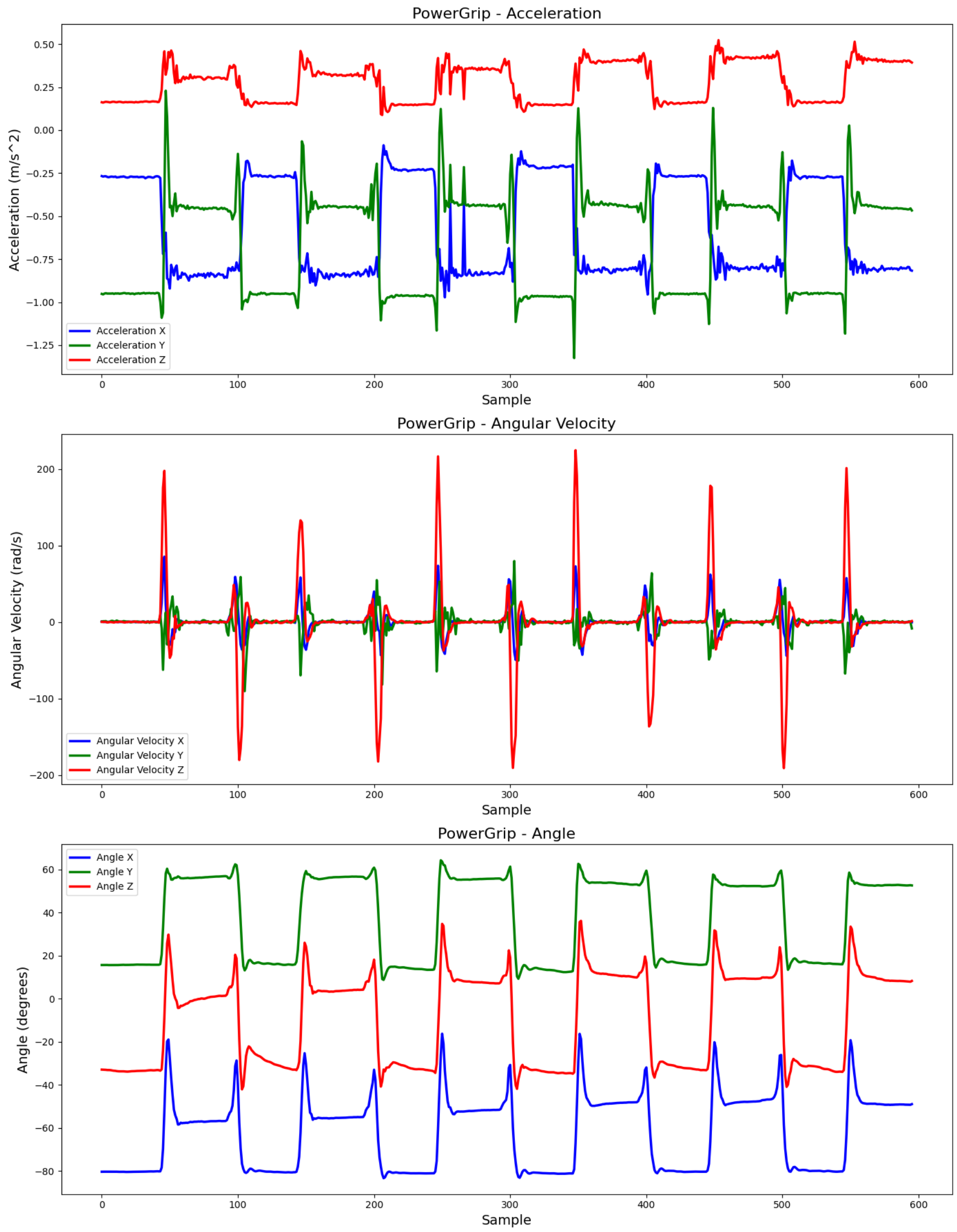

Figure 5.12 Acceleration, angular velocity, and angle in IMU signals for power grasping

The effective control of a prosthetic hand is very important; thus, small mistakes in the prediction will change the performance. Therefore, correct feature extraction and classification of grasping actions are necessary, especially for those with similar grasping actions.

These datasets are overly complex, hence requiring sophisticated methods of feature extraction. After deep research and evaluation of available machine learning models, we apply an autoencoder for feature extraction and reducing dimensionality. An autoencoder is capable of capturing essential features in the data, hence reducing noise and preserving vital information. This step is very important in dealing with the large amount of data and making sure that only important features are considered in further analysis.

In particular, for the sequence analysis part, which is the crucial component of our model, we found the Transformer model to be very effective. Provided with handling sequential data, the Transformer aids us in inferring meaningful insights from our datasets. Drawing from studies on temporal relations and patterns in data, the Transformer model enhances our understanding of the intrinsic mechanisms of grasping actions of various kinds. This is an important feature in realizing differentiation between subtle variations in similar grasping actions that improve prediction accuracy.

In the final classification task, we used an ANN. ANNs are quite robust in general and do a good job of multi-class cases; hence, this will be appropriate for our purpose. An ANN makes predictions with an accuracy rate about hand grasping orientation based on these extracted and sequentially analyzed features. Its adaptability and learning ability ensure that it handles the complexities of our data to give us reliable results in classification.

By integrating these three components, Autoencoder, Transformer, and ANN, we developed a composite model named AutoMerNet. In this regard, AutoMerNet incorporates the advantages of each individual model in developing a very strong predictor of hand grasping orientation. The integrated approach will ensure that we extract the data accurately, analyze it, and classify it to ensure enhanced control of prosthetic hands.

The detailed architecture and implementation details of AutoMerNet will be elaborated in the following.

5.4.1 Preparing the Data for Feeding Autoencoder

We have collected approximately 15,000 EEG, EMG, and IMU data per participant for each task. Given an input matrix of those signals:

$$X \in R^{31\times 15000} \tag{5-16}$$

where (X) represents the EEG signals with 31 channels (rows) and 15000 time points (columns).

We chunked and divided (X) into six submatrices, each of dimensions (31×2500):

$$X = [X_1, X_2, X_3, X_4, X_5, X_6] \tag{5-17}$$

where each ($X_i \in R^{31 \times 2500}$).

It is crucial to ensure sensor data quality before feeding it into an autoencoder for optimal training. Real-world sensor data is rarely pristine. It often contains noise and artifacts that can hinder the autoencoder's ability to learn meaningful features. Techniques like average filtering should be employed to remove high-frequency noise that does not hold relevant information for the task at hand. Filtering techniques can eliminate unnecessary noise, allowing the autoencoder to focus on the important information within the data.

We applied average filtering to each submatrix (X_i). Let's denote the filtered submatrix as (X_i^{filtered}). The average filtering operation can be described as:

$$X_i^{\text{filtered}} = \frac{1}{k} \sum_{j=1}^{k} X_{i,j} \tag{5-18}$$

where (k) is the size of the averaging window, and ($X_{i,j}$) represents the (j) $- th$ segment of(X_i).

The next preprocessing step involves normalization. Sensor data can be collected from various sources with different measurement scales. Normalization techniques address this by transforming the data into a common scale between 0 and 1. This creates a level playing field for all the features within the data, allowing the autoencoder to learn from them more effectively.

5.4.2 Building the Autoencoder Architecture

The effectiveness of an autoencoder hinges on its architecture, which dictates how the network processes and compresses sensor data. Two key aspects to consider are network layers and latent space dimensionality. The network itself is typically comprised of an encoder and a decoder. The encoder progressively condenses the data into a lower-dimensional representation, latent space. The decoder then attempts to recreate the original data from this compressed version. The number of layers in the encoder and decoder determines the network's complexity. While a deeper network with more layers can capture intricate features in rich sensor recordings, it also increases the risk of overfitting, where the model memorizes specific details from the training data that might not work well with new data. Overall view of preprocessing tasks and proposed model is demonstrated in Figure 5.13.

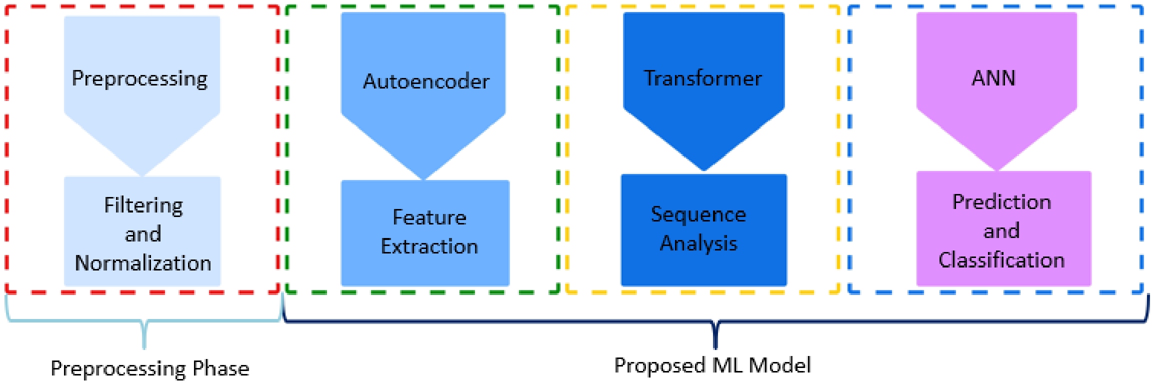

Figure 5.13 Overall view of preprocessing phase and proposed model with their tasks

After the preprocessing phase, each filtered submatrix (X_i^{filtered}) of dimension (31×2500) is fed into the auto-encoder. The encoder compresses the input data to a lower-dimensional latent representation:

$$Z_i = f_{\text{encoder}}\left(X_i^{\text{filtered}}\right) \tag{5-19}$$

where ($Z_i \in R^{31\times512}$) represents the compressed latent vectors. The encoder function (f_{encoder}) can be represented as a neural network with weights(θ_e).

The decoder reconstructs the input data from the latent vectors:

$$\boldsymbol{X}_i^{reconstructed} = f_{\text{decoder}}(Z_i) \tag{5-20}$$

where($\boldsymbol{X}_i^{reconstructed} \in R^{31\times2500}$)is the reconstructed version of (X_i^{filtered}). The decoder function (f_{decoder}) can be represented as a neural network with weights (θ_d).

5.4.3 Training the Autoencoder

With the preprocessed data and a well-designed autoencoder architecture in place, we move on to the training stage. The network learns to compress and reconstruct sensor data effectively. The prepared data segments are fed into the autoencoder. The encoder processes this data, progressively compressing it into a lower-dimensional representation within the latent space. This compressed version captures the key features of the original data. The decoder then takes over, attempting to reconstruct the original data as accurately as possible using only the information contained in the latent space. Through this process of encoding and decoding, the autoencoder learns the underlying structure and patterns present in the sensor recordings. Once the data is compressed into the latent space, the decoder takes over. The decoder's task is to reconstruct the original data as accurately as possible using only the information contained in the latent space representation. Through this process of encoding and decoding, the autoencoder learns the underlying structure and patterns present in the sensor recordings. To train the autoencoder effectively, a suitable loss function is essential. The loss function quantifies the difference between the original input data and its reconstruction. We used the Mean Squared Error (MSE) loss function for autoencoders. The reconstruction loss is calculated using MSE:

$$L_{MSE} = \frac{1}{n}\sum_{i=1}^{n} |\boldsymbol{X}_i^{filtered} - \boldsymbol{X}_i^{reconstructed}|_2^2 \tag{5-21}$$

where (n) is the number of submatrices. The MSE loss function measures the average squared difference between the original and reconstructed data points. By minimizing this error, the autoencoder learns to produce reconstructions that closely match the original inputs.

During training, the autoencoder undergoes several iterations where it adjusts its internal parameters to minimize the MSE loss. This process involves the following steps:

- Forward Pass: The input data is passed through the encoder, resulting in a compressed latent representation. This latent representation is then passed through the decoder to produce the reconstructed data.
- Loss Calculation: The MSE loss is calculated by comparing the reconstructed data to the original input data.
- Backward Pass: The gradients of the loss with respect to the autoencoder's parameters are computed using backpropagation.
- Parameter Update: The autoencoder's parameters are updated using an optimization algorithm (such as gradient descent) to minimize the loss.

Through these iterative steps, the autoencoder gradually learns to compress and reconstruct the sensor data more accurately. By the end of the training process, the autoencoder has captured the key features and patterns in the data, enabling it to perform effective data compression and reconstruction.

Also, we should note, training a robust autoencoder requires a large and diverse dataset of sensor recordings. A large dataset provides the network with a broader range of examples, allowing it to learn generalizable features that can be applied effectively to unseen data.

5.4.4 Feature Extraction: Utilizing the Learned Representation

After successful training, the autoencoder has learned to compress sensor data into its latent space representation. This is where the actual feature extraction takes place. The trained encoder plays a crucial role in feature extraction. We obtain their corresponding latent space representations by feeding new, unseen data segments into the encoder. These compressed representations capture the essential characteristics of the original data in a lower dimension. This allows us to efficiently represent the sensor data while retaining the key features relevant to our analysis. The latent space representation offers a significant advantage in terms of dimensionality. Compared to the original high-dimensional sensor data, the features extracted by the autoencoder are much more compact.

Autoencoders are powerful tools for feature extraction from complex and noisy data such as EEG, EMG, and IMU signals. By learning compact, non-linear data representations, autoencoders can enhance the performance of machine learning models in various applications, including biomedical signal processing, prosthetic control, and human activity recognition.

5.4.5 Advantage of Autoencoder for Feature Extraction of Proposed Model

The model of AutoMerNet begins with a crucial component: the autoencoder. This powerful tool acts as a feature extraction expert tasked with uncovering the hidden gems within the data. It operates in two stages:

- The Encoder: Compressing the data dimension. This phase is fed by data collected from EEG, EMG, and IMU sensors during hand-grasping tasks. The encoder compresses this high-dimensional data into a more manageable, lower-dimensional representation (latent space). This compression is achieved through a series of neural network layers, each applying a non-linear transformation to reduce the data's complexity progressively. The key here is to retain the most relevant features, the essential landmarks on the map, while discarding irrelevant details.
- The Decoder: Reconstructing from the essentials. The decoder takes the compressed representation in the latent space and attempts to recreate the original, high-dimensional data. This process helps the model understand the key features the encoder captured, focusing on the critical elements.

There are two main reasons why autoencoders are a perfect fit for this task. The first reason is for dimensional reduction. Hand-grasping data is inherently complex, with many dimensions. By compressing this data, the autoencoder makes it easier for subsequent model parts to handle and analyze. Another reason is feature retention. The autoencoder focuses on the most relevant features within the data through the compression and reconstruction process. This refined data, rich in essential information, allows the model to learn more meaningful patterns, ultimately leading to more accurate predictions about hand-grasping orientations.

5.4.6 Transformer for Sequence Modeling

Unlike the autoencoder, which focuses on individual features, the transformer excels at understanding the flow and relationships within these features over time. At the heart of the transformer lies the ingenious self-attention mechanism. The self-attention mechanism calculates scores for each data point, indicating how much focus each element deserves when making predictions. This allows the transformer to capture temporal dependencies, understanding how past positions and orientations influence the current state of the hand movement. Furthermore, transformers can analyze multiple parts of the sequence simultaneously. This is like the conductor being able to pay attention to different sections of the orchestra at once. This ability to grasp sequence relationships allows the transformer to capture complex interactions within the data. Perhaps the initial hand position influences how the muscles activate later in the movement, or vice versa. By considering these intricate relationships, the transformer builds a more comprehensive understanding of the hand-grasping dynamics, leading to more accurate predictions.

Autoencoders provide a refined data picture, but hand movements are inherently dynamic. This is where the transformer steps in as a master of sequence modeling. Once the input data is encoded into the latent space, each row vector in (Z_i) is treated as an embedding vector:

$$E_i = \left[e_{i,1}, e_{i,2}, \dots, e_{i,31}\right] \tag{5-22}$$

where each $(e_{i,j} \in R^{512})$ represents the embedding of the $(j) - th$ channel. These vectors capture the compressed and salient features of the original data.

To process these embedding vectors further, we use a Transformer Encoder. The transformer encoder is adept at capturing complex dependencies and relationships within the data through mechanisms of self-attention and feed-forward neural networks.

The transformer encoder processes the embedding vectors with multiple heads. In this case, we use 8 heads, which allows the model to focus on different parts of the input simultaneously, enhancing its ability to capture diverse aspects of the data.

The transformation applied by the transformer encoder can be represented as:

$$T_i = \mathrm{TransformerEncoder}(E_i) \tag{5-23}$$

The transformer encoder consists of multiple layers, each containing self-attention and feed-forward neural networks. The output of the transformer encoder T_i can be broken down into its key components for better understanding:

1. Multi-Head Attention: Multi-head attention allows the model to jointly attend to information from different representation subspaces. Each head operates on the input embeddings and learns to focus on different parts of the sequence. The combined output from all heads provides a richer and more nuanced representation.

$$\mathrm{MultiHead}(Q, K, V) = \mathrm{Concat}(\mathrm{head}_1, \mathrm{head}_2, \dots, \mathrm{head}_8)W^O \tag{5-24}$$

where each head is computed as:

$$\mathrm{head}_i = \mathrm{Attention}\left(QW_i^Q, KW_i^K, VW_i^V\right) \tag{5-25}$$

with $Q, K, and\ V$ being the query, key, and value matrices derived from the input embeddings E_i.

2. Feed-Forward Neural Network: Following the multi-head attention, the transformer encoder applies a position-wise feed-forward neural network to each embedding vector independently. This network consists of two linear transformations with a ReLU activation in between, allowing for additional non-linearity and complexity in the representation.

FeedForward(Ei)=ReLU(Ei·W1+b1)·W2+b2 (5-26)

For simplicity, the overall output of the transformer encoder can be represented as the sum of the contributions from the multi-head attention mechanism and the feed-forward network:

$$T_i = \mathrm{MultiHeadAttention}(E_i) + \mathrm{FeedForward}(E_i) \tag{5-27}$$

This combination ensures that the transformer encoder captures both the intricate dependencies within the embeddings through attention mechanisms and the enhanced feature representations through feed-forward networks.

The transformer encoder consists of multiple layers of self-attention and feed-forward neural networks. For simplicity, the output of the transformer encoder can be represented as:

$$T_i = \text{MultiHeadAttention}(E_i) + \text{FeedForward}(E_i) \tag{5-28}$$

5.4.7 The Artificial Neural Network for Final Classification and Prediction

ANNs offer two key advantages. First, they are flexible. They excel at modeling complex, non-linear relationships within data, making them suitable for various tasks. Second, they integrate features. By receiving both the extracted features from the autoencoder and the sequential information processed by the transformer, the ANN can consider a more comprehensive picture when making its final prediction. This integrated approach allows the ANN to leverage the strengths of both components: the autoencoder's ability to capture essential features and the transformer's understanding of temporal dynamics.

The ANN leverages the processed information to make the final call on hand-grasping orientation. The input layer receives the combined features extracted by the transformer. In other words, the output of the transformer encoder is passed through a fully connected (FC) layer:

$$F_i = \text{FC}(T_i) \tag{5-29}$$

where ($F_i \in R^{31\times128}$).

The output of the FC layer is then passed through another FC layer with seven neurons (number of hand grasping classes), followed by a Softmax activation:

$$y_i = \text{Softmax}\big(\text{FC}(F_i)\big) \tag{5-30}$$

where ($y_i \in R^7$) represents the probability distribution over seven classes.

During training, the classification loss is calculated using Cross-Entropy Loss:

$$L_{\,Cross\,Entropy} = -\sum_{c=1}^{7} y_{i,c} \log\big(\widehat{y_{i,c}}\big) \tag{5-31}$$

where ($y_{i,c}$) is the true label and ($\widehat{y_{i,c}}$) is the predicted probability for class (c).

The total loss function is a combination of the auto-encoder loss and the ANN classification loss:

$$L = L_{MSE} + \lambda L_{Cross\ Entropy} \quad (5\text{-}32)$$

where (λ) is a weighting factor that balances the contributions of the auto-encoder and classification losses. The overall training objective is to minimize this total loss function by optimizing the parameters of the auto-encoder, transformer encoder, and classification layers.

5.5 Results

Integrating AI and ML in controlling prosthetic hands offers significant advancements in creating responsive and adaptive prosthetic devices. Our methodology involved meticulous data collection, preprocessing, and the development of a sophisticated model, AutoMerNet, that combines autoencoders, transformers, and ANNs. AutoMerNet achieved outstanding performance, with all evaluation metrics, including accuracy and F1 score, reaching 99.99%. This high level of accuracy demonstrates the model's effectiveness in predicting and classifying hand-grasping tasks based on the integrated EEG, EMG, and IMU data. The exceptional performance of AutoMerNet underscores the potential of AI and ML in enhancing the functionality and user experience of prosthetic hands, ultimately contributing to improved quality of life for users. Figure 5.14 presents the confusion matrix of AutoMerNet, demonstrating its ability to distinguish different hand grasps and make accurate predictions. Training and testing Loss and accuracy of AutoMerNet are shown in Figure 5.15 To Figure 5.17.

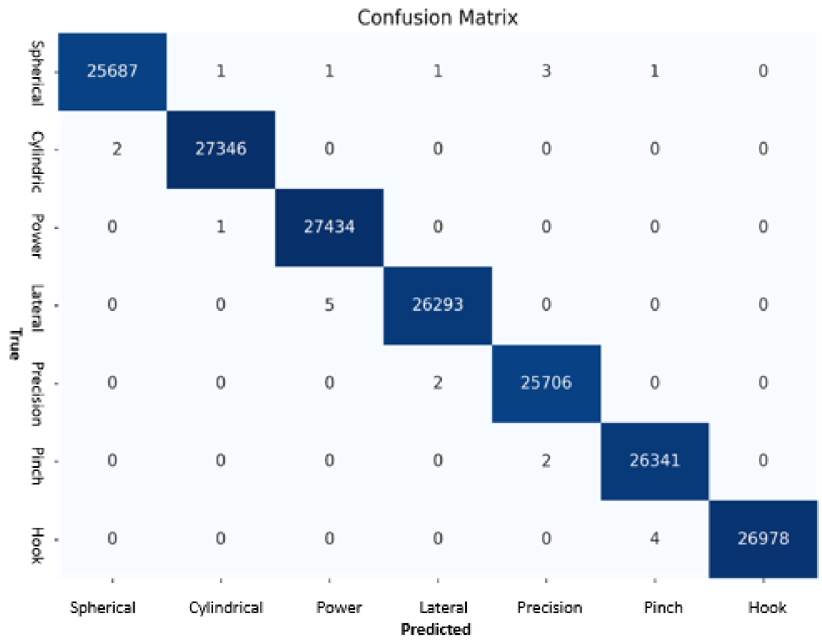

Figure 5.14 Confusion matrix of AutoMerNet

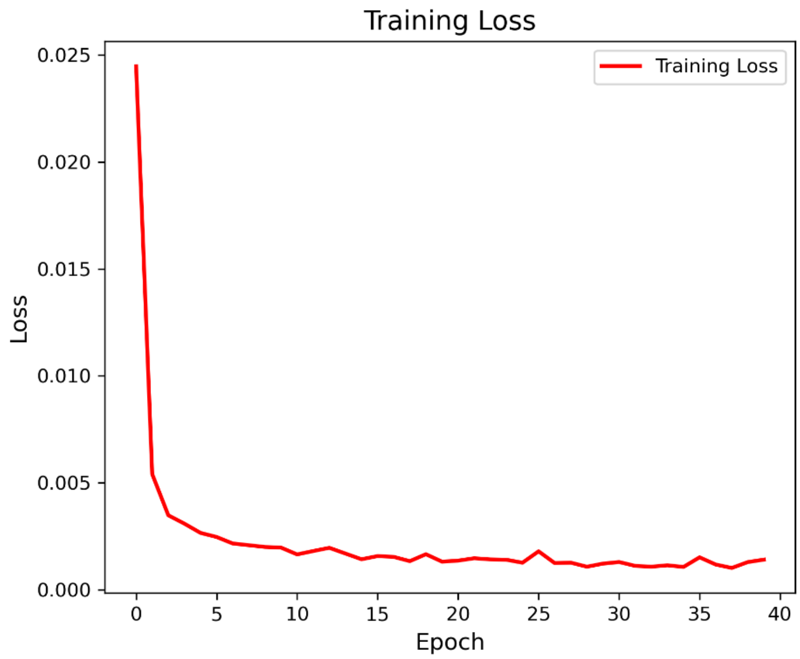

Figure 5.15 Training loss of AutoMerNet

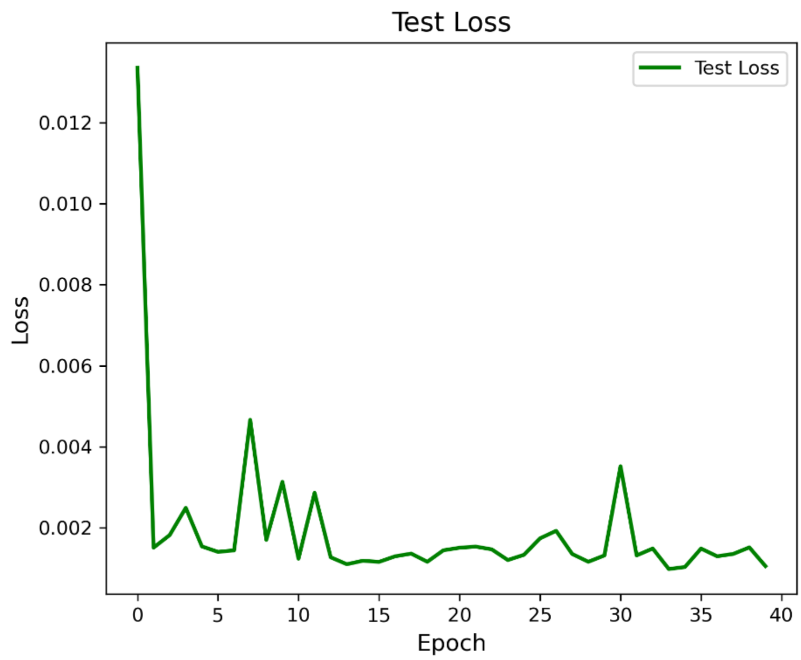

Figure 5.16 Testing loss of AutoMerNet

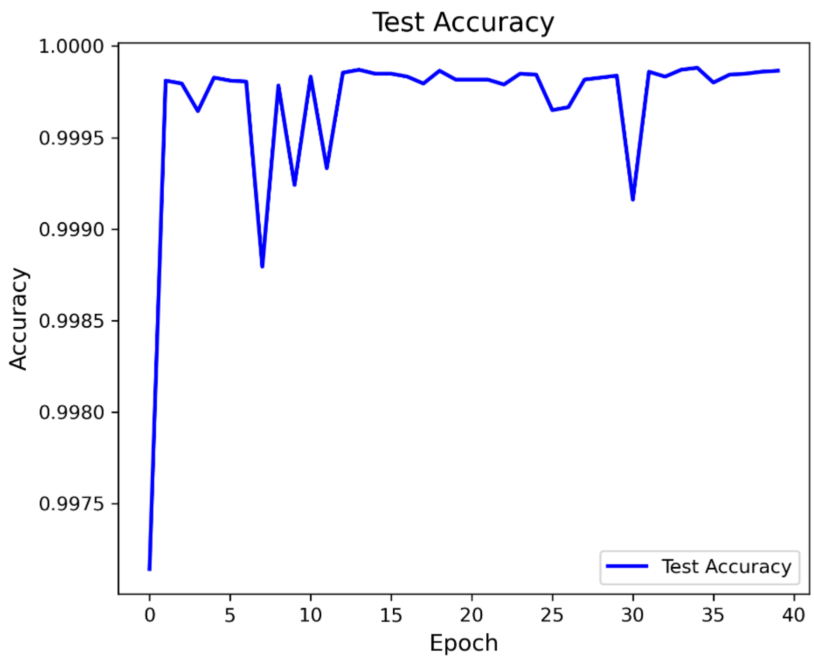

Figure 5.17 Test accuracy of AutoMerNet

5.5.1 Evaluation Metrics

To rigorously assess the performance of the AutoMerNet model, we employed four critical evaluation metrics: Accuracy, F1 Score, Precision, and Recall. Each of these metrics provides unique insights into different aspects of the model's predictive capabilities, ensuring a comprehensive evaluation of its performance.

Accuracy is defined as the proportion of correctly predicted instances out of the total instances. It provides a straightforward measure of the model's overall performance by indicating the percentage of all predictions that are correct. The accuracy can be calculated as follows:

$$Accuracy = \frac{True\ Positive + True\ Negative}{True\ Positive + True\ Negative + False\ Positive + False\ Negative} \tag{5-33}$$

Precision is the ratio of true positive predictions to the total predicted positives. This metric indicates the model's ability to avoid false positives, providing insight into the accuracy of positive predictions. High precision is crucial in scenarios where the cost of false positives is significant, ensuring that the instances classified as positive are indeed positive. The precision can be calculated as follows:

$$Precision = \frac{True\ Positive}{True\ Positive + False\ Positive} \tag{5-34}$$

Recall, also known as sensitivity, is the ratio of true positive predictions to the total actual positives. This metric measures the model's ability to identify all relevant instances within the dataset. High recall is essential in applications where missing a positive instance could have severe consequences, reflecting the model's effectiveness in capturing all true positives. The recall can be calculated as follows:

$$Recall = \frac{True\ Positive}{True\ Positive + False\ Negative} \tag{5-35}$$

The F1 Score is the harmonic mean of precision and recall, offering a balanced measure that considers both false positives and false negatives. This metric is particularly valuable when dealing with imbalanced datasets, as it ensures that both precision (the ability to avoid false positives) and recall (the ability to capture all relevant instances) are given equal importance. By combining these two aspects, the F1 Score provides a more nuanced evaluation of the model's effectiveness, and can be calculated follows:

$$F1\ Score = 2 * \frac{Precision * Recall}{Precision + Recall} \tag{5-36}$$

By utilizing these four evaluation metrics, we ensured a comprehensive assessment of the AutoMerNet model's performance. Each metric provides valuable insights into different aspects of the model's predictive capabilities, enabling us to evaluate its accuracy, balance between precision and recall, and its ability to correctly identify both positive and negative instances. This thorough evaluation approach ensures that the model is robust, reliable, and capable of generalizing well to new data. The value of these four metrics is in Figure 5.18.

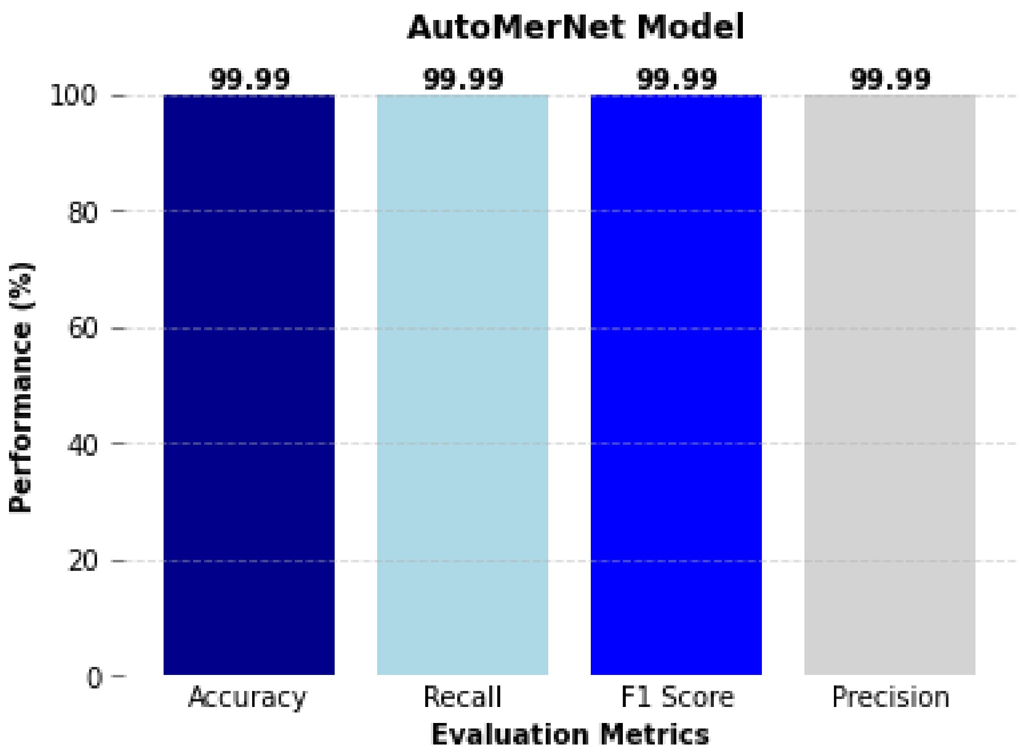

Figure 5.18 Four evaluation metrics and their values for AutoMerNet

5.6 AutoMerNet's Robustness and High Accuracy

One of the key factors behind AutoMerNet's success is its innovative architecture, see Figure 5.19. One of the key factors behind AutoMerNet's success is its innovative architecture, which is both unique and highly effective. It achieves an impressive accuracy of 99.99% in predicting hand-grasping orientations. Accuracy, as discussed before, is a common metric for evaluating the performance of an ML model. It measures the proportion of correct predictions out of the total number of predictions using the following formula which is equal to formula 5-33:

$$Accuracy = \frac{Number\ of\ Correct\ Predictions}{Total\ Number\ of\ Prediction} \tag{5-37}$$

An ML model determines correct predictions by comparing its predictions to the true labels (ground truth) through these steps: making predictions, comparing them to the true labels, and counting the matches.

Achievement of 99.99% accuracy for the proposed model highlights its ability to accurately predict hand movements by deciphering the complex relationship between brain signals, muscle activity, and sensor data.

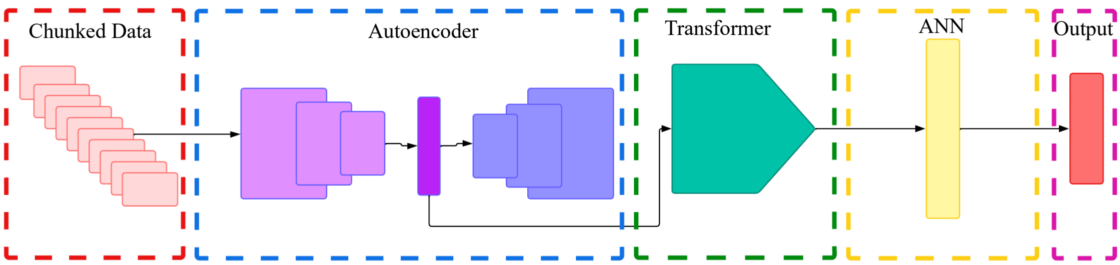

Figure 5.19 AutoMerNet architecture as a combination of Autoencoder, Transformer, and ANN

AutoMerNet's architecture consists of three key components working together. The first component is an autoencoder, which extracts the most relevant features from the EEG, EMG, and IMU data. This ensures that only the most important information is included in the analysis. The second component is a transformer. This component is particularly adept at capturing temporal dependencies within data sequences. This ability is crucial in hand-grasping prediction because it allows the model to understand the flow of information within the data, which is essential for grasping the dynamic nature of hand movements. The third component is an artificial neural network (ANN). This ANN takes the extracted features and the sequential information captured by the transformer and integrates them to make informed and highly accurate predictions about hand-grasping orientations.

The true power of AutoMerNet lies in the strategic way these three components are combined. Each component tackles a specific aspect of the data, and by working together, they achieve a level of accuracy and understanding that would be difficult for any single model to achieve on its own. This combined approach paves the way for significant advancements in prosthetic control and human-computer interaction. In essence, combining these components in the AutoMerNet architecture allows for a comprehensive and robust approach to predicting hand-grasping orientation. By leveraging the strengths of each model, AutoMerNet can effectively handle the complexities of multimodal sensor data.

5.7 Training and Validation

The AutoMerNet model prioritized achieving robustness and generalizability in predicting hand-grasping orientation. This was accomplished through a meticulously designed training and validation pipeline. The model was trained on a curated multimodal sensor data repository. This dataset encompassed various modalities, including EEG, EMG, and IMU data. Stringent preprocessing techniques were applied to each data point within the repository to ensure data quality and consistency.

To rigorously assess the model's performance and mitigate potential biases, a k-fold cross-validation strategy was implemented (k=10). This statistically robust method involves splitting the original dataset into k non-overlapping folds. In each iteration, the model is trained on a combination of (k-1) folds, while the remaining fold is reserved for validation. This process is repeated k times, with each fold being the validation set once. The selection of k folds is crucial, with considerations often leaning towards larger values of k = 10 to achieve a more comprehensive evaluation.

This k-fold cross-validation approach offers several advantages. First**,** it enhances robustness by training and validating the model on diverse data subsets; k-fold cross-validation provides valuable insights into the model's generalizability to independent datasets. This ensures the model is not overly reliant on idiosyncrasies present within a specific portion of the training data. Second, it reduces overfitting risk. The repeated training and validation cycles serve as a safeguard against overfitting. Overfitting occurs when a model performs exceptionally well on the training data but poorly on unseen data. K-fold cross-validation mitigates this risk by exposing the model to a broader range of data during training, promoting generalizability. The third is its comprehensive performance evaluation. K-fold cross-validation provides a more robust estimate of the model's performance by averaging the evaluation metrics across all folds. This comprehensive assessment reduces the variance associated with a single training-validation split, leading to a more reliable characterization of the model's predictive capabilities.

Through this rigorous training and validation process with k-fold cross-validation, the researchers were able to thoroughly validate the AutoMerNet model's ability to predict hand-grasping orientation with high reliability and generalizability to unseen data.

CHAPTER 6

DISCUSSION: AUTOMERNET AND THE FUTURE OF PROSTHETIC HAND

6.1 Introduction

This work presents a groundbreaking contribution to the field of prosthetic hand control through the development of AutoMerNet, a novel model that leverages the power of AI and ML to achieve exceptional performance in prediction hand orientation grasping. By integrating state-of-the-art techniques from these rapidly evolving fields, AutoMerNet addresses some of the most pressing challenges in prosthetic hand control, offering a sophisticated solution that enhances both precision and usability. Beyond the immediate technical achievements, this work explores the far-reaching implications for the future of prosthetic technology, considering how such advancements can transform users' lives, improve the customization and adaptability of prosthetic devices, and pave the way for new research directions and innovations in AI-driven assistive technologies. By setting a new benchmark in the field, AutoMerNet not only demonstrates the potential of AI and ML in enhancing prosthetic hand control but also underscores the importance of multidisciplinary approaches in tackling complex biomedical challenges.

6.2 Strengths of the Methodology

AutoMerNet's core strength lies in its groundbreaking utilization of multimodal sensor data. By incorporating EEG (brain activity), EMG (muscle activity), and IMU (motion data), the model gains a comprehensive and nuanced understanding of the user's intent, setting it apart from other works. This new combined approach offers several advantages compared to traditional methods relying on a single data source, which can be susceptible to limitations or noise.

EEG signals provide valuable insights into the user's brain activity associated with movement planning. The primary advantage of using EEG data is that it can capture the user's intent before the actual movement occurs, offering a predictive edge.

EMG signals measure the electrical activity of skeletal muscles. This data is crucial for understanding the activation of specific muscle groups during hand movements. EMG data is highly valuable for its precision in reflecting muscle contractions and is less prone to external noise compared to EEG.

IMU sensors provide critical motion data, including acceleration and angular velocity. IMU data captures the physical execution of movements, offering detailed information about the motion dynamics. This robust data provides valuable context to the movement captured by EMG, making it a vital component for understanding the complete motion sequence.

The success of AutoMerNet hinges on its innovative architecture, which combines three powerful components. The autoencoder efficiently extracts the most relevant features from the raw sensor data. This process is akin to data compression, focusing the model's learning process on the information most crucial for predicting grasping tasks. By filtering out noise and redundant information, the autoencoder ensures that only the most significant features are used for further processing. This feature extraction is crucial for handling the high dimensionality of the multimodal data, making the model more efficient and accurate. Essentially, the autoencoder acts as a dimensionality reduction tool, transforming the complex, high-dimensional sensor data into a more manageable and informative representation for the subsequent processing stages.

The transformer architecture captures the sequential nature of hand movements, where the order of muscle activations and sensor readings is critical. Unlike traditional models that struggle to capture these dependencies, the transformer can identify relationships between different data points within the sequence. This allows AutoMerNet to understand the dynamic evolution of the user's intended movement. This capability is particularly important for tasks that involve complex, time-dependent sequences of actions, such as grasping objects with different shapes and orientations. The transformer architecture addresses a key challenge in traditional sequence modeling by effectively modeling temporal dependencies and interactions within the data. This enhances the model's ability to predict accurate and context-aware movements. By incorporating the transformer, AutoMerNet can decipher the order and timing of muscle activations and sensor readings, leading to more precise and natural control of the prosthetic hand.

The ANN acts as the final classifier, integrating the processed data from the autoencoder and the sequential patterns identified by the transformer to predict the most likely grasping orientation for the prosthetic hand. The ANN synthesizes the rich, processed information from the previous stages and makes final predictions about the user's intended grasp. Its flexible architecture allows it to learn intricate patterns and decision boundaries necessary for accurate classification. The ANN component ensures that the final predictions are robust and reliable, drawing on the comprehensive understanding built by the preceding components. It culminates the entire architecture, translating the extracted features and sequential patterns into concrete actions for the prosthetic hand.

6.3 Implications for Prosthetic Technology

Integrating multimodal data and sophisticated model architecture in AutoMerNet has several far-reaching implications for the future of prosthetic technology.

Enhanced Control and Precision: This improvement in control precision translates to a more natural and intuitive user experience. Users can interact with objects in a more fluid and controlled manner, mimicking the dexterity and ease of movement of a biological hand. This can significantly improve the user's ability to perform everyday tasks and activities, fostering greater independence and a higher quality of life.

Reduced Cognitive Load: The current generation of prosthetic limbs often requires a high degree of cognitive focus to operate effectively. AutoMerNet's ability to predict user intent through EEG data can alleviate this cognitive burden. By reducing the need for constant conscious control, users can expend less mental effort on controlling the prosthetic and more on the task at hand.

Improved Brain-Computer Interface (BCI): AutoMerNet represents a significant advancement in BCI technology. The ability to decode complex movement intentions from brain signals paves the way for more intuitive and natural control of prosthetic devices in the future. This progress can extend beyond prosthetic limbs to other BCI applications, such as assistive technologies for individuals with neurological conditions.

Personalized Prosthetic Control: AutoMerNet's architecture allows for personalization by training the model on individual user data. This can account for variations in anatomy, physiology, and movement patterns across users. By tailoring the model to each user's specific needs, prosthetic control can become more intuitive and comfortable, further enhancing user satisfaction and functionality.

Continuous Learning and Adaptation: A key advantage of machine learning models is their ability to learn and adapt over time [64]. AutoMerNet can continuously improve its performance as it is exposed to more user data. This continuous learning can address individual user variability and improve the model's generalizability to different users and scenarios.

Fusion with Sensory Feedback: Research is ongoing on integrating sensory feedback mechanisms into prosthetic limbs [65]. Future advancements in sensory feedback, coupled with AutoMerNet's control capabilities, hold immense promise for creating truly biomimetic prosthetic hands that offer a more natural and complete user experience.

AutoMerNet represents a transformative development in prosthetic hand control. This model paves the way for a future of more intuitive, precise, and user-centric prosthetic technology by harnessing the power of multimodal data and innovative machine-learning architectures. The implications of AutoMerNet extend beyond prosthetic limbs, potentially impacting BCI development and other assistive technologies. As research continues in this field, we can expect even more remarkable advancements to further enhance the lives of individuals relying on prosthetic devices.

6.4 A Comparison of Machine Learning Approaches for Hand Grasping Prediction

Several research works explore the use of machine learning for hand-grasping prediction. One approach focuses on the robotic grasping of novel objects. This work utilizes a deep learning model called ML-CNN to analyze an object's depth image and the robot's palm pose [66]. While the exact success rate isn't explicitly stated, it aims for the robot to grasp new objects successfully.

Another work takes a different approach focused on human-robot collaboration [67]. It uses a deep neural network to analyze an RGB image containing human hand key points. The goal here is to recognize the type of object a human is grasping based on their hand posture, not predict robotic grasping configurations.

Similarly, other works explore predicting hand pose but for prosthetic control [68]. This work utilizes a Motion Prior Field model to analyze hand pose trajectory and predict a suitable pre-grasp hand configuration.

Other research evaluates the effectiveness of seven commonly used metrics in real-world settings by generating and testing synthetic grasp candidates on two robotic systems [69]. Experimental results show that while individual metrics have limitations, combinations of metrics can achieve up to 85% accuracy in predicting real-world grasp success. This highlights the potential for using multiple grasp quality metrics to improve robotic grasp planning and execution.

By comparing these approaches and considering how success is measured, we gain a better understanding of how the AutoMerNet model surpassed other models with a high accuracy of 99.99% in hand-grasping prediction using combination Machine Learning. Table 6.1 is a brief comparison of recent works on prediction hand grasping with AutoMerNet.

Table 6.1 Some recent works were compared with AutoMerNet

Work	Input Data	Model	Accuracy	Focus
Deep Learning Method for Grasping Novel Objects Using Dexterous Hands [70]	Object Depth Image, Palm Pose	Multi-Level Convolutional Neural Network (ML-CNN)	Not explicitly stated	Grasping novel objects with dexterous robotic hands
Recognition of Grasping Patterns Using Deep Learning for Human-Robot Collaboration [71]	RGB Image (Hand Keypoints)	Deep Neural Network (CNN or Transformer)	Up to 92.5%	Recognizing grasped object type based on human hand posture
Predicting grasp success in the real world [72]	Quality Metrics as QM	Binary Classification Model	85% Success Rate (simulated)	Learning grasping strategies through trial and error in simulation
Predicting Hand Orientation Grasping	EEG, EMG, IMU	AutoMerNet (Our proposed model)	99.99%	Recognizing Orientation Grasping while Doing 7 Main Grasping

CHAPTER 7

FUTURE DIRECTIONS AND CONCLUSION

7.1 Future Work

AutoMerNet has demonstrated remarkable performance in predicting hand-grasping orientation. However, several promising works for future research and development could further advance this technology. These advancements have the potential to significantly enhance the practical applications of AutoMerNet, making it even more effective and user-friendly for individuals relying on prosthetic hands.

Achieving real-time implementation of AutoMerNet is a key area for future research. This involves integrating AutoMerNet into a system capable of predicting and controlling prosthetic hands in real time. To accomplish this, optimizing the model for lower latency is crucial. The system must process incoming sensor data and generate control signals swiftly to ensure a seamless and intuitive user experience. Techniques such as model compression, efficient design, and hardware acceleration may be explored to reduce computational overhead and enhance real-time performance. Real-time implementation can improve the responsiveness of prosthetic hands and increase their practicality in everyday use, providing users with a more natural and immediate control experience.

Expanding the dataset used to train AutoMerNet is essential for improving its generalizability. The current model might be limited by the diversity of the training data, which we had 13 participants. Researchers can ensure that AutoMerNet can handle a wider range of scenarios and user needs by collecting data from a larger and more diverse population of prosthetic users. This includes considering variations in demographics, different levels of amputation, and various types of prosthetic devices. A more extensive and varied dataset will enable the model to learn from a broader spectrum of user experiences, enhancing its robustness and applicability. By including a wider variety of data, researchers can improve the model's ability to generalize to new users and unanticipated situations, making it more versatile and effective in real-world applications.

Incorporating additional sensor data modalities, such as tactile feedback, could significantly enhance AutoMerNet's predictive power. Tactile sensors can provide valuable information about the interaction between the prosthetic hand and the objects it grasps, offering insights into pressure, texture, and contact dynamics. This additional data can improve the accuracy of grasp and manipulation tasks, enabling more precise and adaptive control of the prosthetic hand. Exploring multimodal data fusion techniques will be critical to effectively integrating these new data sources. By combining tactile feedback with existing EEG, EMG, and IMU data, AutoMerNet can create a more comprehensive understanding of the user's intentions and the physical interactions involved, leading to more nuanced and effective control strategies.

Adopting a user-centered design approach is vital for the continued development of AutoMerNet. We should work closely with prosthetic users to refine both the AutoMerNet model and the control interface. This collaborative approach ensures that the final system meets the specific needs and preferences of users. Conducting user studies and employing iterative design processes are essential for gathering feedback and making necessary adjustments to improve usability and overall satisfaction. Customizing the system to individual users' requirements will enhance the practical utility and acceptance of the technology. By involving users in the design process, researchers can ensure that the system is functionally effective, user-friendly, and tailored to the everyday needs of prosthetic users.

Exploring the integration of AutoMerNet with cutting-edge prosthetic technologies, such as bionic limbs and neuroprosthetics, represents a promising direction for future research. These advanced technologies offer enhanced functionality and user control, and combining them with AutoMerNet's sophisticated predictive capabilities can further improve the overall performance of prosthetic devices. Investigating how AutoMerNet can complement and enhance these technologies will be critical for developing next-generation prosthetic solutions. By integrating AutoMerNet with state-of-the-art prosthetic technologies, researchers can push the boundaries of what is possible, creating more advanced, responsive, and intuitive prosthetic systems that significantly improve the quality of life for users.

7.2 Conclusion

This study presented a comprehensive methodology for predicting hand grasping orientation using multimodal sensor data and an advanced machine learning model, AutoMerNet. The exceptional accuracy achieved by AutoMerNet underscores the potential of combining autoencoders, transformers, and artificial neural networks for this application. By effectively integrating EEG, EMG, and IMU data, the model provides a nuanced understanding of user intent and movement, setting a new benchmark in prosthetic hand control.

Our findings contribute to the growing body of research aimed at improving prosthetic hand control, offering new possibilities for enhancing the independence and quality of life of prosthetic users. AutoMerNet's innovative approach demonstrates how leveraging multimodal data and advanced AI architectures can overcome the limitations of traditional methods, providing a more robust and intuitive control system for prosthetic hands. Using autoencoders for feature extraction, transformers for sequential data modeling, and artificial neural networks for classification ensures a comprehensive analysis of the complex signals involved in hand movements.

In conclusion, AutoMerNet represents a significant advancement in the field of prosthetic hand control, showcasing the potential of AI and ML in developing intelligent assistive technologies. The future work outlined will not only enhance the current capabilities of AutoMerNet but also pave the way for further innovations in prosthetic technology, ultimately leading to more effective and user-friendly solutions for individuals relying on these devices. Integrating real-time processing, expanded datasets, additional sensor modalities, and advanced prosthetic technologies will continue to drive progress in this field, offering hope for more sophisticated and adaptive prosthetic systems. This study highlights the importance of a multidisciplinary approach, combining insights from neuroscience, engineering, and computer science to create transformative solutions for prosthetic users.

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VITA

Nafiseh Ghaffar Nia was born in Tehran, Iran. Her passion has always been combining Biomedical fields with Artificial Intelligence. She received her master's degree in Mechatronics Engineering from Tehran University in Iran. Before attending the University of Tennessee at Chattanooga, Nafiseh led a robotics and computer institute where she excelled as a researcher, teacher, and manager. Concurrently, she co-founded an engineering company, contributing to innovative and groundbreaking projects. Her work was characterized by extensive involvement in interdisciplinary projects, consistently leveraging artificial intelligence as a tool in all her endeavors. Nafiseh remains passionate about learning and implementing the latest AI techniques in her work.