Chapter 1

Introduction

Abstract

Recent advancements in EEG and EMG signals have shown promising results in gait analysis and brain-computer interfaces. However, noise and variability can affect classification accuracy. This thesis aims to address these challenges by using scalograms (Visual representations that capture both the time and frequency components of signals) to improve the accuracy of EEG and EMG signal classification. This chapter provides an in-depth discussion of the thesis's motivations, objectives, and contributions, along with a comprehensive overview of the research gap. It also outlines the thesis structure, detailing the organization and interconnections between subsequent chapters.

In recent years, the utilization of electroencephalogram (EEG) and electromyogram (EMG) signals to classify neuromuscular activity has gained significant importance, particularly in the fields of brain-computer interfaces (BCI) and gait analysis (Welihinda et al., 2024; McDonald et al., 2024; Nazmi et al., 2024). These signals are crucial in diagnosing and comprehending neurological and neuromuscular disorders, making them invaluable in medical research, diagnostics, and treatment (Haufe et al., 2023; Saminu et al., 2023). EMG signals measure the electrical activity of skeletal muscles during motion and are crucial for studying neuromuscular function and disorders (Negi et al., 2024; Achmamad et al., 2023). EMG is also used extensively in gait analysis, offering detailed insights into muscle function and its impact on movement. Abnormalities in muscle activation patterns identified through EMG analysis can help diagnose underlying conditions (Al-Ayyad et al., 2023). EEG signals are generated by the brain and recorded using electrodes placed on the scalp. The analysis involves several steps: preprocessing to remove artifacts and noise, feature extraction to capture relevant information, and classification using machine learning algorithms (Gosala et al., 2023; Altaheri et al., 2023).

1.1 Gait Analysis

Gait refers to the pattern of movement of the limbs and the body during walking or running. It involves the coordination of multiple joints and muscles and can be affected by various factors, including age, injury, and disease (Bonanno et al., 2023). Gait analysis is the study of gait patterns, and it is used to evaluate and diagnose the conditions that affect gait, including neurological disorders, musculoskeletal conditions, and metabolic disorders (Hulleck et al., 2022). Gait analysis can be performed using visual observation, force plate measurements, motion capture technology, and sensor-based methods. Sensor-based techniques involve modalities like Inertial Measurement Units and EMG (Saboor et al., 2020). EMG can provide insights into how muscles are activated during different gait cycle phases. By measuring muscle activity during walking, researchers can better understand the underlying mechanisms of gait and identify potential areas for improvement in individuals with gait abnormalities (Kim et al., 2020). EMG can also identify abnormal muscle activity patterns in individuals with gait abnormalities or pathologies. For example, individuals with rheumatoid arthritis often exhibit antalgic gait, i.e., abnormal movement patterns (Carroll et al., 2015). By identifying these abnormal muscle activity patterns, researchers and clinicians can develop targeted interventions to help improve gait function (Papagiannis et al., 2019).

1.2 Brain Computer Interface

EEG is a non-invasive method for recording brain activity, enabling users to control devices or interact with virtual environments through thoughts, particularly beneficial for those with severe physical disabilities (Abiri et al., 2019; Lotte et al., 2018). A key area of research in EEG is the brain-computer interface (BCI), which spans multiple disciplines, including computer science, neurobiology, electronics engineering, and instrumentation engineering (Giri et al., 2024; Zheng et al., 2023, Sun et al., 2024). BCIs translate brain signals, captured via EEG, into commands for operating computers, prosthetic limbs, and assistive devices (Dong et al., 2023). EEG-based BCIs use non-invasive scalp electrodes to record brain activity, while invasive BCIs use microelectrodes implanted in the brain for higher-resolution data (Rouzitalab et al., 2023). When combined with EMG, which records muscle activity, a more comprehensive understanding of hand movements is achieved, enhancing real-time feedback and control (Tortora et al., 2020; Lin et al., 2016). BCIs have diverse applications, including aiding individuals with motor impairments, enhancing human-computer interaction, and neurorehabilitation (Tang et al., 2023; Gao et al., 2021; Chaudhary et al., 2016).

1.3 Challenges in Signal Processing

1.3.1 Limitations of EEG

While EEG remains a valuable tool for BCIs, it has significant limitations that must be addressed. One major challenge is EEG's limited spatial resolution, making it difficult to pinpoint specific brain regions accurately. This can affect the precision of fine motor control classification (Nunez and Pilgreen, 1991). Additionally, EEG signals are susceptible to interferences, such as environmental noise and non-brain-related electrical activity (Kumar et al., 2008). Sophisticated signal processing is necessary to mitigate these issues and accurately interpret user intent. Customized setups are often required to account for individual variability in brain anatomy and signal patterns, which can be time-consuming and less user-friendly, particularly for individuals with cognitive impairments or limited technical expertise (Gupta and Singh, 1996; Izdebski et al., 2016). Lastly, EEG-based BCIs face challenges in accuracy and reliability due to a relatively low signal-to-noise ratio (Sadiya et al., 2021). Thus, it is crucial to explore innovative and alternative approaches to fully harness the potential of BCI technology in various applications.

1.3.2 Limitations of EMG

EMG allows for a comprehensive evaluation of muscle function and diagnoses neurological disorders by recording and analyzing the electrical activity of muscles. Despite having good classification accuracy, the EMG signal becomes weak in certain neuromuscular disorders and is insufficient for accurate classification of movement activity and, subsequently, for prosthetic device control. Another major challenge is its difficulty capturing complex and subtle movements in tasks requiring fine motor control (Enders and Nigg, 2016).

Additionally, EMG signals can become unreliable over time due to muscle fatigue during prolonged activities (Dimitrova and Dimitrov, 2003).

1.3.3 Cross-talk in biological signals

Cross-talk refers to unwanted interference or contamination of electrical signals caused by neighboring sources. EEG and EMG are highly susceptible to cross-talk phenomena (Mesin, 2020). In EEG, cross-talk often occurs when signals from adjacent electrodes pick up electrical activity from unintended sources like muscle contractions, eye blinks, and movements (Kamble and Sengupta, 2023). On the other hand, in EMG, cross-talk results from signals from one muscle recording site being contaminated by electrical activity from neighboring muscles (Solomonow et al., 1994). Both techniques require careful electrode placement and signal processing techniques like filtering and source localization to reduce cross-talk (Mesin, 2018). Failure to address cross-talk can lead to misinterpretation of data and impact patient treatment and rehabilitation plans (Talib et al., 2019).

1.3.4 Inter-subject variability

Inter-subject signal variability is a crucial aspect of EEG and EMG research, referring to individuals' inherent differences in electrical activity (Fauvet et al., 2019). In EEG studies, the brain's electrical activity can differ significantly among people due to variations in brain structure, age, genetics, and cognitive state (Saha and Baumert, 2020). This variability poses challenges when comparing EEG data between individuals or establishing normative standards for specific brain activities. Researchers mitigate inter-subject variability using large sample sizes and statistical techniques (ŠŤASTNÝ et al., 2014). It is crucial to consider individual differences when interpreting EEG results, as results might vary across individuals. In EMG, inter-subject signal variability is primarily related to muscle structure, size, body composition, and motor control variations (Winter and Yack, 1987). These variations can affect the interpretation of muscle activity and assessment of neuromuscular disorders. Researchers establish baseline measurements for each individual or use normalized measures to compare muscle activity across different subjects (Guidetti et al., 1996). Clinicians also need to consider these natural differences when diagnosing conditions related to muscle function or evaluating the effectiveness of rehabilitation or physical therapy (Hug, 2011).

1.4 Proposed Solution

The wavelet transform is widely known for extracting specific frequency components or scales from a given signal of interest (Phinyomark et al., 2011). Scalograms, generated using Continuous Wavelet Transform (CWT), transform 1D signal data into a 2D image format, capturing temporal information. This enables the application of Convolution Neural Networks (CNNs) for image classification, improving accuracy (Kim and Seo, 2023). The CWT has proven to be a valuable tool in biomedical signal processing (Krishnan and Athavale, 2018). Further, EMG-based scalograms have effectively quantified simulated muscle activity even in noisy conditions (Di Nardo et al., 2022). Scalograms have also been used in identifying EMG time-frequency activity related to gait abnormalities, such as Parkinson's disease (Romanato et al., 2021). Wavelet-based analysis of EMG signals has shown promise in noise elimination, improving muscle force identification and classification (Veer and Aggarwal, 2014). This thesis aims to utilize scalograms to classify EEG and EMG signals. The effectiveness of scalograms is thoroughly evaluated across these modalities to assess their performance. The study encompasses vital areas like gait abnormality classification using EMG scalograms and the combination of EEG and EMG scalograms for classifying hand movements. This study also explores various classification techniques, from traditional machine learning classifiers to advanced methods such as CNN, attention networks, and transfer learning.

1.5 Objectives of the Thesis

The thesis investigates the influence of scalograms on the classification accuracy of two biomedical signals, specifically EEG and EMG. Tasks involving scalograms in this thesis include classifying gait abnormalities using EMG signals and hand gesture classification using a combination of EEG and EMG signals. Initially, traditional machine learning algorithms, alongside ensemble classifiers, are utilized. Further, scalograms are classified using CNNs, attention networks, and transfer learning to assess their impact on accuracy. The objectives of this thesis are summarized as follows:

1. Utilize EMG signals and traditional machine learning classifiers to classify gait abnormalities.

2. Enhance classification accuracy by incorporating scalogram images for classifying gait abnormalities using EMG and foot insole data.

3. Improve classification accuracy, Utilize advanced deep neural architectures, such as attention networks and transfer learning.

4. Evaluate the efficacy of applying scalograms to combined EEG-EMG signals for hand gesture classification in BCI applications.

1.6 Contribution of the Thesis

Human activity classification presents a significant challenge due to the constraints of EEG and EMG signals (Elsayed et al., 2017). EEG signals are hampered by limited spatial resolution and susceptibility to interference, while EMG signals struggle to capture intricate movements and encounter reliability issues stemming from muscle fatigue. Furthermore, cross-talk and inter-subject variability can lead to misinterpretation during signal analysis and classification (Enders and Nigg, 2016). However, scalograms can effectively address these limitations, which enhance classification accuracy by transforming signals into the time-frequency domain, revealing hidden signal patterns, and mitigating the impact of noise (Narin, 2022; Alyasseri et al., 2019). This thesis emphasizes the usability of scalograms for biomedical signal classification tasks. The contributions of the thesis are:

1. Presents a robust algorithm for classifying gait abnormalities by utilizing EMG scalograms, resulting in enhanced precision compared to traditional approaches.

2. Explores the fusion of EEG-EMG signals for multimodal classification, expanding the scope of brain-computer interface (BCI) technologies.

3. Utilizes advanced deep learning models, such as attention networks and transfer learning, to assess their influence on classification accuracy.

1.7 Organization of the Thesis

The thesis thoroughly explores each topic, building on previous chapters for a systematic approach and comprehensive understanding of the presented research. The thesis is structured as follows:

Chapter 2 presents an in-depth review of the current literature on gait abnormalities and analysis. The chapter covers the methodologies and technologies utilized in gait analysis, including signal processing techniques and feature extraction methods. Additionally, it outlines the applications of EEG and EMG across different domains and briefly introduces machine learning and deep learning concepts, highlighting their importance in the present study.

Chapter 3 presents the classification of hemiplegic gait abnormalities through EMG signals. The chapter presents the application of an ensemble classifier to identify hemiplegic gait patterns effectively.

In Chapter 4, EMG scalograms are used to classify gait abnormalities such as Hemiplegia, Rheumatoid Arthritis, Osteoarthritis, and PIVD. Additionally, the chapter extends the classification to other neurological disorders, such as Parkinson's, ALS, and Huntington's, using scalograms of foot insole data.

In Chapter 5, attention networks are examined for their application in classifying EMG scalograms related to various gait abnormalities. The study highlights the effects of combining different wavelet family scalograms on classification accuracy. The chapter provides a comprehensive overview of the network architecture, training methodology, and performance assessment, emphasizing the advancements facilitated by attention mechanisms in EMG signal classification.

Chapter 6 presents a study on classifying hand movements based on EEG and EMG scalograms using attention networks and transfer learning. It describes the integration of these technologies, demonstrating the potential of combining EEG and EMG signals for enhanced classification performance.

Chapter 7 summarizes the key findings of the thesis, highlighting the contributions made to gait analysis and signal processing. It discusses the current study's limitations and proposes directions for future research.