
Wearable Mechanomyography Sensory Advancements for Robust Prediction of Human Motor Intention: From Multi-channel Technology to Data-driven Computational Modelling

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This thesis is dedicated to my family, my two brothers who have always been a source of my motivation and admiration, my sister who has given me countless moments of joy and smiles, my dad who has always supported me no matter how challenging the circumstances, and especially my mum, who has inspired and motivated me tirelessly to follow and pursue my dreams.

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Finally, I would like to give special thanks to the rest of my family and friends, in particular to my grandparents for their encouragement and unconditional love and support.

Declaration

I hereby declare that except where specific reference is made to the work of others, the contents of this thesis are original. This thesis is my own work and contains nothing which is the outcome of work done in collaboration with others, except as specified in the text and Acknowledgements.

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Abstract

Analyzing, predicting, and decoding electrical and mechanical responses of the human muscular system in reaction to neural drive have attracted a great deal of interest in both medical and bioengineering fields. The common goal is to understand (and possibly model) the neurophysiological behaviour and to translate that into actionable functions. Mechanomyography (MMG) is a myographic signal modality which records the mechanical activity of the muscle fibres during a contraction. This modality has been investigated in the past specifically thanks to the benefits that it can propose in comparison with other modalities, such as electromyography (EMG). Specifically, the non-invasive mechanical nature of MMG makes it suitable to tackle the limitations of more established methods which rely on electrical activity. However, despite the existing literature, there are several unknown factors affecting the usability of mechanomyography signals for clinical and non-clinical applications.

This thesis introduces novel wearable MMG sensing technology that sheds light on the functionality, modelling, and information context of this neural interfacing modality.

The first part of this thesis introduces a new mode for MMG signal capture by the modulation of normal pressure at the sensor location, enabling a systematic evaluation of different levels of contact force between the sensor and the skin. Seven able-bodied and three amputee participants took place in an experiment that consisted of the analysis of acoustic MMG activity under different levels of contact force for the classification of hand gestures. The muscles of interest for this analysis were the flexor carpi radialis (FCR), brachioradialis (BRD), extensor digitorum communis (EDC), and flexor carpi ulnaris (FCU). Results of this study indicate that increasing levels of normal force between the sensor and the skin can improve the discriminative power content of the MMG signal, showing user-specific patterns of improved classification at different levels of contact force. These user-specific results suggest an influence of physiological and anthropomorphic factors on the properties of the MMG signal. In addition, these results provide further evidence on the effect of the level of contact force between the sensor and the skin and not only demonstrate the importance of sensor-to-skin attachment but also provide a better notion of the parameters to be considered when analysing MMG activity.

A second study was conducted to investigate the feasibility of the MMG modality in the analysis of functional muscle networks. A functional muscle network is a concept developed in the last decade which describes the functional organization of groups of muscles that play a role in the execution of a motor task. In this study, mechanomyography is introduced as a potential tool to evaluate functional synchronization and muscle connectivity based on the mechanical response of the muscles.

The analysis encompasses the study of the same muscles analysed previously in the evaluation of contact force vs acoustic MMG. Ten able-bodied and three amputee participants took part in this study, which consisted of the execution of four sustained hand gesture tasks. MMG muscle activity acquired from all four muscles was used to perform functional muscle connectivity analysis at multiple frequency bands to evaluate the topological characteristics of MMG information at low (i.e., $< 5\text{ Hz}$) and high (i.e., $> 12\text{ Hz}$) activation frequencies. The resulting muscle networks showed distinct topological signatures and specific significant differences ($p\text{-value} < 0.0028$) in the network characteristics describing the functional segregation of the networks (i.e., clustering coefficient) across gestures and frequencies. The results also showed evident topological differences between demographics, amputees and able-bodied. These results show the potential of MMG as a tool to evaluate functional muscle connectivity and provide key insights into the neural circuitry involved in motor coordination. The findings demonstrate the feasibility of MMG for the mapping of synergistic functional synchronization of upper-limb muscles and provide a basis for the translation of the analysis into clinical applications.

A third study was conducted in this thesis to exploit the multi-directionality property of MMG and evaluate muscle connectivity networks in the context of a multi-dimensional space based on muscle fibre alignment. The study not only explores the usability of MMG to generate multi-dimensional muscle networks but also examines the use of intermuscular coherence for human intention detection based on the multi-directionality space of accelerometer MMG and the effect that contact force variations have on the spectrotemporal properties of this MMG modality. In this study, for the first time, three-dimensional muscle networks are proposed based on orthogonal vibrational mechanomyography (vMMG) to evaluate the functional co-modulation of muscles across multiple frequency bands and along the longitudinal, lateral, and transverse directions of the muscle fibres. MMG activity was collected from twenty subjects using a custom-made armband of accelerometer sensors while participants performed four hand gestures. Target muscles and gestures were similar to those selected in the previous studies. IMC from all superficial muscles was decomposed into the constituent frequency bands of MMG (1-5 Hz, 5-12 Hz, 12-40 Hz). Muscle connectivity networks were generated for all frequency bands for each gesture along the three anatomical directions of muscle fibre alignment. Results show distinct topographical differences across frequency bands, gestures, and directions, and provide further evidence to support the use of vMMG in muscle connectivity analysis. This study also shows the feasibility of using vMMG-based muscle networks to compose a feature space for the classification of multiple hand gestures. To evaluate the translational capacity of the proposed technique, an analysis is also conducted on the effect of contact force, considering the changes in quality and discriminative power of vMMG. No statistical evidence was observed when a higher level of contact force was applied, supporting the robustness of the vMMG muscle networks to variations in sensor placement and tissue compression.

Through the above-mentioned three studies conducted in this thesis, it can be concluded that MMG not only offers a solution for those applications where EMG is not feasible, but it also shows to be a

potential tool for clinical and non-clinical applications. The results of these studies showing limitations and the potential of the myographic signal provide the opportunity to improve the design and applicability of the technology and enable the use of the signal in new areas where MMG has not yet been applied. Results presented in this thesis show the effect that attachment of the sensors to the skin has on both modalities of the signal (i.e., accelerometer and microphone) and guide future studies en route to exploit the properties of the signal as much as is viable based on the desired application. The analysis of functional muscle connectivity networks opens a new area of use for MMG to expand the analysis of muscle synergies and further apply the analysis and technique in the context of prosthetics, rehabilitation, and assistive devices.

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Chapter 1

Overview

Findings on the studies of mechanomyography (MMG) carried out in this doctoral thesis are summarized in this chapter. An overview of the objectives, methodologies, and key contributions of each study are also included.

Studying the neurophysiological responses of the human peripheral nervous system through various myographic modalities has been performed in the literature for clinical diagnosis [70, 75] and for neural interfaces, such as those used in prosthesis [50, 106] and exoskeletons [37]. The majority of these applications rely on the use of electromyography (EMG), a myographic modality that captures the electrical activity of the muscles during a contraction. Despite the fact that EMG has been established as the standard myographic modality for the vast majority of these aforementioned applications, there are still some significant challenges that exist with the practical uses of this modality, such as (a) variations due to skin conditions and impedance (for example due to sweating on the sensor site), (b) high sensitivity to sensor positioning, (c) the need for clean electrical electrode-skin contact surface, and (d) expensive hardware requirements for electromagnetic noise cancellation and sophisticated signal amplification [1, 100, 153]. All of these challenges have restricted the use of EMG in commercial-powered prosthetic limbs and applications for in-home conditions. As an alternative approach, mechanomyography (MMG) has attracted a great deal of interest in the field of prosthetics and rehabilitative devices since it is a low-cost myographic modality which records the mechanical responses of the muscle activation as opposed to the electrical activity of the motorneurons [76]. Measuring mechanical responses can add some benefits in terms of usability in home and unconditioned environments. In the literature, MMG has been acknowledged for its low sensitivity to skin conditions and low variability of response over time of use in unstructured environments. This minimizes the need for the skin to be cleaned, dry, and perfectly conditioned for the whole duration of use. Examples of the use of MMG technology are the evaluation of muscle fatigue [82], muscle strength [208], balance [10], muscle function [97], or the analysis of the mechanical response of the muscle after exercise [69]. Other applications of MMG technology include the examination of neuromuscular disorders [98], and prosthetic limb/robotic control [55, 201, 207]. However, various findings in the study of mechanomyography have emphasized the importance of having a better understanding of the limitations of the technology behind MMG signal capture and the relation of these limitations with anthropomorphic and physiological

factors. Based on the literature, sensor attachment to the skin has proved to be an evident factor showing different effects on the signal characteristics depending on the method and the strength of the attachment. This thesis seeks to shed more light on some of these understudied limitations and their relation to the different properties of the signal. The literature shows evidence that changes in sensor attachment parameters may have some overall alteration on the quality of the MMG signal, however, these studies do not provide insight into how changes in the attachment characteristics can be used to extract more useful information for analysis and use regarding human motor intent.

The coordinative activation of groups of muscle is controlled by the central nervous system (CNS) for the execution of complex motor tasks. The CNS simplifies these tasks by controlling groups of muscles, also called muscle synergies, as opposed to individual muscles [29]. Studies in the analysis of motor activity have found that the musculoskeletal system and the nervous system work together to be able to perform this functional coordination of muscle synergies for the execution of a motor task [47, 188]. This functional synchronization of muscles suggests a common neural drive, which at the level of the muscles has been studied by a method called intermuscular coherence (IMC). Coherence analysis has been largely used to study and quantify the synchronization between motor neurons. As such, it has been further used to analyze the neural input to the muscle synergies based on the common spectral characteristics of the signal, typically EMG, by a method called muscle network analysis. Muscle network analysis is a novel method developed in the last decade which is used to investigate the functional connectivity between muscles involved during motor tasks by analysing specific characteristics of the neural drive which enable the CNS to encode this synchronous functional organization and simplify the execution of those tasks. Functional muscle networks describe the functional synchronization of synergies during the execution of motor tasks by decomposing the IMC into frequency bands of commonly multi-channel electromyography signals. However, these methods have yet to be used to determine the outcome of coherence and muscle network analysis when implemented based on MMG activity. Temporal and spectral features of the MMG signal have been found to contain essential information regarding motor unit recruitment strategies and firing rate, providing the neurophysiological basis for their use in coherence analysis. The feasibility of implementing coherence and muscle connectivity analysis to evaluate functional muscle networks based on MMG activity give the ability to investigate the motor function from a mechanical neurophysiological perspective by providing additional information regarding the motor function and the muscle mechanical response to the synchronous neural activation, as well as providing the basis for future applications in the clinical setting.

In this thesis, a method for using MMG activity as a tool for coherence and muscle network analysis is introduced for the first time in the literature. The study is motivated by evidence in the literature demonstrating the complementary characteristics between EMG and MMG and the potential for the latter to provide more usable information about the neurophysiology of motor activity. The find-

ings and characteristic topologies of muscle networks based on MMG activity could provide novel insights into the neural basis of muscle synergies. Also, the analysis of MMG-based functional muscle networks can offer a new toolset for examining the neural circuitry involved in the motor function.

1.1 Objectives

The objectives and research questions that this doctoral thesis addresses and the hypothesis for each research paradigm are organized by the studies presented in each chapter as listed below.

1. **Chapter 3: Effect of contact force on acoustic MMG activity**

This chapter focuses on investigating the effect of different levels of contact force on the signal properties and the discriminative power of the acoustic MMG signal.

Method of investigation:

In order to perform this study in a systematic manner, the following methodology is followed:

- Development of a wearable custom-made armband to evaluate the MMG response when different levels of contact force are applied.
- Analysis of the relationship between MMG and three different levels of contact force regarding the quality and discriminative power of the acoustic MMG signal.

Hypothesis:

Specifically, the hypothesis to be investigated include:

- An increase in normal force will affect the visco-elastic properties of the muscular tissue (due to its nonlinear nature) which will cause changes in the properties of the MMG signal as it impacts the propagation of mechanical waves related to muscle activation.
- An optimal level of normal force, meaning an optimal strength of sensor attachment to the skin can be used to enhance the signal quality of MMG.
- Changes in the MMG signal quality due to variations in the level of force between the sensor and the skin are reflected in the discriminative power of a classification model when discerning between multiple motor tasks.

2. **Chapter 4: Muscle connectivity network analysis using MMG**

This chapter focuses on introducing coherence and muscle network analysis based on MMG activity for functional network analysis in healthy and impaired muscles.

Method of investigation:

In order to perform this analysis, the following method for investigation is followed:

- Intermuscular MMG-based coherence extraction between superficial upper-limb muscles during the execution of sustained contractions.
- Decomposition of the MMG-based coherence spectral space into frequency bands for the generation of functional muscle networks.

- Generation and analysis of functional connectivity networks in all spectral bands by the use of MMG across a cohort of amputee and able-bodied participants.

Hypothesis:

The hypothesis to be investigated include:

- The MMG information captured across its different components related to muscle activation which are evident at multiple frequency bands will be reflected in the unique characteristics of muscle networks between frequency bands.
- Based on the role that each muscle has during the execution of different hand gestures, it is expected to find distinctive muscle network topologies for the different hand gestures.
- Muscle networks extracted from able-bodied participants will show evident topographical differences compared to muscle networks of amputees due to the physical alterations of the muscles and the level of activity of the residual muscles.
- Muscle networks from each amputee participant will not only reflect physical alteration of the muscles but also the neural adaptation of the neuromuscular activation, resulting in unique topographies for each amputee participant.

3. Chapter 5: Analysing three-dimensional muscle networks using MMG

This chapter focuses on studying functional muscle connectivity by the use of multi-dimensional MMG using accelerometer-based sensors. The analysis not only explores the multi-dimensional space of the sensor in the context of coherence and muscle network analysis but also studies the effects of contact force on this modality of MMG.

Method of investigation:

This analysis is performed following the method described below:

- Adaptation of custom-made armband developed in chapter 3 for the study of accelerometer MMG.
- Derivation of functional intermuscular connectivity between forearm muscle pairs by the use of the aforementioned armband comprised of multi-axis MMG transducers during the execution of different hand gesture tasks.
- Decomposition of the MMG-based coherence spectra at low-, medium-, and high-frequency bands for the generation of functional muscle networks.
- Generation and analysis of gesture-based muscle connectivity networks across all spectral bands for each direction of muscle fibre alignment.

As part of this study, the analysis of contact force on accelerometer-based MMG is also performed and includes the following methodology:

- Temporal and spectral feature extraction under two different levels of contact force.
- Implementation and analysis of a classification model based on the intermuscular coherence extracted.
- Analysis and comparison in classification performance between single-axis vs multi-axis trained models.

Hypothesis:

The hypotheses to be investigated are:

- Muscle networks will not only show distinct topographical characteristics across gestures and frequency bands but also across axes as the signal propagates differently in all directions.
- A higher level of normal force between the sensor and the skin for accelerometer MMG will alter the propagation properties along the different directions of muscle fibres which will show evident effects in the spectrotemporal properties of the signal.
- Changes in the spectral properties of the MMG signal caused by the increasing levels of normal force will result in evident variations in the performance of classification models built based on the intermuscular coherence between muscles.
- The multi-directional trained classification model will surpass the classification performance of single-axis trained models as the former encompasses all the unique characteristics of the MMG activity along the different directions of the motor fibre alignment.

1.2 Thesis Overview

This thesis is structured in five chapters in addition to this overview.

- *Chapter 2* gives background details in order to contextualise the work and explain its relevance. This chapter describes the aspects of mechanomyography that are relevant to the research presented in this thesis as well as describing the investigations most relevant to this thesis around the use of MMG to obtain our current understanding.
- *Chapter 3* seeks to introduce a new modality for MMG, namely MMG-plus-One. This chapter describes in detail the process of developing this sensor as well as the methodology to carry out experiments in which different levels of contact force are applied to the sensor-skin location. The experiments described here explore the information captured by the new sensing modality. The chapter contains the analysis and discusses the results and findings. Chapter 3 contains elements taken from the published conference paper in AIM 2020 [115] and elements from the journal paper published in IEEE Transactions in Neural Systems and Rehabilitation Engineering (TNSRE) [36].
- *Chapter 4* describes a set of experiments that use the aforementioned armband to introduce the analysis of functional muscle connectivity networks by the use of mechanomyography. This chapter details the methodology used for the spectral decomposition of MMG information and the muscle network analysis introduced based on coherent spectral information. Results from this chapter have been published in IEEE Transactions on Biomedical Engineering (TBME) [116].
- *Chapter 5* describes additional experiments regarding the use of multi-channel multi-directional MMG transducers for the introduction of multi-dimensional muscle networks. Different levels of contact force using accelerometer mechanomyography are also evaluated to determine the changes in the characteristics of the MMG signal under different levels of contact force and evaluate such effects in muscle connectivity. The results of this work are currently under review for publication as of October 2022 in IEEE Transactions on Biomedical Engineering (TBME).
- *Chapter 6* is a summary chapter which describes related works of MMG and the research gaps that this doctoral thesis has addressed. Results are discussed in the context of continuing the research and future perspectives of the work, including potential avenues for new sensing technologies.

1.3 Contributions

The contributions of this thesis include the following:

Chapter 3: Effect of contact force on acoustic MMG activity

To summarize, the contributions of this chapter are:

- Introduction of a novel wearable MMG armband that has an additional degree of freedom for changing the levels of contact force for MMG-based man-machine interfacing.
- Method for analysis of the relationship between MMG and different levels of contact force regarding the quality and discriminative power of the acoustic MMG signal.

Chapter 4: Muscle connectivity network analysis using MMG

In summary, the main contributions of this chapter are:

- Method for the identification of functional intermuscular connectivity between superficial upper-limb muscles by the use of MMG.
- Identification of different muscle network topologies for different hand gestures.
- Identification of characteristic topologies for the different frequency bands of the MMG signal.
- Identification of characteristic topologies of muscle network patterns for able-bodied and amputees.
- Identification of alterations in muscle network characteristics associated with amputation.

Chapter 5: Analysing three-dimensional muscle networks using MMG

In summary, the main contributions of this chapter are:

- Method for the derivation of functional intermuscular connectivity between superficial muscle pairs at low, medium, and high-frequency bands by the use of multi-directional MMG transducers during the execution of different hand gesture tasks.
- Identification of multi-dimensional muscle networks, based on intermuscular coherence extracted from each axis of accelerometer MMG.
- Identification of different muscle network topologies and muscle network characteristic differences between gestures, frequencies, and axes.
- Method for the analysis of the relationship between accelerometer MMG and two different levels of contact force regarding the quality and discriminative power of the signal.

- Method for the implementation of a novel classification model based on intermuscular coherence derived from MMG activity.
- Comparison of classification performance of IMC-based models trained using uni-directional information vs the combination of all directions.

1.3.1 Publications

Journal Papers

- C. S. M. Castillo, S. F. Atashzar and R. Vaidyanathan, "3D Muscle Networks based on Vibrational Mechanomyography" in IEEE Transactions on Biomedical Engineering, IEEE Transactions on Biomedical Engineering, in review – October 2022.
Author Contributions: Conceptualization, writing, review and editing C.S.M.C., S.F.A., and R.V.; Experiments and Analysis, C.S.M.C.
- C. S. M. Castillo, R. Vaidyanathan and S. F. Atashzar, "Synergistic Upper-Limb Functional Muscle Connectivity Using Acoustic Mechanomyography" in IEEE Transactions on Biomedical Engineering, vol. 69, no. 8, pp. 2569-2580, Aug. 2022, doi: 10.1109/TBME.2022.3150422.
Author Contributions: Conceptualization, writing, review and editing C.S.M.C., R.V., and S.F.A.; Experiments and Analysis, C.S.M.C.
- C. S. M. Castillo, S. Wilson, R. Vaidyanathan and S. F. Atashzar, "Wearable MMG-Plus-One Armband: Evaluation of Normal Force on Mechanomyography (MMG) to Enhance Human-Machine Interfacing" in IEEE Transactions on Neural Systems and Rehabilitation Engineering, vol. 29, pp. 196-205, 2021, doi: 10.1109/TNSRE.2020.3043368
Author Contributions: Conceptualization, writing, review and editing C.S.M.C., S. W., R.V., and S.F.A.; Experiments and Analysis, C.S.M.C.
- Gardner M, Mancero Castillo CS, Wilson S, Farina D, Burdet E, Khoo BC, Atashzar SF, Vaidyanathan R. A Multimodal Intention Detection Sensor Suite for Shared Autonomy of Upper-Limb Robotic Prostheses. *Sensors*. 2020; 20(21):6097. <https://doi.org/10.3390/s20216097>.
Author Contributions: Conceptualization, R.V., M.G., D.F., E.B. and B.C.K.; Experiments and Analysis, C.S.M.C., M.G., R.V., S.F.A., B.C.K. and S.W.; Writing-review & editing, C.S.M.C., M.G., R.V. and S.F.A.

Conference Papers

- C. S. M. Castillo, S. F. Atashzar and R. Vaidyanathan, "3D-Mechanomyography: Accessing Deeper Muscle Information Non-Invasively for Human-Machine Interfacing," 2020 IEEE/ASME International Conference on Advanced Intelligent Mechatronics (AIM), 2020, pp. 1458-1463,

doi: 10.1109/AIM43001.2020.9159036.

Author Contributions: Conceptualization, writing, review and editing C.S.M.C., S.F.A., and R.V.; Experiments and Analysis, C.S.M.C.

The Ethics application used for the studies conducted in this thesis was originally submitted by Marcus Gardner in 2016 and subsequently amended for the continuing studies.

Chapter 2

Literature Review

This chapter introduces the various aspects of mechanomyography that this thesis addresses. Applications, uses, limitations, latest research, and research gaps are also presented.

This chapter discusses the physiology behind mechanomyography (mechanical and neuromuscular), the characteristics of the signals and the methods employed to measure it. The literature focuses on the features of the signal, uses of the signal characteristics for different applications, limitations of MMG technology, and the motivation for the studies carried out in this thesis.

2.1 Introduction

2.1.1 Physiology of voluntary muscle contraction

Muscles can be divided into cardiac, smooth, and skeletal. Out of these three types of muscles, skeletal muscles are the ones responsible for motor activities. Contrary to smooth and cardiac muscles, skeletal muscles are mainly activated voluntarily. This type of muscle functions together with the bones to be able to produce body movements. Their main function includes locomotion, body support and stabilization, temperature regulation, and protection of internal organs. Skeletal muscles are composed of a series of tissues and membranes. Muscles are surrounded by a connective tissue called the epimysium, a dense fibrous irregular tissue that surrounds the skeletal muscle and protects them from friction against neighbouring muscles, bones, and other tissues [163].

A muscle is formed by bundles of muscle fibres. These groups of muscle fibres are called fascicles. Surrounding the fascicle there is another connective tissue layer called perimysium. Muscle fibres, also called muscle cells, are surrounded by a connective tissue called endomysium. It is this connective tissue through which blood vessels and nerve fibres enter the muscle. The membrane surrounding the muscle fibre and sitting underneath the endomysium is called the sarcolemma, an excitable plasma membrane that shares many properties with the neuronal cell membrane. Skeletal muscle is a complex biological material that is composed of muscle fibres and extracellular tissue consisting of the epimysium, perimysium, and endomysium. These three connective tissues are continuous with one another, meaning that once a contraction occurs at a muscle fibre level, it is transmitted continuously from the endomysium to the perimysium, subsequently to the epimysium and in turn to the bone, thus producing force and movement [117]. Figure 2.1 shows an illustration of the structure of the skeletal muscle.

The function of a muscle also depends on its insertion and origin. The proximal attachment to the muscle is known as the origin while the distal attachment is known as the insertion. In other words, muscle origin refers to the attachment of the muscle to the fixed or more stable bone. If the muscle is attached to a bone that remains immobile during the activation of the muscle, the location of the attachment is called the 'origin' of the muscle. On the other hand, if the muscle is attached to a bone that moves during the muscular action, the attachment is called 'insertion'. For example, the extensor digitorum communis, a superficial muscle located in the forearm, has two points of attachment: one origin at the lateral epicondyle of the humerus and one insertion on the extensor expansion of the medial four digits. During muscle activation, the origin remains immobile while the insertion produces extension of the medial four digits or extension of the wrist [117]. Almost all skeletal muscles are connected to bones, either directly or by a tendon or aponeurosis.

A single muscle fibre consists of hundreds of rod-like elements called myofibrils. These myofib-

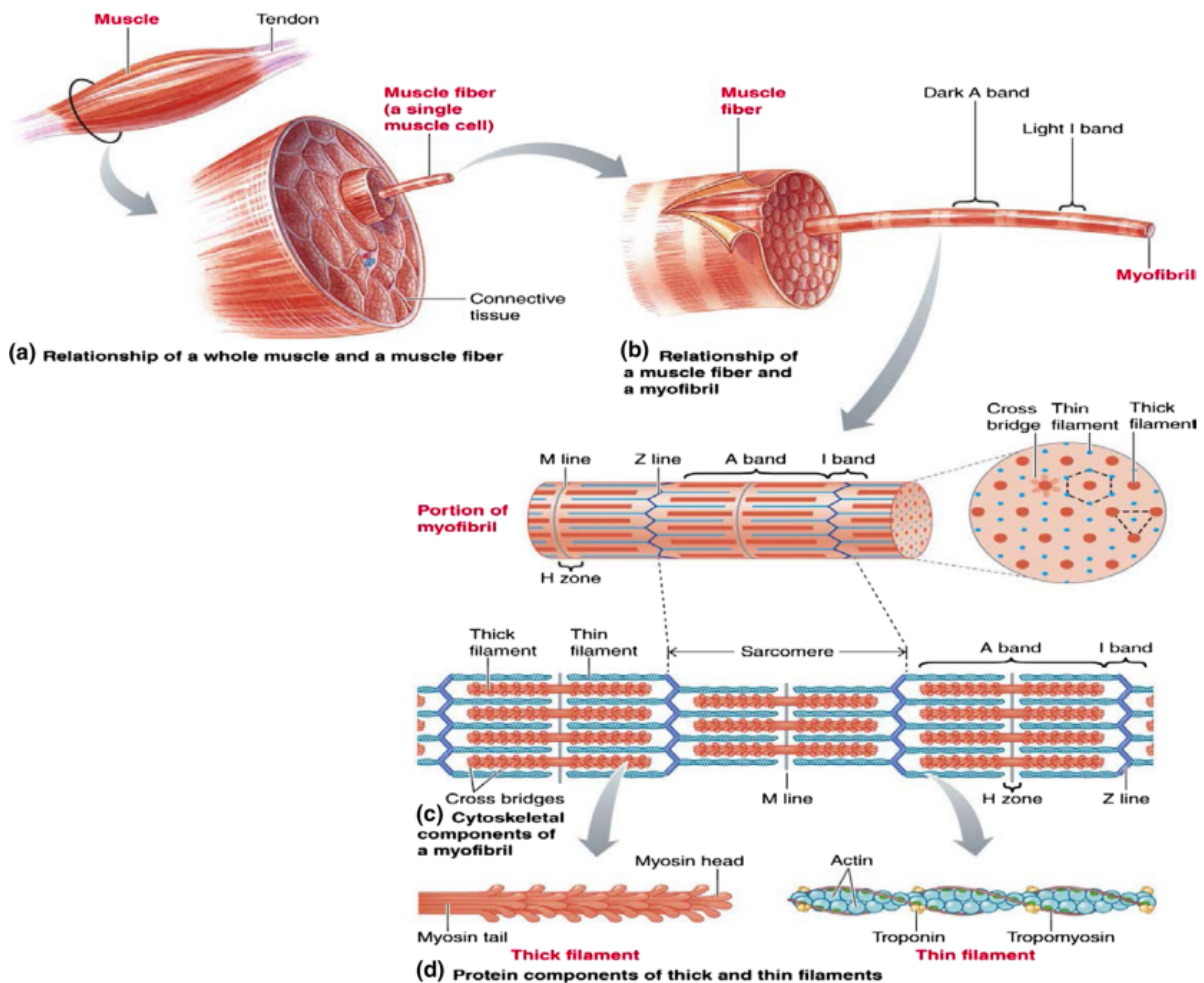


Figure 2.1: Skeletal muscle structure. Thin and thick protein filaments function together forming myofibrils. Groups of myofibrils form a muscle fibre. These muscle fibres constitute the fascicles which bundled together form a muscle. Reprinted with permission from [163]. See appendix 7.1 for © information.

Myofibrils consist of sarcomeres within which overlapping thick and thin filaments contain the proteins myosin and actin, respectively. The functional units of the muscles are the sarcomeres. Each myofibril is composed of a series of sarcomeres joined together. While the different types of muscle (i.e., smooth, cardiac, skeletal) differ in many aspects, they all rely on actin sliding against myosin to create muscle contraction and relaxation. In skeletal muscle, contraction is stimulated at each cell by nervous impulses that release acetylcholine at the neuromuscular junction, creating action potentials along the cell membrane. Skeletal muscles contract as the binding of acetylcholine takes place. The neural signal travels through a network of tubules known as t-tubules to reach the myofibrils, hence innervating the muscle fibres. Upon receiving the neural signal, the myosin cross-bridges are activated and bind strongly with actin causing the sliding of actin and myosin filaments. The actin filament is pulled and slides past the myosin filament shortening the sarcomere and propagating along the skeletal muscle structure to finally produce force.

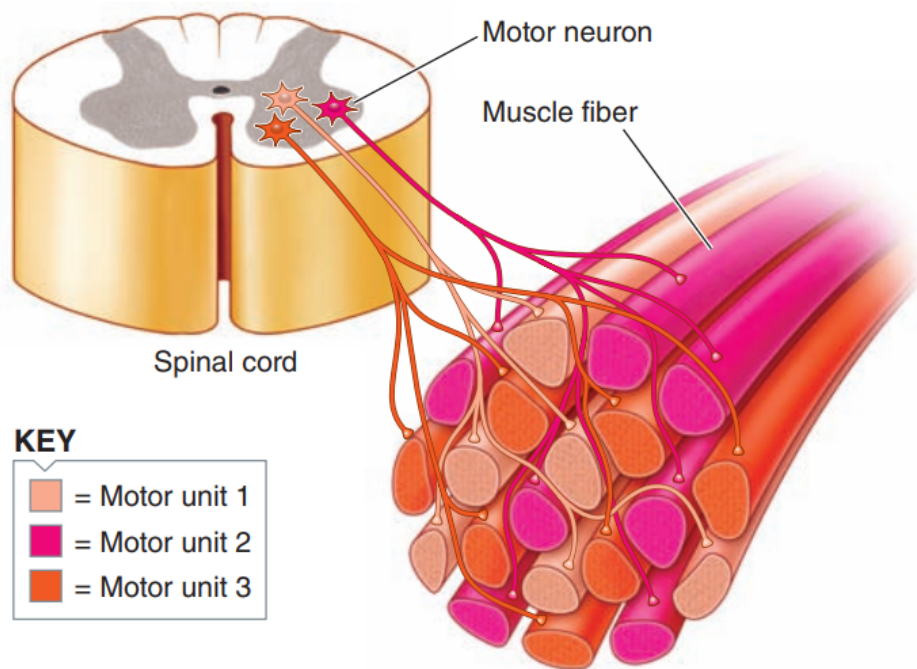


Figure 2.2: Illustration of motor neuron innervation of muscle fibres via motor units. Reprinted with permission from [163]. See appendix 7.1 for ©information.

2.1.2 Functional Muscle Groups

Skeletal muscles can be generally classified into four functional moves depending on the movement performed. These are agonists, antagonists, synergistic, and fixators. Agonist muscles are the prime movers for a particular action [117]. At the same time, the antagonist muscles work in reverse of that specific action in order to keep the prime movers from overextending. Synergistic muscles support the prime movers and help stabilise the joints against dislocation. If a synergistic muscle immobilizes the muscles' origin bone for the agonist to be more effective, then the synergistic muscle is called a fixator.

2.1.3 Motor Units

Muscles are coordinated by the commands sent from the central nervous system directly to motor units [73]. A motor unit (MU) is a single motor neuron and all the muscle fibres it innervates, all of which are of the same type, i.e., either fast twitch or slow twitch muscle fibres. Since all muscle fibres listen to only one neuron they act together as a unit. Motor units are the functional building blocks of muscle fibres. An illustration of the attachment of motor units with muscle fibres is shown in Figure 2.2. Motor neurons may synapse and innervate various muscle fibres. Groups of motor neurons innervating hundreds of muscle fibres form a large motor unit. These big units are typically found in muscles that perform big movements, e.g., walking. The innervation ratio of a muscle is the average number of muscle fibres per neuron in a muscle. As an example, the thigh muscle

has an innervation ratio of 1000 or higher while a hand muscle has an innervation ratio of 100. Muscle fibres are spread throughout the muscle. When the motor unit is stimulated the resulting contraction is propagated through the entire muscle. Electrical stimulus originated at the level of the motor neurons and known as action potentials travel through the axons of these cells down to the motor units to eventually produce a muscular contraction. When a muscle cell is innervated by a single action potential, the fibres rapidly contract and release. During this brief period, the force rises to a maximum to then rapidly fall back down to a relaxed state. This phenomenon is known as a muscle twitch, and it occurs in three stages, the latent period, the period of contraction, and the period of relaxation [163].

The latent period consists of the instant immediately after a muscle fibre is stimulated by a nerve when calcium ions are flowing into the sarcomeres to remove the proteins tropomyosin and troponin from the actin. In this phase, the stimulus has arrived, but no force is being produced. After this period, contraction occurs by the sliding of the filaments when the myosin heads are binding continuously, producing muscle contraction. This later phase is known as the period of contraction. After the contraction, the relaxation period starts when the fibres slowly slide back down as the calcium invades the sarcoplasmic reticulum and the actin and myosin stop the binding cycle. Muscles can produce a variety of smooth forces, called graded muscle responses. These are generally affected by the frequency and strength with which the muscle is stimulated. In this way, muscles increase their force by increasing the frequency with which motor neurons are firing. The faster the nerve impulses fire, the stronger each successive twitch gets. Muscle force is a product of the number of myosin heads bound to actin in each sarcomere. More frequent activation results in more calcium being released enabling more available binding sites which in turn produce more force. In this way, continuous twitches are added together as they get closer in time, a phenomenon called temporal summation. Once all of the actin-binding sites are exposed and the myosin heads are no longer able to run through a sliding cycle, muscle force cannot increase anymore. This stage is called tetanus, a period of maximum tension of the muscle where force cannot increase any longer. Eventually, the finite supply of Adenosine triphosphate (ATP) results in a limited period during which vigorous muscle activity can be maintained. Prolonged muscle contraction leads to fatigue of the muscle.

As mentioned before, twitches are driven by action potentials, which have only one intensity. Due to this reason, the frequency with which action potentials are fired is the only mechanism to create a range of forces. However, action potentials travel down motor units at different speeds and rates, allowing for smoother contractions. Contractions intensify as motor neurons stimulate more and more muscle fibres; a process known as motor unit recruitment/summation. Depending on the level of force to be exerted, motor units of different sizes are activated gradually. In this sense, small motor units are activated by the most excitable neurons, then larger motor units with larger muscle fibres are activated, thereof increasing the strength of the contraction, and finally, the largest motor units are activated. Hence, the more motor units are recruited, the greater the force that can be

generated. In addition to the number of fibres recruited, the amount of force also depends on the size of the muscle fibres (i.e., the size of the muscle), the frequency of the stimulation, and the degree to which the muscle stretches at the level of the sarcomeres. Skeletal muscle fibres can be categorized based on the speed of contraction and the amount of strength they produce. In this way, there are two types of muscle fibres. Type I fibres are referred to as slow-twitch fibres and have the ability to contract slowly and repeatedly for long periods. Type II are fast-twitch fibres and have a fast contraction speed able to produce high strength and power. Each fibre type possesses distinct metabolic and contractile properties which are driven by its motor unit composition. In terms of speed of contraction, slow twitch fibres take approximately 110 ms to reach the highest tension, while fast twitch fibres reach the highest possible tension at 50ms [160].

In summary, the central nervous system regulates force production by modulating and balancing motor unit recruitment and firing rate activity. During voluntary isometric and concentric contractions, motor units are recruited in the order of their size. The first MU to be recruited are small motor units which commonly contain slow-twitch muscle fibres and possess the lowest activation threshold. As higher levels of force are needed, larger motor units with faster and stronger capabilities (i.e., fast-twitch) are recruited [160]. The neural activation produced by the motor neurons is transmitted in the form of a series of impulses to the muscle fibres at different frequencies. The frequency of action potential transmission is called the firing rate. These frequencies are regulated based on the demand to produce and modulate force from frequencies low enough to produce a series of single twitches, hence producing low-level contractions, to frequencies high enough to produce twitch summation as higher production of force is required. In general, the firing rate of a motor unit increases with the demand for higher muscle effort up until a maximum rate is reached (tetanus).

2.2 Mechanomyography

Mechanomyography is the term assigned to the mechanical signal produced when a muscle contraction occurs. It has been shown that the signal is composed of different factors: the gross lateral movement of the muscle once a contraction is initiated, subsequent smaller lateral oscillations which vibrate at the muscles' resonant frequency, and dimensional changes produced by activation of muscle fibres [14, 128, 130]. During a muscle contraction, a shortening of the long axis of the muscle occurs as the myosin (thick filaments) of the muscle fibres slide past the actin (thin filaments). These changes in muscle length cause further dimensional changes in the transverse axis of the muscle. These dimensional changes along with the lateral oscillation of the muscle produce vibrations at low frequencies, which can be measured on the surface of the skin. These low-frequency vibrations have been named acoustic-myogram [11], sound-myogram [138], phonomyogram [118], vibro-myogram [216] or accelerometer-myogram [102]. However, in 1995 all these metrics were accorded to be named mechanomyography (MMG) [177].

2.2.1 MMG detection techniques

There has been increased interest in research and applicability of MMG, in particular regarding sensing technology and signal processing techniques for MMG's wider utilization. The MMG signal originates from a muscle contraction as the length of the muscle fibres shortens and the fibre diameter increases [51]. During a muscle contraction, as the muscle fibres shorten and the muscle is being pulled towards its origin, the transverse diameter of the muscle changes in shape (increases) at the level of the muscle belly [136]. The lateral oscillations of the muscles as well as the dimensional changes of the fibres produce pressure waves that propagate through muscle tissue and are detectable on the surface of the skin. These pressure waves are generally detected as acceleration signals captured by sensors such as an accelerometer or as a skin displacement signal acquired by piezoelectric contact sensors [195], laser distance sensors [132], or condenser microphones [129]. Even though each transducer measures the same phenomenon, the signal acquired is influenced by the nature of the signal acquisition transducer, meaning that the sensor utilized could potentially introduce different loading pressure and mechanical obstruction on the skin. In addition, each transducer may present different levels of sensitivity to the MMG signals and external artefacts. The different sensing technology employed for MMG detection has been thoroughly validated [76, 129, 179]. Standardization of the signal has been suggested for reproducibility and consistency of the measurements [76]. As mentioned, the MMG signal properties may vary depending on the physical quantity measured (e.g., acceleration or displacement) [196]. However, the muscle action, as well as the size and type of muscle also play an important role in the selection of a transducer. Measurements that are acquired in the fundamental units of vibration (i.e., m/s^2) are preferable for the purpose of comparative studies [18]. However, each transducer comes with its disadvantages and limitations.

Micro-electromechanical system (MEMS) microphones are one of the most common sensing technologies that have been widely used in the literature to acquire MMG activity [129]. These sensors are typically attached to the surface of the skin by the use of custom-made elastic straps [168]. In [196], evidence showed that the use of microphones to capture the MMG activity, also known as acoustic MMG, shows robustness against motion artefacts compared to other MMG sensing technology such as accelerometers [92, 196]. However, the same study showed that the spectrotemporal properties of the signal are influenced in great part by the dimensions and shape of the air chamber. Furthermore, acoustic MMG has been shown to have some level of sensitivity to the pressure with which the sensor is attached to the skin [171]. The frequency spectrum of the acoustic MMG has shown to resemble the spectral activity of that of the double integral of the accelerometer transducer, suggesting that the microphone transducer acts as a displacement-meter acquiring the MMG signal [196].

Accelerometer sensors are another type of transducer commonly used for MMG signal acquisition. Some of the advantages of accelerometers are their lightweight and therefore ease of fixation to the skin, commonly done by the use of double-sided adhesive tape. Another important advantage is the sensitivity to low frequencies, making it an ideal tool for MMG data collection. Given that no extra pressure is applied to the skin at the sensor location, the interference with muscle activity is minor. Thanks to the fact the physical units collected using accelerometers have a physical representation, comparison between studies is facilitated. Advantages of accelerometer-based MMG in comparison to other formats of MMG modalities, the following can be mentioned: (a) the high bandwidth of the accelerometer-based MMG [195], (b) the independence of the signal quality to coupling methods of the transducer to the muscle (i.e., accelerometers do not necessarily require direct contact with the skin), (c) the small dimensions and lightweight [197], and (d) the ability to measure muscle mechanical response in the 3-axis (longitudinal, lateral, and transverse) with respect to the muscle fibres.

Lastly, laser distance sensors have also been used in the literature to measure skin displacement during muscle activities. These sensors output a direct current voltage proportional to the distance between the transducer sensing beam and the skin. Similar to accelerometers, one of the main advantages of this transducer is the physical representation of its output (mm). Other characteristics include the bandwidth of the sensor, as high as 10 kHz, the high resolution of the information (μm), and the ease of use thanks to the fact that the transducer does not require to be attached to the skin. However, due to the fact that the sensor does not require skin attachment, its use outside the laboratory and clinical settings remains limited.

Previous studies have shown that the signal acquisition method should be selected according to the experimental needs [177]. For example, accelerometers and laser sensors are typically used in studies involving isometric and sustained contractions thanks to their characteristic ease of use [129]. Microphones, being more robust to external artefacts compared to the other MMG transduc-

ers, are more suitable for MMG signal acquisition during dynamic activities [196]. A big amount of effort has been put into developing multi-sensing transducers which can not only collect the MMG activity but at the same time detect ambient noise and external disturbances. Thanks to the ability of both sensors (i.e., accelerometer and microphone) to pick up vibrations, they have both been used for noise cancellation of background noise. In this regard, a combination of microphone-accelerometer transducers [166], and microphone-microphone transducers [202] have been proposed to detect background noise. By applying a thresholding method [166], or a mathematical source-separation approach [167] it is possible to separate the MMG signal from ambient noise, thus providing a cleaner signal.

There have been various investigations dedicated to mitigating the presence of motion artefacts in the MMG signal. The most common are Fourier-based techniques which include the use of Butterworth band-pass filters of different orders [99]. Other approaches include Fourier truncation [59], coherence analysis [80], and restricting body movement during tasks [212]. More recently, a novel empirical decomposition method has been proposed in order to minimize the level of distortion introduced by motion artefacts [194]. The challenge of minimizing the effect of motion-induced artefact in the MMG signal is well documented and numerous studies have proposed different methods in this regard [149]. According to the literature, the recommended technology for MMG activity capture is acoustic MMG (i.e., microphones) [196] and piezoelectric contact sensors [25], in particular for those applications involving dynamic activities and where external and motion-induced artefacts cannot be avoided [95].

The MMG signal is characteristic for containing power information at frequencies below 100 Hz [138]. Various studies have shown that the majority of MMG power information resides at frequencies lower than 30 Hz [128, 130], however, depending on the muscle of interest, other studies have found MMG power information at frequencies between 2-120 Hz [27]. In this respect, the cut-off frequency of filters applied to the signal is generally applied in the range of 1-120 Hz.

2.2.2 Characteristics of the MMG technology

It has been suggested in the literature that for the signal to be reliable, minimal interference between the muscle surface and the sensor needs to exist, including any interference caused by the weight of the sensor, particularly for accelerometers [197]. The desirable characteristics of an MMG transducer should include (a) high sensitivity to low-frequency vibrations; (b) ease of use and attachment to the skin; (c) a skin-friendly characteristic; and (d) robustness against external artefacts [45]. In addition, sensor firmness while attached to the skin and the level of contact pressure should be considered in order to reduce the variability of the signal between trials [171]. The muscle location for placement of the sensor plays a significant role in the MMG signal acquisition. It has been demonstrated that the predominant frequency in the spectral characteristics of MMG correlates positively with the firmness with which the sensor is attached [31]. In addition, the skin-fold

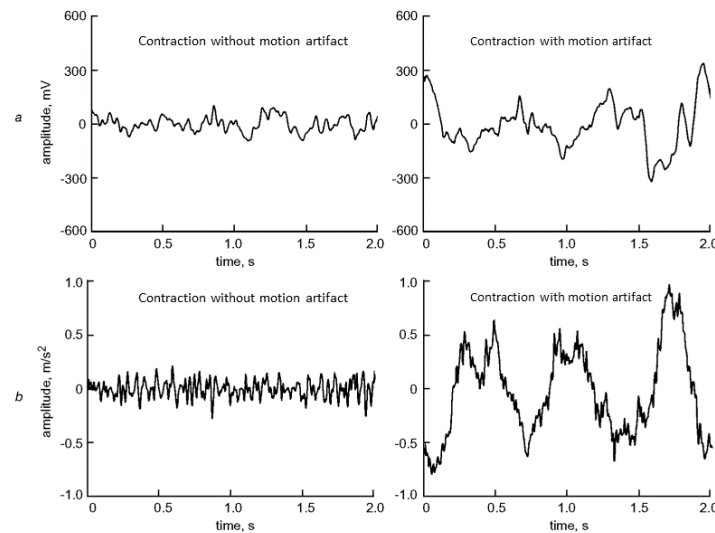


Figure 2.3: Representation of (a) microphone and (b) accelerometer MMG signals collected from the biceps brachii muscle during the execution of voluntary contractions. Adapted with permission from [196]. See appendix 7.2 for ©information.

thickness may affect the MMG signal to some extent due to the attenuation of the MMG waves passing through soft tissue from muscle fibres to the transducer [81]. The MMG signal characteristics have shown to be dependent on the transducer being used [25]. Fig 2.3 shows the MMG signals acquired with two different types of transducers, microphone and accelerometer.

Given the mechanical nature of the MMG signal, the acquisition of the same may be eased thanks to the fact that no additional hardware is required to mitigate electrical noise interference, as it occurs with EMG. Contrary to EMG, the MMG signal acquisition can be realised by a single sensor without the need for a reference signal. Thanks to these advantages, MMG technology results in a cost-effective solution for bio-signal detection [76]. One of the main benefits of MMG against other myographic modalities is that MMG signals are not influenced by changes in skin impedance. As such, skin preparation is not required during sensor attachment to the skin. Nevertheless, for consistency and signal integrity, it is recommended to ensure a consistent level of sensor-skin contact pressure. Whenever possible, the experimental design should be carefully designed such that artefacts and crosstalk from muscles non-related to the motor task at hand can be isolated. Custom-made commercially available dynamometers have been proposed to mitigate the effects of crosstalk in the signal [78]. However, the adverse effect of motion-induced artefact and crosstalk in the MMG signal is well recognized in the literature [182]. Tremor, clonus, and other forms of artefacts have been suggested to be inherent characteristics of muscle contractions [74] which reside within the low-frequency band (<10 Hz), therefore overlapping with the active frequencies of the MMG signal. Therefore, it is important for investigations to apply efforts into applying methods to minimize this effect and mitigate these artefacts for the analysis of reliable mechanomyographic activity [12].

The signal sampling rate is based on the muscle of interest and the available hardware. According to the Nyquist-Shannon sampling theorem, the sampling rate should be at least twice the highest frequency content of the signal [205]. Hence, for MMG signal the sampling rate should be at least 200-250 Hz since MMG power information has been found at frequencies up to 120 Hz [27]. Nonetheless, a common sampling rate for MMG activity in the literature is 1-2 kHz [41, 45]. A higher sampling rate has been used to determine phase differences between sensors placed along the longitudinal and transverse axis of the muscle [142]. It is a common practice to select the sampling rate within the standard limits at the same time as considering the storage space available. In order to save system storage, it can be safely recommended that the sampling frequency be kept at 1 KHz.

2.2.3 Muscle Physiology - MMG Prospects

The MMG signal has been verified to contain valuable information on the underlying neuromuscular parameters responsible for muscle contraction, making them a reliable tool for muscle function assessment [135]. Numerous investigations have shown how properties derived from vibration, acceleration, and displacement can be used to evaluate muscle activity and performance [76]. Furthermore, spectrotemporal features of the MMG signal have been used for the analysis of muscle physiology at the motor unit level [181]. Muscle contractile properties have been linked to properties of the MMG signal [95]. Analysis of physiological aspects related to muscle condition and performance include muscle stiffness, muscle dehydration, muscle contractile properties, muscle contraction mechanics, and exercise hypertrophy [181].

MMG has been utilized for the assessment of motor unit strategies and the study of muscle mechanics [38]. The signal properties have proved to be fundamental when assessing muscle function and performance in the medical field [77]. Thanks to the emergence of new MMG sensing technology, the physiological aspects analysed by MMG broaden the potential of the signal and invite the use of MMG in new fields. The literature shows that, during the last decade, there has been an increase in the amount of research and investigations conducted to support the application of MMG as a reliable clinical tool for understanding and assessing different muscular properties [76, 191].

There are a number of studies that have used MMG technology for the analysis of the contractile properties of muscles. These contractile properties include time delay (T_d), contraction time (T_c), half relaxation time (T_r) and maximal amplitude (D_m), all of which contain relevant information about muscle stiffness [147] and muscle deformation [169]. A high number of investigations have focused on the use of MMG for the assessment of muscle fatigue [39, 96, 184, 209]. MMG has also been extended to applications regarding muscle damage to monitor muscle performance during rehabilitation [179]. As previously mentioned, the quality of the MMG signal is affected by physiological factors such as muscle stiffness (type of muscle), muscle length, and intramuscular fluid

pressure [26]. MMG signals collected from impaired muscles reflect lower amplitude, lower frequency, and longer duration of activity when compared to healthy muscle signals [134, 154].

As previously described, during a muscular contraction the muscles involved contract and relax such that the force produced is a result of the firing frequency and the recruitment strategy of the active motor units. The MMG response to a single twitch shows a brief impulse response denoted by a fast rise in the amplitude with biphasic [145] or polyphasic [17] oscillations that slowly decay over time. Typically the MMG response to single evoked twitches is in the range of 60-90 ms [134]. The temporal characteristics and the distinct shape of the MMG response to evoked twitches suggest that MMG represents the mechanical response of the activity produced by active motor units [145]. MMG has been suggested to represent muscle fibre twitch activity summation where the amount of active muscle fibre twitches amount to the characteristics of the signal [137, 146]. However, the relationship between motor unit firing frequencies and MMG output shows a non-linear behaviour. The amplitude of the MMG signal has shown to decrease as motor unit stimulation increases, indicating a connection between MMG activity response and contractile properties of activated motor units, in particular, the development of fusion of individual motor twitches [211]. In [142], their analysis showed that during isometric voluntary contractions the muscle remains in a state of vibration in which all locations along the longitudinal axis of the muscle vibrate in phase and sensors located on opposite sides of the longitudinal axis of the muscle vibrate with opposite phases, thus confirming the bending movement of the muscle during a contraction and suggesting that the MMG signal is a reflection of the muscle as a global resonant structure to the local fluctuations of pressure as opposed to a response to fluctuations derived from the asynchronous summation of motor unit twitches.

During motor activity, an increase in force results in different types of muscle fibre activation. Initially, slow-twitch fibres are activated at low forces. As the force increases, fast-twitch muscle fibres are innervated. Once all the relevant motor units are activated force is dynamically controlled by the frequency of the firing rate of those motor units. During this recruitment of motor units, the MMG root mean square (RMS) value has shown to increase as more motor units are recruited. Similarly, an increase in the mean power frequency (MPF) of the MMG signal has been found with increasing global MU firing rates [26]. Slow-twitch motor units are initially activated with further increases in force recruiting additional fibres which are reflected by an increase in the RMS of the MMG signal. Recruitment of additional fast-twitch motor units results in an increase in RMS and MPF of the MMG signal. At high force, the RMS of the MMG signal decreases, associated with motor unit fusion, while MPF increases as the firing rate of the motor units play a higher role in the production of force. A linear relationship between the contraction force and RMS amplitude of the MMG signal has been demonstrated for the forearm muscles [140]. In summary, the amplitude of the MMG signal has been shown to correlate with motor unit activation while the frequency of the signal shows a relationship with motor unit firing rate [26, 76].

2.2.4 MMG Applications

Mechanomyography measures the mechanical response of the muscle to the motor units' activation during a muscular contraction [60]. As previously mentioned, studies have demonstrated a correlation between the motor unit recruitment strategy and the amplitude of the MMG signal [210]. Similar studies have been conducted to further investigate the relationship between motor unit recruitment and MMG signal activity [40, 135]. A comprehensive analysis of the spectrotemporal characteristics of the MMG signal was conducted by [39] and [159] to shed more light on the mechanism involved in force generation and the different aspects of neuromuscular functions. MMG activity has been used to analyse the differences in motor control during force modulation for static and dynamic tasks in voluntary [108] and non-voluntary muscular tasks [18]. Previous studies have shown that the recruitment and firing rate of motor units are dependent on the intensity of the contraction [140, 154]. Accordingly, MMG properties were later studied to conduct research about motor unit activation and firing rate strategies [14, 137].

As the mechanical response of muscle activity, MMG has been used for a number of studies including the assessment of properties such as muscle strength [119], balance [10], muscle function [97], mechanical responses during exercise [122], and vastly applied in the analysis of fatigue [15, 67, 82, 112, 164]. Thanks to its advantages compared to other myographic modalities and its ease of use, MMG has also been used in clinical applications to detect and monitor muscular pain [57, 109, 133, 138], monitor neuromuscular blockade during anaesthesia [66, 190], monitor the dystrophic process [134], diagnose muscle disease [14], diagnose muscle hypertrophy and atrophy [179], provide biofeedback in ergonomics [111], and to control externally powered prostheses [11, 168, 207]. One important characteristic of MMG is its robustness to electrical interference, which makes it a good candidate signal to replace EMG for unsuitable applications of such a technology [128]. Thanks to this characteristic of MMG, research has been conducted on the analysis of the signal for the examination of neuromuscular disorders [6, 98], and the facilitation of prosthetic control methods [207, 214].

All the literature mentioned above shows evidence of the widespread use of MMG technology in different studies and fields. MMG offers a non-invasive method to evaluate muscular function while providing indicators of functional and physiological parameters of the muscles during motor activities. Thanks to the mechanical nature of the signal, the underlying process of muscle fibre activation that generates muscular contractions could be better analysed [76]. Further investigation of the signal is needed in order to better understand the potential and limitations of the signal before translation of the technology into the clinical setting [75]. Therefore, the studies presented in this doctoral thesis intend to expand on the potential and constraints of the MMG signal.

2.3 Mechanomyography Parameters

Applications of MMG activity for research and clinical purposes have been well-documented [75, 76]. A combination of linear and non-linear methods for time and frequency domain analysis has been used to study the MMG signal for different applications. During static activities, the signal can be assumed to be stationary, allowing for conventional parameter extraction methods to be applied. However, variations caused by changes in muscle length, number of active motor units, and skin-fold thickness, among other factors result in a non-stationary signal during dynamic tasks [53, 81]. Feature extraction methods largely depend on the type of muscle activity (i.e., static or dynamic) since the spectral and temporal characteristics vary accordingly [75]. Thus, the application of the conventional time series analysis methods is carefully considered when analysing the MMG signal. Appropriate selection of a processing method is crucial for an objective analysis of the MMG characteristics.

Commonly used temporal features of the MMG signal include peak-to-peak (PTP) amplitude, root-mean-square (RMS), mean average value (MAV), and average rectified values (ARV). Spectral parameters of the signal include mean power frequency (MPF), median frequency (MDF), centre frequency (CF), and frequency variance (FV) [75]. Furthermore, joint time-frequency methods have been proposed to extract MMG parameters, including short-time Fourier transform (STFT), and wavelet transform (WT). These spectrotemporal parameters have been widely used across studies to estimate muscle contractile properties during muscle activities. Differences in the methodologies employed, muscle activity, and the purpose of the studies often dictate the number of parameters extracted.

The well-established and widely studied theory behind EMG provides a foundation for signal processing methods to analyse MMG [215]. Therefore, many of the signal processing technique methods applied to EMG have been translated for their application in MMG studies to relate the signal characteristics with the functional and physiological aspects of muscle activity. Similar to EMG signal processing, MMG undergoes a filtering process to clean the signal off external artefacts before the extraction of signal features. Commonly, these extracted features, which retain muscular contractile information, are employed for the classification of different muscular tasks [217]. Similarly, MMG signal features have been used for real-time practical implementations such as the evaluation of muscular performance [212]. Applications of MMG features have been used for the analysis of muscle fatigue monitoring [67], motor unit activation strategies [26], force estimation [159], muscle fibre distinction [68], control of muscle machine interfaces [11, 57], muscle performance evaluation in individuals with limited voluntary skills [48] and clinical examination of muscular disorders [75].

The literature shows different techniques to analyse the temporal and spectral parameters of MMG. Commonly, traditional methods using Fourier-based analysis are employed to analyse the power

spectra of the MMG signal. Fourier analysis has been applied to determine the spectral patterns of normalized MMG and EMG during fatiguing dynamic actions [20]. However, the complex relationships between the time and frequency content of the signal call for more sophisticated approaches to account for the non-stationarity of the signal. These techniques include WT and STFT, and other methods to compute time-frequency representations. due to the non-stationarity of the signal. Studies have shown that WT algorithms exhibit good performance in the detection of muscle activity [5]. Wavelet analysis combined with singular value decomposition has been used successfully for the classification of hand gestures [207]. Due to the non-stationary characteristic of the MMG signal, time-frequency methods may result in a better tool for pattern recognition of functional grasps [4]. MMG activity acquired during dynamic activities can be classified using Fourier or Wavelet methods. The latter has been a preferred technique due to the non-stationary nature of the MMG signal. However, MMG can be described as a time-varying signal whose power information resides at multiple frequencies. In order to fully describe the physiological phenomena underlying the MMG activity, a time-variant and frequency discriminative approach is needed. Such a candidate method is the Hilbert transform, an equivalent method to Fourier and wavelet transforms for the analysis of time-varying signals.

2.4 MMG-Challenges

As previously described, MMG signal parameters have been used for a number of applications across different fields. An important application of MMG is the discrimination of muscle fibre types and the evaluation of muscle performance [76]. There is a continuous interest in the development of MMG technology that could require minimal sensor and skin preparation while being easily fixable to the skin. Thanks to the advantages of MMG compared to the EMG modality discussed earlier, the signal has increasingly gained interest in clinical and out-of-the-laboratory settings as a complementary tool to EMG. Thanks to the nature of MMG, mechanical deviations of motor functions between healthy and injured limbs have been possible [144]. Furthermore, temporal and spectral components of MMG have been utilised to estimate motor control strategies during dynamic activities [22] by applying wavelet analysis to extract time and frequency-related features while maintaining a good level of resolution across the MMG frequency range (i.e., 1-120 Hz) [27]. However, MMG presents limitations and caveats when it comes to variations in anthropological parameters. For example, changes in muscle length, the thickness of the skin at the sensor location, muscle fibre compositions, and the motor unit recruitment strategy have been found to affect the properties of the MMG signal [53].

One of the main caveats of MMG technology is its sensitivity to the presence of external artefacts. Multiple studies have found that the most common types of MMG transducers (i.e., microphones, accelerometers, and piezoelectric sensors) are susceptible to different sources of external artefacts [38]. For example, Silva et. al. [165] found that during the execution of motor activities, limb movement produces a significant amount of motion artefacts which are detected by microphone MMG. Another anthropological factor which also was found to affect the condition of the MMG signal is the thickness of the fat skin layers of the dermis [81]. Frequency domain variations of the signal seem to be dependent on the thickness of the tissue between the sensor and the skin. This phenomenon occurs due to the fact the muscle tissue, such as the layers of the dermis and tendons, act as low-pass filters to MMG activity, effectively changing the spectral characteristics of the signal [79]. Results presented by Posatskiy and Chau [149] show that during dynamic activities, microphone-based MMG sensors are a better tool against motion-induced artefacts compared to accelerometer MMGs, in accordance with [175] who showed a higher degradation of the signal-to-noise ratio for accelerometer-based MMG compared to microphone MMG. However, the main complication with microphone MMG is the dependency of its spectrotemporal properties on the dimensions of the air chamber [196], a paradigm that is yet to be fully understood.

To minimize the presence of external artefacts in MMG, guidelines applied in the analysis of EMG are also commonly used in MMG studies [215]. One of the most common considerations is the location of the sensor with respect to the origin of the signal. This distance, between the sensor and the signal source, has been shown to play a significant role in the acquisition of consistent

MMG activity between trials [171]. These results are in accordance with other investigations [138, 175], where the findings show a signal with better characteristics when the sensor is located over the muscle belly compared to when the sensor is located closer to the periphery of the muscle, in particular when the location is closer to the tendon. However, Beck et. al., [19] showed a high level of association between sensors' placement in different axis/planes on the same muscle. These results were followed by studies which showed that the MMG signal shape does not depend on the sensor placement location, however, the amplitude of the signal does vary with the sensor location [42, 51]. For larger muscles, e.g., trapezius or latissimus dorsi, MMG activity collected from the same muscle site may not reflect the whole mechanical activity of the muscle, resulting in signals with variations in shape and amplitude which are dependent on sensor placement [19].

Sensor firmness during the attachment to the skin must be maintained to mitigate the variability of MMG signal characteristics during multiple trials, ensuring the consistency of the acquired signal [171]. As mentioned, the consistency of recording the MMG activity also depends on the sensor positioning and the uniformity of the location. Findings in [31] showed that the dominant frequencies of the MMG signal (below 30 Hz) positively correlate with the firmness of the attachment between the transducer and the skin. Even though skin preparation is not needed for the collection of MMG activity, considerations must be kept in order to reduce the effects of motion-induced artefacts. MMG is not influenced by skin conditions and does not require rigorous preparation during muscle activity acquisition [7], however, the appearance of external artefacts and variations due to sensor-to-skin attachment is a common problem in the study of the signal. In the case of accelerometers, standard practice is the use of double-sided tape to fix the MMG sensor to the skin while ensuring constant pressure. The effects of wiring in any type of transducer are considered negligible as it does not interfere with MMG signal collection and as long as the fixation method is not impaired by the movement of the wiring. For microphone-based MMG the use of elastic straps and custom-made Velcro bands is commonly employed. In general, since MMG activity is greatly influenced by the sensor attachment, sensor location, thickness of the subcutaneous layers, and the relative size and weight of the sensor, appropriate noise reduction techniques must be adopted. Similarly, the use of appropriate signal processing methods is needed to obtain reliable MMG parameters [22]. Equally important is the design of the experimental protocol and the proper delivery of guidance and instructions to the participants such that familiarization with the experimental protocol and experimental setup is carried out and systematic repetition of trials is achieved across participants. There still exists the need for further research to achieve a better understanding of the MMG response to more complex static and dynamic activities [76]. Particular attention may need to be paid to factors which could influence the MMG response such as skinfold thickness, sensor position, sensor orientation, and environmental noise. Furthermore, sensor selection has to be carefully considered in muscle assessment during static and dynamic motor tasks since technical characteristics of the signal have shown to be dependent on the type of sensor used [25].

2.5 Motivation

Electromyography is the myographic modality most widely established across research and clinical applications for muscle activity analysis. In particular, surface electromyography has been used in the majority of studies involving muscle activity. However, the caveats of this modality lay in the need for specific skin conditions, the sensitivity of the signal to variations in skin conditions (electrode-skin impedance) and sensor positioning, and the need for specific hardware requirements [1, 100, 153]. Temporal and spectral features of the EMG and MMG signal have been correlated in multiple studies to show the relationship between the electrical and mechanical response of the muscle during the production of muscle torque output [62], force [110], and on fatigued muscle during static isometric and dynamic actions [170], all of which supports the validity of MMG to analyse the mechanical properties of the muscle response. Mechanomyography offers a good myographic alternative at a low cost and with higher ease of use. MMG records the mechanical response of the muscle contractions in the form of vibrations retaining functional and physiological characteristics within its properties [41] at the same time that is distinctively less sensitive to variations in skin conditions [76]. As mentioned earlier, MMG can be collected using a variety of different types of transducers, the most common being accelerometers [197], piezoelectric contact sensors [195], and microphones [196]. Even though each one of these mechanical transducers captures the same MMG activity, the means and the method with which this signal capture occurs for each sensor are different, which renders them more or less effective depending on the application. For example, accelerometers have been found to return a better estimation of MMG activity compared to piezoelectric sensors thanks to the linear characteristic of the spectral space of the signal [195]. Microphone MMG, on the other hand, has proved to be better suited for dynamic activities compared to accelerometers and piezoelectric sensors as these two technologies are more susceptible to motion artefacts [196]. However, these three types of MMG sensors have a common limitation related to factors affecting the MMG signal intrinsically such as external sources of noise and anthropomorphic variations between subjects [76]. Furthermore, MMG has been shown to provide limited information when used as a stand-alone sensor as opposed to a multi-channel system primarily due to the fact that force production, which in turn drives the MMG signal as discussed previously, is dependent on the location of motor units [111]. This behaviour has motivated investigators to implement multi-channel configurations of MMG transducers for a better analysis of the muscular activity. A system using a multi-channel MMG sensor approach should result in a more suitable tool to analyse motor functions. As a multi-channel sensor system improves the MMG signal capture it remains susceptible to the common factors affecting the signal. A factor which has repeatedly been mentioned in the literature to affect the MMG signal is the level of force found between the sensor and the skin regardless of the attachment method. This effect has been documented in a number of studies using different kinds of MMG transducers [31, 105, 149]. The literature shows only a small number of studies focused on the evaluation of the relationship be-

tween contact force attachment and MMG activity [171, 195, 197]. The findings of this limited bank of information on the effect of contact force suggest that depending on the type of MMG technology being used and the amount of force with which this sensing technology is attached to the skin, the MMG temporal and spectral properties vary significantly. It remains unknown if the related changes to different levels of contact force are a product of the sensors acquiring MMG activity under different mechanical constraints or if the transducers effectively acquire more information from deeper and neighbouring muscles. In the case of surface electromyography (sEMG), acquiring information from a higher number of motor units results impossible due to the superimposed property of activation of motor units, a task which results even less feasible when considering motor units located deeper within the muscle tissue [71]. The use of intramuscular EMG has been developed to overcome the limitations of recording deep motor unit activity, and high-density EMG has been intensively investigated to enable the acquisition of a high number of motor units from the skin surface [174]. However, both of these technologies preserve the limitations of conventional EMG at the same time as they are invasive (intramuscular EMG) [192] or require more sophisticated hardware (HD-EMG). MMG offers a good alternative with the potential to capture deep muscle information while remaining a non-invasive technology by modulating the amount of sensor-to-skin contact force.

As mentioned, the MMG modality has gained particular attention in the research community thanks to the advantage of the technology to overcome some of the limitations commonly encountered when using EMG. However, one of the understudied phenomena behind the MMG signal capture is the role that contact force between the sensor and the skin play regarding the quality and characteristics of the MMG signal. A handful of studies have tried to alleviate this effect by maintaining the pressure between the sensor and the skin at a constant level by using custom-made apparatus [149, 171]. However, in order to take into consideration all the different components of the MMG signal, without limiting the bulk movement of the muscle along both the longitudinal and transverse directions, which could be an impediment to sensor translation into wearable technology which requires firm attachment to the skin, the attachment method must ensure a set amount of pressure against the radial expansion of the muscle which could allow for natural changes in the contact pressure between the transducers and the surface of the skin. To take into account these dimensional changes, the development of specialized hardware is developed in this doctoral thesis. Two custom-made wearable armbands of multi-channel MMG (accelerometer and microphone) are designed and used for the analysis of the signal when different levels of contact force are applied. The first system includes the use of four microphone MMGs freely movable around the arm. The second design includes the use of four 3-axis accelerometers which also can be positioned at any location around the arm. These designs aim to facilitate the investigation of the effect of different levels of contact force on the quality and properties of MMG activity.

The physiological and mechanical characteristics determining the direction of MMG propagation through muscle tissue are not yet fully understood. It has been suggested that oscillations gener-

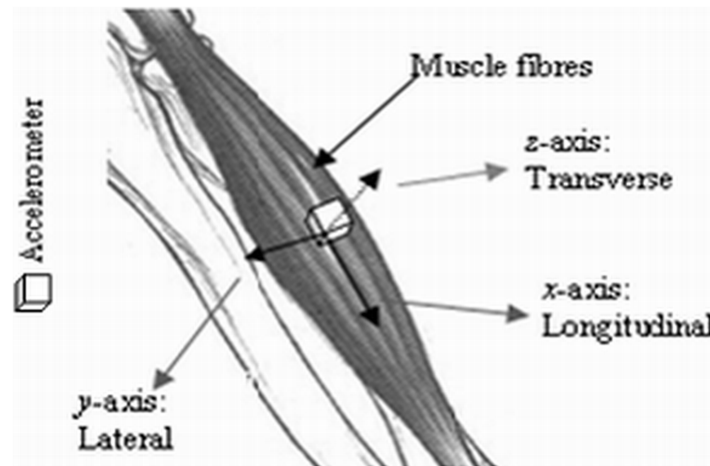


Figure 2.4: Illustration of accelerometer sensor orientation with respect to the alignment of muscle fibres. Figure reprinted from [79] under Creative Commons license CC BY 4.0. See appendix 7.3.

ated during a muscular contraction propagate evenly in all directions from its origin (muscle central region [53] and active muscle fibres [60]). Such mechanical oscillations are in time attenuated as they propagate through soft tissues towards the skin surface [81]. Research on MMG signal propagation has found that the signal radiates mainly along the longitudinal and transverse directions with respect to the muscle fibre alignment [41]. Fig 2.4 shows an illustration of sensor alignment with respect to the muscle fibres. Analysis of MMG activity generated by individual motor units found that the signal mainly originates from muscle fibre displacement. According to the study performed in [51], the signal is driven by the location of the active motor units. In this respect, the amplitude of the MMG signal is mainly driven by the oscillations captured along the transverse axis and the frequency is dependent on the propagation along the longitudinal and transverse axes, all with respect to the muscle fibres alignment. Archer *et al.* [9] found similar results showing that for frequencies below 25 Hz propagation of the signal takes place along the longitudinal and transverse directions, however, if the signal frequency rises above this level, the propagation occurs mainly along the longitudinal direction. These findings present evidence that the spectrotemporal properties of the MMG signal are subject to the direction of propagation of the same. Because of the character of the MMG signal and the method for capturing it, MMG is known for containing crosstalk from neighbouring and synergistic muscles. Even though there is no sufficient investigation in the literature regarding crosstalk identification and reduction for MMG [182], research has shown that higher levels of crosstalk activity are found along the lateral and longitudinal directions with respect to the muscle fibres and low levels of crosstalk are found along the transverse direction [79]. This characteristic difference in crosstalk found between directions is suggested to be caused by the attenuation and filtering process of the signal as it propagates through muscle tissue. The phenomenon of wave propagation of the MMG signal during the assessment of muscle activity needs to be further explored. Minimal research has been done in the last decade regarding the analysis of crosstalk in MMG activity, with only a few studies found in the literature [21, 79]. This

phenomenon could be better understood not only by the use of a higher number of MMG channels but also by analysing the effect of contact force on the MMG signal characteristics.

As higher levels of pressure are applied between the sensor and the skin, the information content of MMG is expected to augment as the signal picks up muscle activity from deeper muscles. Based on the visco-elastic properties of muscle tissue, more pressure between the sensor and the skin should facilitate MMG propagation through muscle tissue, resulting in a better quality signal. In addition, the measurement of MMG from multiple channels should provide a preferable representation of muscle activity compared to conventional stand-alone strategies. The evidence presented in this section motivates the investigation of the effect of contact force on a multi-channel microphone- and accelerometer-based MMG technology, including the study of the effect that these contact force variations have on the MMG signal features when used for the classification of motor tasks. Further details about the analysis performed in this doctoral thesis are presented in the next chapter.

Chapter 3

Effect of contact force on acoustic MMG

This chapter introduces a new sensing modality, named MMG-plus-One. The sensor design, methodology, experiments, and results are presented.

The content and findings discussed in this chapter are published in the 2020 IEEE/ASME International Conference on Advanced Intelligent Mechatronics (AIM) [115] and in IEEE Transactions on Neural Systems and Rehabilitation Engineering [36].

3.1 Overview

In the literature, there is evidence suggesting the need for further systematic investigation of the relationship between MMG and the force with which the sensor is attached to the skin. As a result, the design and development of a new sensor are introduced in this chapter. The aim of the study carried out in this chapter is the systematic assessment of the effect of contact on the quality and signal characteristic variations underlying the information collected by the use of acoustic MMG, effects which are reflected in the discriminative power of the signal regarding the classification of motor tasks. Furthermore, the investigation includes the analysis of the muscle mechanical response during the steady state of the contraction, with particular attention to the effects that different levels of contact force have during this phase. This investigation entails the acquisition of muscle activity information from tasks similar to those followed in related studies where conventional MMG technology is used, and includes gestures related to actions occurring during activities of daily living.

3.2 Introduction

Over the last few decades, surface electromyography (sEMG) has been widely used as the standard myographic modality for recording and decoding human motor intention and muscle activity. This modality has been used to classify a high number of actions (e.g., multiple gestures) while maintaining a good level of accuracy [44]. There are several techniques and algorithms in the literature regarding the use of EMG for gesture detection. For example, taking advantage of deep neural network architectures, in [151], the possibility of securing accuracy above 90% for 52 classes is shown for EMG signals. Despite the fact that by the use of sEMG a high number of gestures can be classified with a high level of accuracy, there are some significant challenges that exist with the practical uses of this modality related to the high dependency to skin conditions and the sensitivity to sensor positioning and to external sources of noise which demand specialised equipment for the proper acquisition of the signal [1, 100]. Despite the reported high quality of myoelectric control under the research laboratory environments, the challenges mentioned above have restricted the use of EMG in commercial-powered prosthetic limbs and for in-home conditions. One result is that many of the current prosthetic devices work based solely on sequential state machine rules, which take the commands of the patient by only picking up the co-contraction of the muscles, tracking which is straightforward. However, this technique cannot realize intuitive control. Thus, the abandonment rate is high for several upper-limb prostheses devices due to the unintuitive and cumbersome control [141].

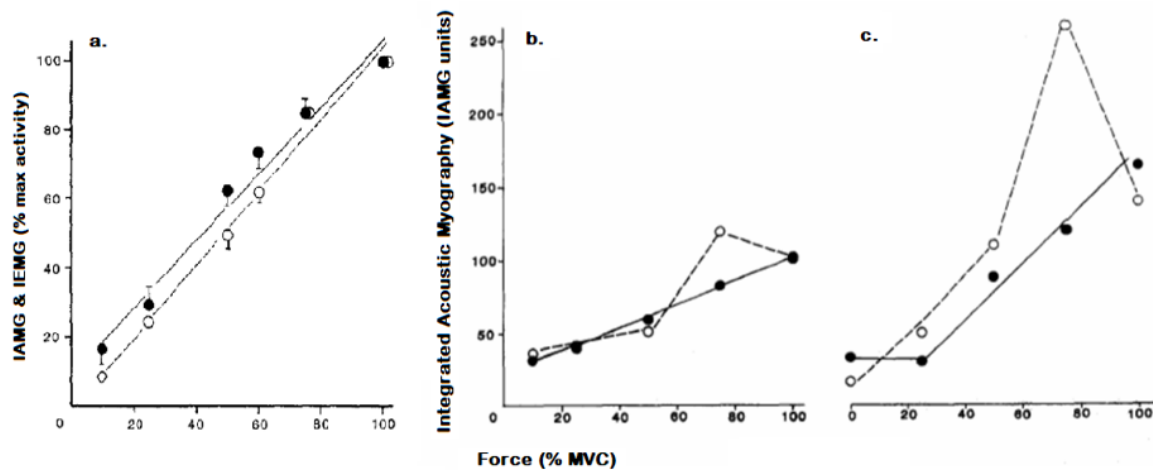


Figure 3.1: (a) Force vs integrated acoustic myography (IAMG; filled circles) and integrated electromyography (IEMG; empty circles) at various levels of maximal voluntary contraction (MVC) acquired from the quadriceps muscle. Reprinted with permission from [178] (b, c) Force vs IAMG during voluntary isometric contractions. The solid symbols and lines on both graphs represent data when 180 Pa of contact force is applied. Empty symbols and dashed lines indicate data when 790 Pa (b) and 1200 Pa (c) of contact force are applied. The relationship between IAMG with the increase of force at low levels is approximately linear; however, the signal decays at high forces. Reprinted with permission from [171]. See appendix 7.4 for © information.

In this respect, mechanomyography, a technology based on the quantification of the mechanical response of the muscle, has shown promising results thanks to its particular ease of use and non-invasive property. Over the last three decades, the study of mechanomyography has gained more interest thanks to advances in technology, the use of novel signal processing methods related to the signal, and the use of the signal for a wide variety of new applications. At the same time, using MMG (instead of EMG) could result in the reduction of the potential physiological information rate as it measures the mechanical response of an electrical source, rather than directly measuring the electrical response. Thus, MMG is mainly promoted for applications in which the user intention should be decoded in a consistent manner and under unstructured conditions rather than studying the neuro-physiology of the muscles. This makes MMG a good candidate for in-home uses of prosthetic systems. The mechanical responses are captured in the form of oscillations produced by displacement and dimensional changes of muscle fibres that occur during a contraction [41].

In comparison to EMG, this mechanical method may be classically considered as a modality with a lower information transfer rate, in particular regarding the neurophysiology of muscle activation and the peripheral nervous system. However, by using MMG, some practical difficulties related to the use of EMG (in particular for in-home uses) can be addressed, such as sensitivity to skin conditions or sensitivity to electromagnetic noise caused by electrical devices (e.g., elevators, air-conditioning systems, among others) [56]. This makes MMG a good alternative for practical applications that require in-home compatibility, a non-invasive method, and a low-cost solution for

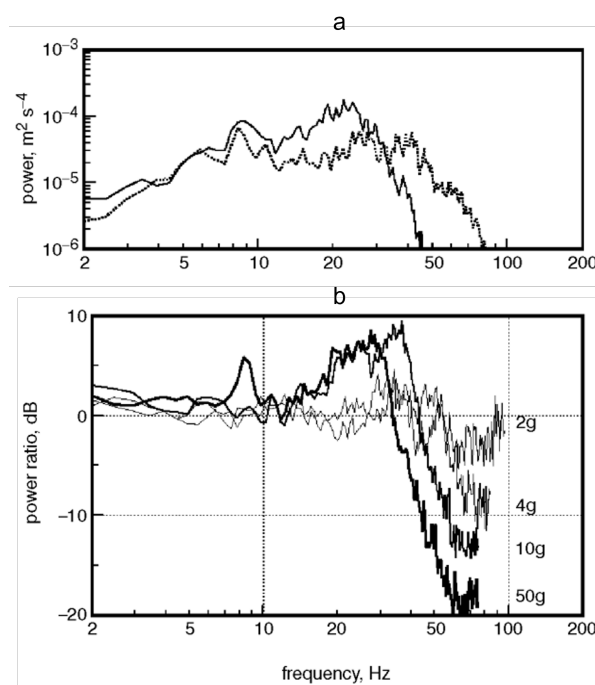


Figure 3.2: (a) Power spectral density of MMG with no load (solid line) and with the addition of 50g (dotted line). (b) Comparison of normalized power spectrum density recorded during the addition of weights (2, 4, 10 and 50g). Reprinted with permission from [197]. See appendix 7.6 for © information.

muscle monitoring while being robust to electrode-skin conditions and requiring simple calibration and placement procedures (with no need for skin preparation). Research related to MMG has rapidly grown to further enhance the information rate of the modality. Understanding the limitations and potential of the signal, as well as the factors that play a major role in the MMG signal acquisition, could help increase the applicability of the signal and improve the performance and accuracy of the classification and intention detection of human-machine interfaces.

3.2.1 Contributions

The main objectives of this chapter are summarized as follows:

1. The first objective of the work presented in this chapter is to investigate the variations in the characteristics of the signal when different levels of contact force are applied.
2. The second objective of this work is the classification of hand gesture tasks based on the spectral and temporal characteristics of the MMG signal.
3. The third objective is the analysis of the changes caused by different levels of contact force on the discriminative power information of the MMG signal when classifying multiple hand gesture tasks.

3.3 Related Works

3.3.1 Existing Challenges

Investigations around the use of MMG gained particular attention during the last two decades of the 20th century as a result of research efforts towards finding different means to evaluate muscle activity via non-invasive and simpler methods [177]. MMG signals have been collected using different sensory solutions, each with different frequency bandwidth and information rate, such as accelerometers [197], piezoelectric contact sensors [195], and microelectromechanical (MEM) microphones [148, 196]. Each one of these sensory solutions has particular advantages and limitations. For example, accelerometers have been found to provide a flatter spectrum and higher bandwidth when compared with piezoelectric contact sensors [195]. Acoustic/microphone MMG, on the other hand, has shown to be more robust to motion artefacts compared to accelerometers, making it ideal for dynamic tasks [196]. Nonetheless, all of these MMG modalities have been found to be affected by different factors, such as the length of the muscle being tested, motion artefacts, or the thickness of the fat layers of the dermis [76]. The limitations are more pronounced for neurophysiological studies of motor unit action potentials [111]. It is imperative to mention that all the above-mentioned MMG sensors have shown some level of sensitivity to contact force. Although the effect of contact force has been reported as an influential factor in the MMG response [31, 105, 149, 171, 195, 197], the literature on this topic is still not clear and is partly heterogeneous. There is a need for a more detailed understanding of the effect of normal force and the information context of the MMG signal.

One of the first studies on this topic emphasized the importance of sensor calibration prior to the signal acquisition, the influence of the sensor positioning (relative to the muscle), and the effect of contact force (between the sensor and the skin) on the quality of the MMG signals [31]. Similar findings were found in [178] during the study of the relationship between the MMG response and force production during isometric contractions (see Fig. 3.1a). This study was followed by [171] to evaluate the influence of three levels of contact force on a piezoelectric MMG sensor during voluntary isometric contractions (see Figs. 3.1b,c). Their findings were in agreement with those in [195] in which the MMG signal of a piezoelectric sensor was evaluated under different conditions by loading the sensor with values ranging from 0.5 N. to 1.5 N. Although the literature suggests that contact force may have some overall alteration on the quality of the MMG signal from piezoelectric and microphone sensors, they do not provide insight into how/if, with the use of different force levels, it would be possible to tune the detection accuracy regarding the user intent. In the case of accelerometer MMG, which provides a 3-dimensional mechanical response on each sensor spot (a multi-dimensional characteristic of only this type of MMG sensor), there is a very small number of studies regarding the effect of contact force. An early study suggested that accelerometers are not influenced by changes in contact force [171]. However, a later study in this matter suggested a

heterogeneous response, including signal distortion for acceleration-based MMG, when different weights ranging from 2 grams to 50 grams were placed over a single channel sensor [197] (see Figs. 3.2a,b). All these previously mentioned studies show evidence that contact force plays an essential role in the signal quality and magnitude of MMG transducers (accelerometers, piezoelectric contact sensors, and microphones). However, there is a lack of systematic investigation about the effect of contact force on not only the quality and alterations of the signal properties but also on the discriminative power of MMG activity. The sensor design described in this chapter focuses on adding a new “dimension” to MMG, which can further enhance the information rate, discriminative power, and practicality of this bio-signal modality for its use in prosthetic control.

Analyzing the MMG activity at different levels of contact force can shed light on a new direction that can be potentially exploited to get access to deeper muscle information. This elucidates the proposed paradigms of the MMG-plus-One modality and provides an understanding of the mechanical behaviour of this modality. The previously mentioned challenges show a heterogeneous understanding of the effect of normal force on MMG. This calls for further investigation which may result in a novel approach to improve the MMG signal acquisition and therefore the discriminative power of MMG.

3.3.2 MMG-Plus-One Concept

The previously mentioned findings in the literature have motivated the design of a novel armband using which the level of contact force is systematically adjusted on multiple sensor locations around the forearm. It is worth mentioning that there has been minimal to no related investigation in the literature regarding the use of different levels of contact force to extract richer information for the classification of hand gestures. This chapter focuses on the mechatronic design of the MMG-plus-One armband.

The MMG-plus-One concept is motivated by the fact that, in theory, the increase of the normal force at the point of contact with the skin alters the viscoelastic properties of the tissue (due to its nonlinear nature), which can impact the propagation of mechanical waves related to muscle activation. The aim is to utilize the mentioned physical characteristic to modulate the information content of the MMG signal modality, and consequently enhance the discriminative power for human intention detection when utilized for the classification of multiple hand gestures. This feature has the potential to be used as an additional adjustable degree of freedom for MMG, which can be exploited to enhance the performance of MMG-based man-machine interfaces. It should be emphasized that the normal force not only can result in higher viscoelasticity of the tissue, which increases the conductivity of the mechanical wave from the muscle to the skin, but it can also reduce the volume conduction effect (signal damping due to the tissue between source and sensor) which can enhance the signal to noise ratio.

In this chapter, the investigative focus is based on these properties through designing and imple-

menting a new wearable MMG technology that allows to systematically increase the normal force at the point of contact of each independent sensor without the need to unmount the device. The prototype implemented and tested is an armband composed of four MMG modules. The number of modules has been selected considering the complexity of the system, accuracy of the prediction, and potential artefacts (to prevent the sensors from potentially capturing crosstalk from synergistic and neighbouring muscles during the recording, which could hinder the focus of the investigation). The normal force applied on each sensor of the armband can be adjusted onto three distinct projection depths by the use of a particular mechanical design. Additionally, the length of this wearable can be adjusted to a wide range of dimensions thanks to the distinctive design of the armband segments. The armband not only explores the gradient of information distributed around the arm but also allows one to take into account the gradient of information caused by the normal force. The focus of this study is to investigate for the first time the effect of distributed normal force on the information context of MMG. It is worth mentioning that the armband design presented in this chapter can be further adapted and scaled to different dimensions for custom applications with different needs on the number of MMG sensors.

3.4 Materials and Methods

The following sections describe the design of the sensor, the characteristics of the armbands and assembly steps, the methodology employed for data collection, and the analysis carried out.

3.4.1 Sensor Design

The MMG sensor introduced here has followed an acoustic MMG structure, as presented in [148, 165, 196, 203]. The dimensions and shape of the acoustic chamber have been adjusted to the optimal measurements following the findings presented in [148], a conical shape, a diameter of 7 mm, and a height of 5 mm. The sensor consists of 4 components: a case, used to hold all the parts together, a microphone (Knowles SPU1410LR5H-QB), used to capture the MMG activity, a portion of transparent mylar membrane of 3 μm , used to amplify the changes in pressure in the acoustic chamber, and a stabilizing ring, which dimensions have been adjusted to snap-fit around the frontal side of the case, causing the mylar film to remain firmly stretched at the same time as preventing the sensor from shifting or tilting. As the mylar film is excited by propagated muscle vibration, changes in air pressure in the acoustic chamber are captured by the microphone which is placed on the backside of the case at the bottom of an isolation chamber. This chamber has been sealed and filled completely with hot glue. Fig. 3.3 shows a schematic of the custom-made microphone MMG sensor developed for this study.

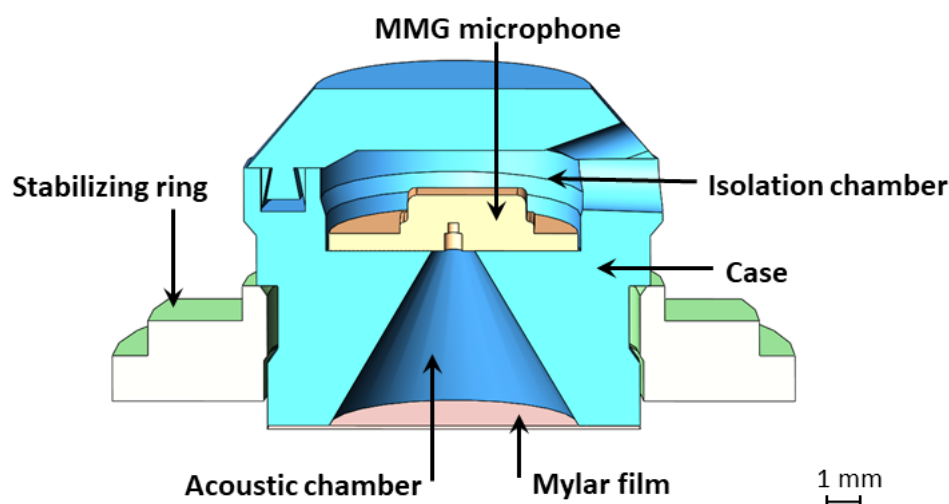


Figure 3.3: Cross-section view of custom-made microphone MMG. The device is comprised of 4 parts: a case used to hold the rest of the components together, microphone, mylar film, and a stabilizing ring, which is used to stretch the film and prevent the case from tilting. As the mylar film is disturbed, changes in pressure within the acoustic chamber are captured by the MMG microphone, which is isolated in a chamber filled with hot glue.

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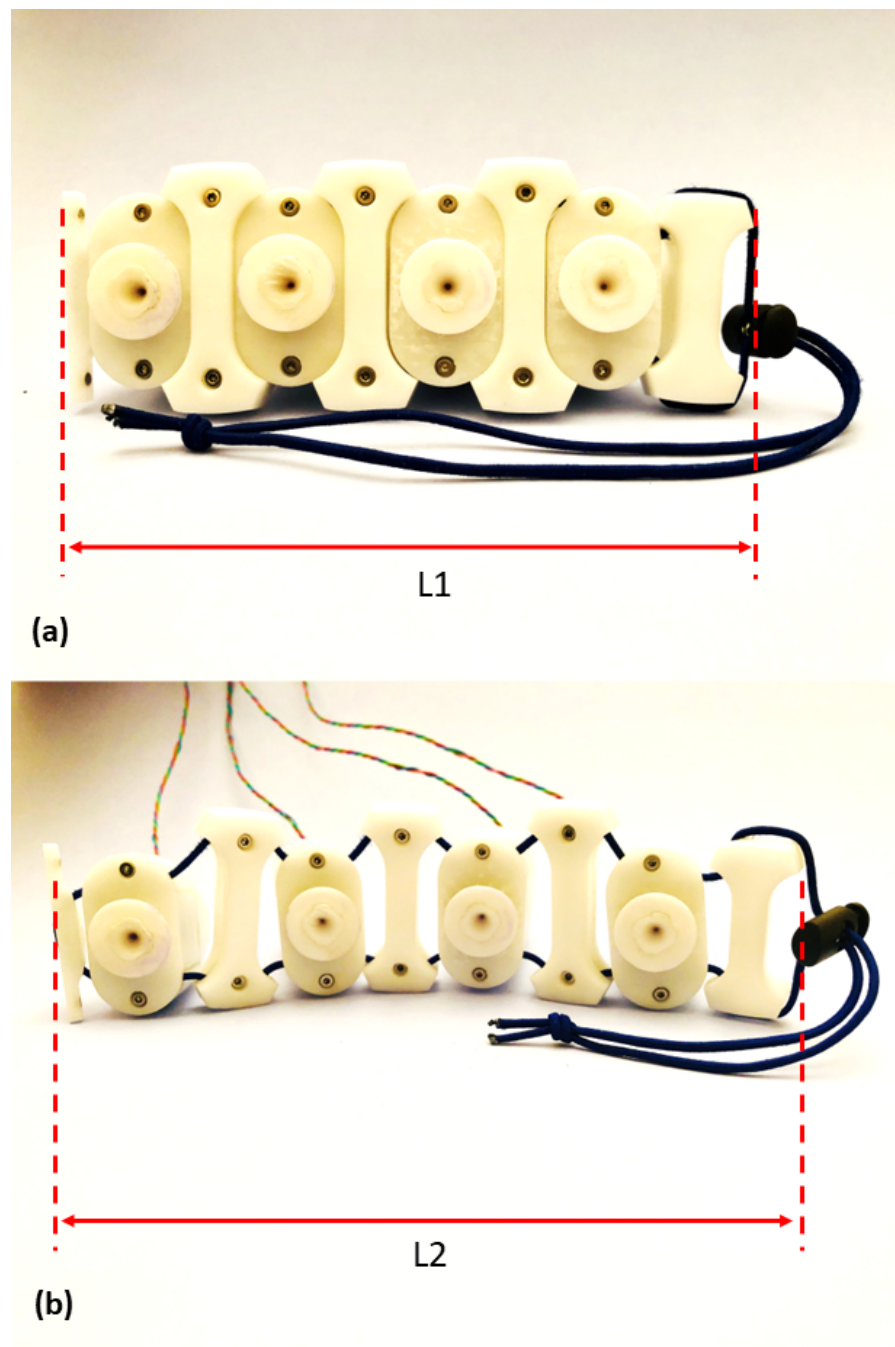


Figure 3.4: (a) MMG armband design at lowest length L1 (13.5 cm). (b) MMG armband with length extended to L2 (18 cm). Depending on the arm diameter of each individual, the active length of the elastic cord is adjusted by the use of the spring buckle to match the length of the armband to the arm diameter of each participant. The length of the armband can be adjusted to values ranging from 13.5 cm to 28.5 cm. Each segment can be slid along the cord to be placed over the target muscles.

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3.4.2 Armband Design

A wearable armband, comprised of four MMG segments and four separation segments, was designed for the purpose of this study. The four MMG segments of the proposed armband allow to

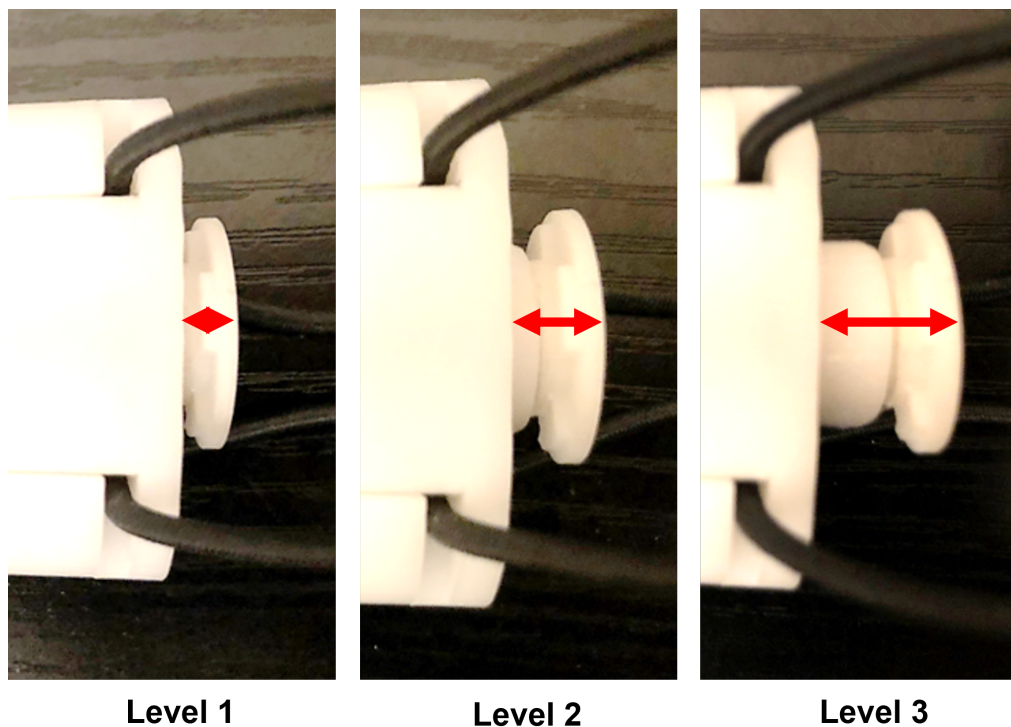


Figure 3.5: Increasing levels of protrusion for MMG design. From left to right, custom-made sensor at levels of protrusion 1, 2 and 3, respectively.

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systematically increase the contact force between the MMG sensor and the skin. The four separation segments prevent the MMG segments from shifting by maintaining the tension on an elastic cord (2 mm spindle braided, Fabmania part number: FM-02), which holds all the components together. In each one of the segments, two housing parts are coupled together using socket head cap screws to form slots through which the elastic cord is passed. To take into account the variability of the arm diameters (between users), and to ensure similar initial conditions for all participants, a spring buckle is attached to the elastic cord at one end of the armband to allow for the use of larger or shorter lengths of the cord (see Fig. 3.4). Prior to the experiments, the arm diameter of each participant, at the level of the sensor location, was measured. Depending on the arm diameter of each individual, the active length of the elastic cord was adjusted by the use of the spring buckle to match the length of the armband with the arm diameter of the participant, ensuring the same conditions for every participant. The length of the armband can be adjusted to values ranging from 13.5 cm to 28.5cm. Thanks to the use of the design, each segment was slid along the cord to be placed over the target muscles.

Each one of the MMG segments is comprised of five parts: a custom-made MMG sensor, a compressible unit into which the sensor snap-fits, a rotational mechanism which permits the investigator to increase the contact force levels, a plunger onto which force is applied and transmitted to the compressible unit, thereby compressing the spring to reach the different levels of projection, and two main housing parts which hold all the components together. Force is applied over the back

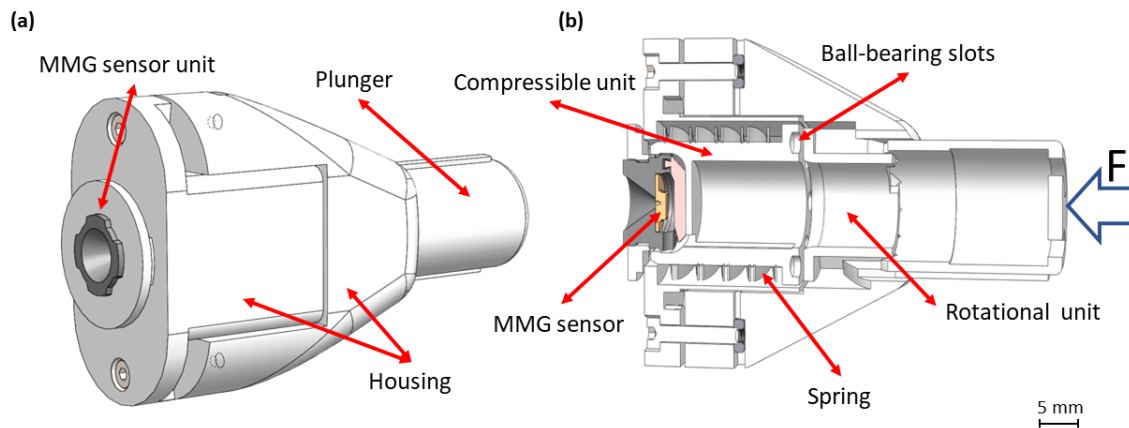


Figure 3.6: (a) 3D-MMG design. (b) Cross-section view of 3D-MMG design. Force is applied over the back of the plunger. By the use of a spring the MMG acoustic chamber protrudes onto two increasing levels separated by 3mm. Each of these levels is reached by turning the rotational unit once the plunger has reached the corresponding slots.

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of the plunger in order to protrude the MMG sensor to the next levels. By the use of the spring, the compressible unit is cyclically pushed out onto two increasing projection levels (see Fig. 3.5). Each one of these levels is separated by 3 mm. The levels are reached once the force applied on the plunger has enabled the turning of the rotational unit to the corresponding slot. The use of ball bearings facilitates the turning of the rotational unit and prevents the rotation of the compressible unit, which holds the sensor in place. The use of the spring makes it possible for the mechanism to retract to the first level of projection after the highest level has been reached (see Fig. 3.6). Except for the printed circuit design (PCB) board containing the sensor, the spring, and the ball bearings, all the rest of sensor components were 3D-printed using photo-polymer Rigid 10K resin from Formlabs.

3.4.3 Demographics

Seven able-bodied right-handed individuals (5 males and 2 females) between the ages of 19 to 35 years old and three trans-radial amputees (2 males and 1 female) between the ages of 30 to 50 years old participated in this study. The study took place in a single session per participant. All participants were considered to be within the range of healthy body mass index (BMI) for their respective age groups. All participants gave their informed consent before taking part in the experiments. All experiments were approved by the Imperial College Research Ethics Committee (ICREC reference: 15IC3068).

3.4.4 Experimental Protocol

The experiments involve the collection of MMG activity while participants are asked to perform different hand gestures. Able-bodied participants were asked to perform six gestures, and amputees

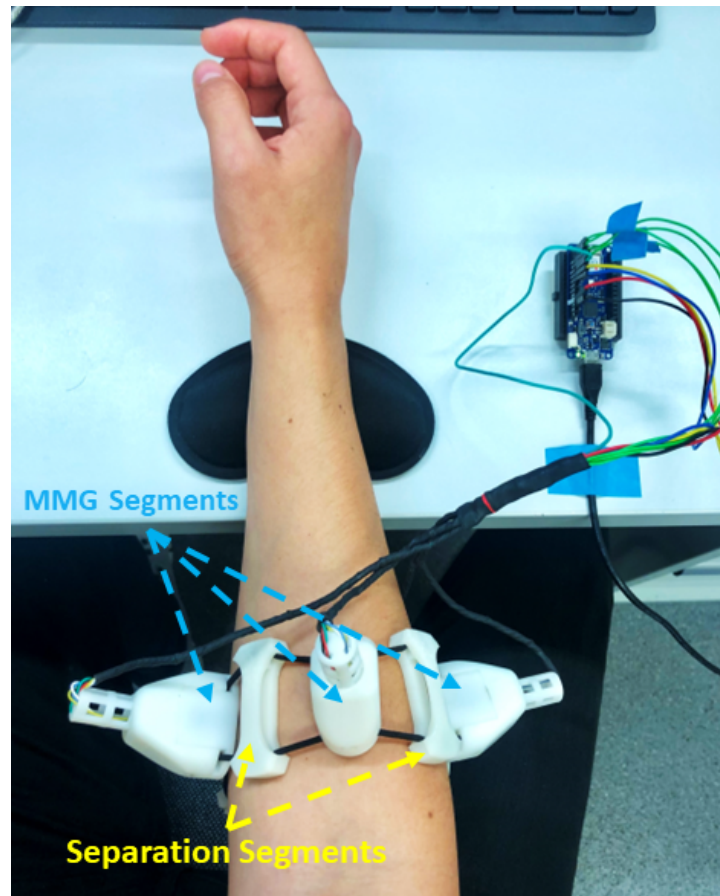


Figure 3.7: The armband is comprised of 4 MMG segments (4th segment not visible) and four separation segments (2 segments not visible).

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were asked to perform four gestures. The information is collected at different levels of contact force using the proposed armband. Three levels of contact force were tested in able-bodied participants, and two levels of contact force were tested in amputees. Four MMG sensors are placed around the forearm using the proposed stretchable armband (see Fig. 3.7). The six hand gestures used for able-bodied participants were: Flexion, Extension, Pronation, Supination, Adduction, and Abduction, See Fig. 3.8 for an illustration of the different hand gestures. The four gestures used for amputees were Flexion, Extension, Pronation, and Supination. Participants were asked to perform the gestures to the maximum extent to which they felt comfortable. For Flexion and Extension, participants were asked to maintain all the digits extended during the duration of the contraction. To minimize the effect of motion-induced artefacts during the experiment, participants were asked to hold their arms still while performing the trials and their dominant arm was placed over an armrest (see Fig. 3.7). Amputee participants did not use the armrest. The armband was positioned around the forearm, and the MMG segments were shifted accordingly in order to be placed over the flexor carpi radialis (FCR), brachioradialis (BRD), extensor digitorum communis (EDC), and flexor carpi ulnaris (FCU) muscles. These muscles were selected because of their superficial location and the ease of palpation. The flexor muscles (FCR and FCU) were selected due to their role during the dif-

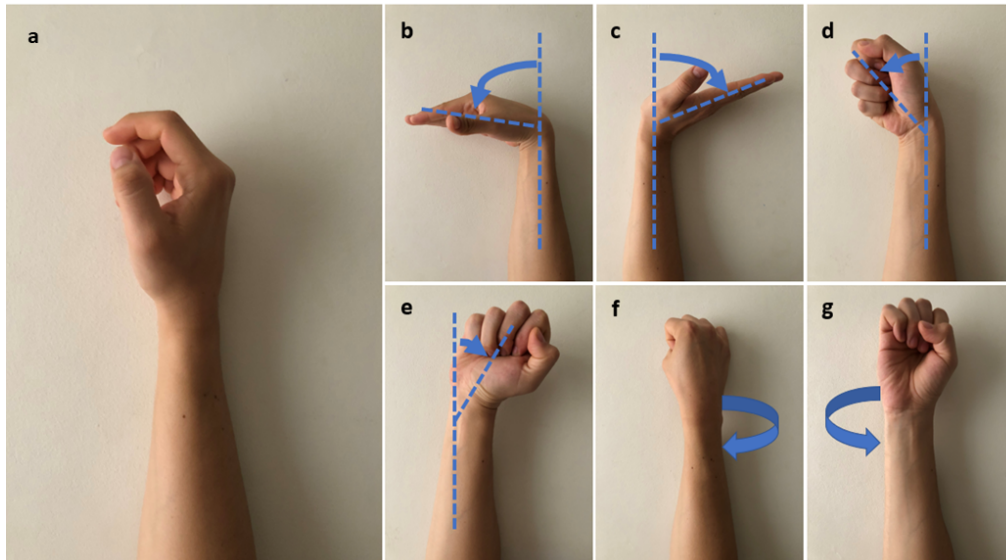


Figure 3.8: Illustration of the different hand gestures: (a) Hand at rest, (b) Flexion, (c) Extension, (d) Adduction, (e) Abduction, (f) Pronation, (g) Supination.

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ferent motor tasks, particularly during Flexion, Extension, Adduction, and Abduction. The extensor muscles were selected particularly due to their role during Pronation and Supination. A palpation method was used to locate the target muscles. Considering the origin and insertion of each muscle, the brachioradialis muscle was first palpated, and an MMG sensor was placed over the widest area of the muscle in the forearm. At this level of the forearm, the rest of the target muscles (i.e., FCR, FCU, and EDC) were subsequently palpated, and the sensors were placed accordingly around the forearm. It should be noted that due to the differences in the neurophysiology of various subjects, it is to expect differences between the performance of subjects, part of which can be caused by differences between the muscle location, muscle length, and skinfold thickness.

Data collection for both demographics consisted of the following; the user's dominant arm was positioned at rest mid-way in supination at the forearm, with the arm held approximately 15 cm above the surface of the table. The seat was adjusted for the participant to rest the elbow at approximately 90°. An armrest was used to rest the elbow while the participants were asked to perform different gestures. Prior to commencing the experiment, all participants underwent a training trial which consisted of the participants performing five repetitions of a randomly selected group of gestures with intervals of 5 seconds between each contraction, taking approximately 2-3 minutes per participant. For amputee participants, in terms of the time duration after amputation and the remaining muscle condition, the first participant had the amputation 7 years back and makes use of a body-powered prosthesis on a day-to-day basis for activities of daily living (ADLs) and for regular exercise on a hand-cycle, maintaining a high level of activity. The second amputee participant had the amputation 5 years back and uses a Mitt prosthesis on average every 3 days for ADLs, self-describing the activity level as moderate. The third participant had the amputation performed

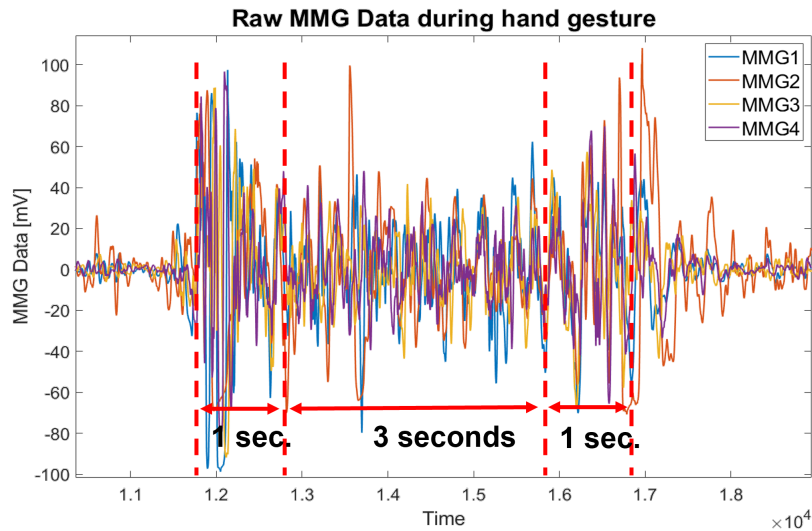


Figure 3.9: Illustration of data extraction. The first and last seconds of information are discarded, and the remaining 3 seconds are extracted for analysis.

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6 years back and uses primarily a Mitt prosthesis, self-describing the activity level as moderate. All amputee participants are quadruple amputees and needed amputation after sepsis. The first participant has a high-level trans-radial amputation on the tested limb. The other two participants have distal trans-radial amputations.

After training, data collection was divided into three groups with a 30-second resting period between each recording. Groups were divided as follows: Flexion-Extension, Pronation-Supination, and Adduction-Abduction. Only the first two groups apply for the amputees. Each group consisted of 5 repetitions of each gesture. Initially, participants were asked to place their hands in the resting position. After initiating data collection, participants were asked to maintain the resting position for a period of 10 seconds before carrying out the first contraction. Participants were then asked to perform the sustained contractions for a period of 5 seconds with a 5-second interval to rest between each contraction. At the end of each trial, participants were asked to maintain their hands at rest for a period of 10 seconds before stopping the recording to facilitate data extraction. After the three groups of recordings finished, each one of the MMG sensors was pushed out to the next level of projection to increase the amount of contact force. The increases in the levels of contact force were performed in situ to maintain sensor location. Once all four sensors had been pushed to the next level of contact force, the process of data recording for the three groups of hand gestures was performed again. This process was repeated two times for able-bodied participants to record data of all hand gestures for three levels of contact force. In order to avoid the fatigue of the muscle and due to time restrictions, the amputee data collection process was repeated only one time in order to collect data on all gestures for two levels of force. The data collection process took approximately 45-60 mins for able-bodied participants and approximately 30 mins for amputees.

3.4.5 Data Collection

The raw acoustic signals of the MMG channels were divided into two sets of information for the purpose of training and testing a classifier. For the purpose of this analysis, a hold-out validation method was applied as it shows a more realistic view of the performance of the proposed MMG-plus-One armband. In this regard, the testing is done on a completely unseen dataset to maximize the validity of the technique and strictly avoid any potential unwanted information leak between the test and training sets. The training set contained the first three trials of each hand gesture, and the testing set contained the remaining two trials. Similar to the existing literature on gesture detection for electromyography [155, 186], and mechanomyography [4, 207], the signal was analyzed during the steady-state phase of the contraction, thus discarding the transient phases. This is a common practice in the literature since signals during transient phases have a high degree of stochastic non-stationarity, making the steady-state of the signal more robust for classification and gesture detection purposes [49, 139]. In addition, the duration of the transient phases cannot be controlled accurately for systematic training of machine learning algorithms under practical situations and without rigorous and excessive calibration. These are the main reasons based on which in the literature, and in this analysis, the steady-state phase of the contractions is investigated. It should be highlighted that detecting the transient phases of the contraction has very recently attracted some interest, as indicated in recent studies [85, 173]. Thus, the first and last seconds of information were discarded in order to leave out the transient state and analyze only the steady-state phase of the contraction. Data segmentation was performed as follows: the onset and offset of each gesture were manually marked and labelled in the timeline of the trial by using an adjustable threshold value which was tuned during the analysis of each one of the trials. In this way, all the trials for each gesture were labelled manually for every participant. Once the onset of a gesture was marked, the following 1 second of information was discarded, and the subsequent 3 seconds of data were extracted for analysis. The timestamp of the remaining 1 second of information was compared against the offset label to ensure that the participant held the contraction for a period longer than the 3 seconds of interest (see Fig. 3.9). This last second of information was eventually discarded.

Supported by the literature, most of the information context of the MMG signal is below 150 Hz [128]. Frequencies between 1 Hz and 25 Hz have been reported for containing most of the power of the signal [13]. Thus, it is widely accepted that the region of interest for frequency analysis of the MMG signal falls between 1 Hz to 150 Hz [31, 128, 130]. This frequency window (1-150Hz) is used in this study, accordingly. A sampling frequency of 1 kHz was used to capture the MMG data. Signals were filtered using a second-order band-pass Butterworth filter, then passed through a Hilbert transform function. This data preparation process was performed for the training and testing sets of data. The computation of the signal-to-noise ratio (SNR) and the occupied bandwidth, within the active range of frequencies of the MMG signal (i.e., 1-150 Hz), was performed at each level of contact force for every participant. These two parameters were derived from the power spectral

density estimation found using Welch's overlapped segment averaging estimator.

3.4.6 Data Collection

A total of 213 spectrotemporal features are extracted for each channel, including 200 features in the frequency domain and 13 features from the time domain. Data were segmented into windows of 200 ms with no overlapping. Frequency features were extracted using fast-Fourier transform. Time domain features formulated based on the literature [126, 189, 213] are:

- Root Mean Square
- Integrated Absolute Value
- Mean Absolute Value
- Modified Mean Absolute Value type 1
- Modified Mean Absolute Value type 2
- Simple Square Integral, Variance
- 3rd Temporal Moment
- 4th Temporal Moment
- 5th Temporal Moment
- Average Amplitude Change
- Difference Absolute Standard Deviation Value
- Difference Absolute Mean Value

After feature extraction, a Neighborhood Component Analysis (NCA) was applied to extract the most relevant features for classification purposes. NCA [58] is a relatively new feature scoring technique that assigns a power weight to each feature based on the discriminative power of the corresponding feature. This technique enables ranking of the features, comparing the importance of each feature based on the discriminative power, and selecting features which contain most of the power for classification. After feature scoring and selection, using a hold-out validation method, features from the first set of data were used to train a linear support vector machine (SVM) classifier, and the second set of data was used to test the performance of the model.

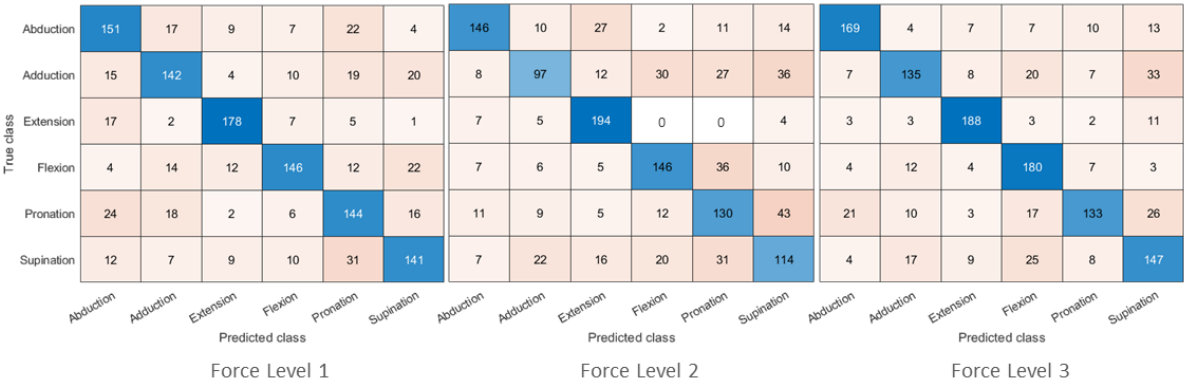


Figure 3.10: Sum of confusion matrices for all able-bodied participants. Numbers represent counts from predicted and actual hand gestures. From left to right, confusion matrix for force levels 1, 2, and 3, respectively. Figure reprinted from [36] under Creative Commons license CC BY 4.0.

3.5 Results & Discussion

In this work, the length of the armband was adjusted and normalized based on the diameter of the limb of the user, to maximize the similarity of conditions. Each participant is compared to themselves. Different force levels are analyzed for each participant to evaluate the relative behaviour of the information context of the signals. Two levels of normal force were evaluated for amputee participants and three levels of normal force were evaluated for able-bodied participants.

3.5.0.1 Observations related to contact force 1 (lowest force level)

Gesture classification was strong for Extension, Abduction, and Flexion. Extension showed the highest performance. The classification deteriorates for Adduction and Supination. Adduction shows the lowest performance overall (see Fig. 3.10).

3.5.0.2 Observations related to contact force 3 (highest force level)

Force level 3 shows the highest performance for Abduction, Flexion, and Supination across all force levels. Extension shows the highest performance among all gestures.

3.5.1 Discussion

Below, the pattern with relevant statistics based on the accuracy of the classifier for the different levels of contact force (see Fig. 3.11). For amputee participants, the median accuracy of the classifier resulted in 78.3% for force level 1 and 90.8% for force level 2. The mean accuracy yielded 81.3% and 90.28% for force levels 1 and 2, respectively. A mean improvement in accuracy of 8.89 % is observed with a standard deviation of 0.12 and 0.06 when increasing the normal force level from 1 to 2, respectively. The change in the pattern of improvement was user-specific. For amputee participant-3, the higher level of contact force increased the accuracy by 20%. For amputee participant-1, improvement near to 5% was observed and for amputee participant-2, the performance remained similar for both levels of normal force.

For able-bodied participants, the experiments showed a very interesting pattern. For several participants, the increase in the level of contact force shows a performance deterioration, while the second increase of force considerably improves the performance. For example, for participant-2 of the able-bodied group, increasing the contact force from the first level to the second reduces the performance from 79% to 73%. However, the second increment of normal force increases the accuracy from 73% to 81%. The results for able-bodied participants seem to indicate that there is a strong relationship between the normal force and the performance of MMG-based gesture detection.

The Wilcoxon signed-rank test shows that the observed difference in performance between force level 2 and force level 3 is significant ($p = 0.028$). A statistically significant difference between

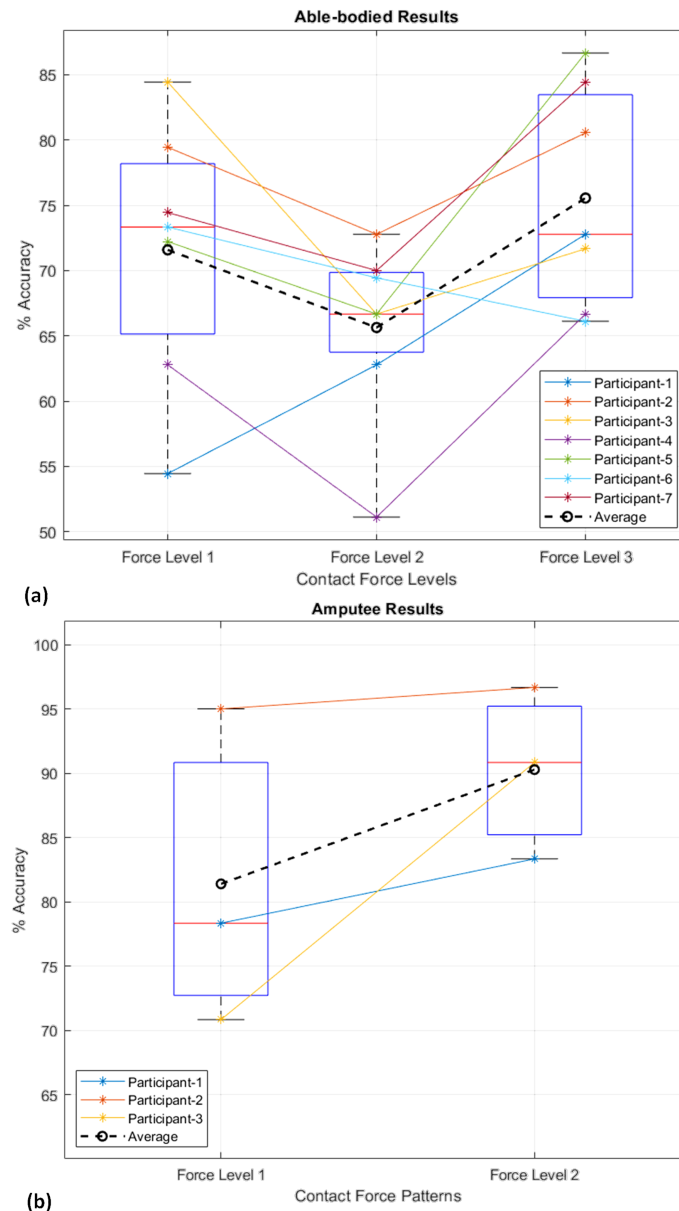


Figure 3.11: Accuracy of the classifier for all participants vs levels of force. (a) Accuracy of able-bodied participants for three levels of force. (b) Accuracy of amputee participants for two levels of force.

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force levels 1 and 2, however, was not observed ($p > 0.128$). Results on amputee participants are encouraging, as a relationship between normal force and classification accuracy is demonstrated. Characteristics of performance among amputees vary significantly depending on underlying conditions triggering limb loss and surgical procedures for amputation. Consequently, adjustment to residual muscle performance and individual preference is of critical importance. Furthermore, the results of the analysis suggest accuracy is not linearly related to the normal force; instead, each participant may have an optimal level of normal force to maximize the performance. Due to the user-specific signature of performance and the corresponding nonlinear connectivity with the

normal force, an average behaviour may not be representative of the overall performance. However, for the purpose of objective assessment, the following results are also given. For able-bodied participants, a mean decrease on accuracy of 6% and a subsequent increase of 10% is observed for increments of normal force 1-2 and 2-3, respectively. The median accuracy resulted in 73.3%, 66.6%, and 72.7% for force levels 1,2, and 3, respectively.

The analyses of the SNR and occupied bandwidth were performed at each level of contact force for every participant. The mean SNR values across all able-bodied participants yielded 5.5 dB, 5.6 dB, and 6.1 dB for force levels 1, 2, and 3, respectively, with standard deviations of 0.76, 0.51, and 0.71, respectively. In the case of the amputee data, the mean SNR values resulted in 5.7 dB and 5.8 dB for force levels 1 and 2, respectively, with standard deviations of 0.62 and 0.54. A calculation for the occupied bandwidth was also performed for every level of force and averaged across all participants. The estimated mean bandwidth of the signal of able-bodied participants for the levels of force 1, 2, and 3 resulted in 34.1 Hz, 35.1 Hz, and 31.5 Hz, respectively, with the lower bound of the bandwidths at 1 Hz and standard deviations of 0.39, 0.43, and 0.28, respectively. The mean occupied bandwidth of the signal of amputee participants for the levels of force 1 and 2 yielded 35.6 Hz and 34.5 Hz, respectively, with the lower bound also at 1 Hz and standard deviation of 0.76 and 0.98. These results provide insight into the potential effect of different levels of normal force on the quality of the MMG signal reflected in SNR and bandwidth. A gradual improvement of the SNR value and a decrease in the bandwidth can be observed, as given above.

3.5.2 Force Pattern Study

To further expand the understanding of the effect of contact force on mechanomyography, a separate user study evaluating different contact force patterns (heterogeneously distributed around the arm) was conducted for each sensor around the forearm, while following the same data collection protocol described in section 3.4. Five able-bodied participants who took part in the first section of this study participated in this second experiment which took place in a single session per participant. In order to prevent the fatigue of the muscle and to avoid a prolonged experiment, two combinations of force patterns between contact force levels 1-2 and contact force levels 2-3

Table 3.1: FORCE PATTERN DATA ANALYSIS

Force Pattern	SNR[dB]	Occupied Bandwidth [Hz]
1111	3.8 (std:0.17)	26.9 (std:0.07)
2121	3.7 (std:0.27)	26.4 (std:0.67)
2211	3.1 (std:0.76)	28.5 (std:0.68)
2222	3.5 (std:0.98)	27.5 (std:0.70)
3232	3.2 (std:0.84)	30.4 (std:0.74)
3322	3.4 (std:0.76)	29.1 (std:0.70)
3333	4.1 (std:0.95)	26.3 (std:0.67)

were selected. The first pattern alternates the location at which a higher and a lower level of force is applied. Higher contact force is applied over the FCR and the EDC muscles while a lower level of contact force is applied over the BRD and FCU muscles. The second pattern consists of applying a higher level of contact force over the FCR and BRD muscles, while a lower level of force is applied over the EDC and FCU muscles. The levels of force 1, 2, and 3 applied over all muscles, as performed in the previous experiment, were kept for comparison against the new patterns. Results of the analyses of the SNR and bandwidth for all the seven force patterns evaluated are reported in Table 3.1.

The classification results of the evaluation of the different contact force patterns can be seen in Fig. 3.12. The x-axis represents the different contact force patterns applied. The numbers represent the 3 different levels of contact force applied over each of the target muscles around the arm in a counterclockwise direction, starting with the FCR muscle, followed by the BRD, EDC, and FCU muscles. For example, the fifth label indicating '3232' represents the pattern of force using contact force level 3 for the FCR muscle, contact force level 2 for the BRD muscle, force level 3 for the EDC muscle, and force level 2 for the FCU muscle. As can be seen in the figure, results show strong

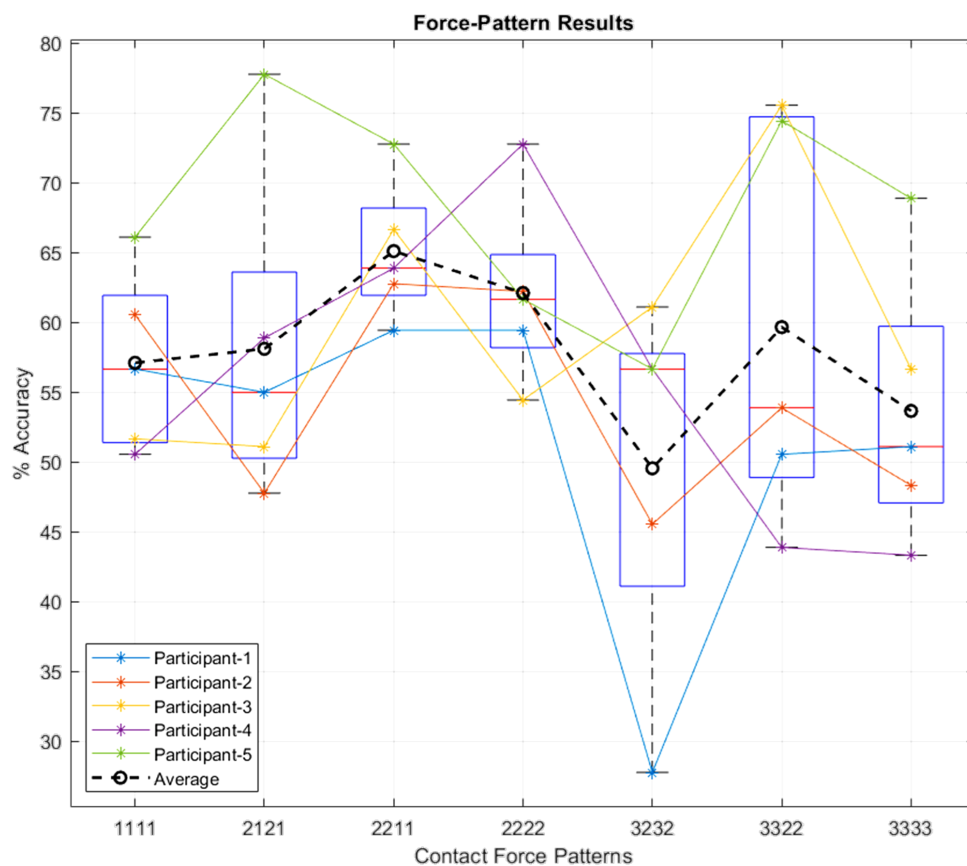


Figure 3.12: Accuracy of classifier for force patterns. The x-axis indicates the different sequences of contact force patterns. Numbers represent the different levels of contact force applied over each muscle starting at the FCR muscle location, followed by BRD, EDC, and FCU. Figure reprinted from [36] under Creative Commons license CC BY 4.0.

variations in the accuracy of the classifier within each subject depending on the contact force pattern utilized. For example, for participant number 5, the highest accuracy is found for pattern '2121' and the lowest accuracy is found for pattern '3232' with different variations in performance for the rest of the force patterns. These variations in performance (as high as 30% for some participants) depend on the distribution of contact force applied over specific sensors and support the hypothesis that different levels of normal force affect the discriminative power of MMG, suggesting that the best level of normal force to be used with MMG depends on the physiological factors of the subject. This shows that, unlike EMG, for MMG armbands and sensors, not only the location of the sensor can be optimized for each user, but also the normal force should be considered to achieve the maximum possible performance for each user.

3.6 Conclusions

In this chapter, a new method for augmenting the design of wearable MMG systems focusing on enhancing signal quality and discriminative power based on the variation of the distribution of normal force/skin contact is introduced. While the literature on MMG signal capture is becoming more common, studies have relied on the use of straps, tape, or non-conventional methods, which disregard the effect that contact force has on the quality and discriminative power of the MMG signal. Results presented in this chapter show that for MMG modality, not only the location of the sensor is important, but also the normal force with which the sensor is attached to the skin and the corresponding distribution can considerably change the performance. The proposed novel mechanomyography armband enables control of the distribution of normal force in a heterogeneous manner.

Results suggest that the applied level of contact force unequivocally alters the MMG SNR, bandwidth, and discriminative power. Therefore, the distribution of the normal force should be adjusted and further investigated. This chapter reports the first implementation of the mechatronic design of the novel MMG-plus-One armband, which allows for variations of the normal force field on the distributed mechanomyography sensory system around the limb. This investigation was done with the goal of adjusting the discriminative power and the information context of the MMG signal space. The concept of modulation of the normal force levels on the MMG sensor is evaluated for the first time with a focus on enhancing man-machine interfacing and gesture intention detection performance. The armband was tested on amputees (see Fig. 3.13) and on able-bodied participants. Results showed a unique user-specific pattern of performance modulation of the man-machine interface and a high potential for enhancing the accuracy of the system. These user-specific results suggest that a different anthropomorphic factor, such as skinfold thickness, might be related to the overall changes in the discriminative content of the MMG signal. A limitation of this study is the collection of skin-fold thickness and BMI from participants. Future perspectives will focus on (a) the collection of a clinical dataset for testing the proposed armband on a larger group of able-bodied and amputee participants to run a wider statistical analysis, (b) analysis of the effect of normal force distribution on acceleration-based MMG, and (c) incorporation of multi-modal sensing to address sensitivity to motion induced artefacts.

It is important to mention that the dimensions and bulkiness of the sensor developed for this study were due to the mechanism required to allow for the systematic increase in the level of contact force. However, advancements in the technology include the miniaturization of the device and the addition of the simultaneous collection of MMG and contact force (see section 6.2). In addition, it is worth mentioning that the highest level of contact force was reported to be uncomfortable after a period of time for some participants. Due to this reason, this level of contact force was discarded for the subsequent studies.



Figure 3.13: Amputee participant performing the experiment.
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Chapter 4

Muscle connectivity network analysis using MMG

This chapter introduces functional muscle networks based on MMG activity. Using the MMG sensing armband described in the previous chapter, experiments, methodology, and results are presented and discussed in the context of coherent spectral information and its use for muscle network generation and analysis.

The method, analysis, and results described and discussed in this chapter are published in IEEE Transactions on Biomedical Engineering [\[36\]](#).

4.1 Overview

Coherence analysis has been extensively studied through surface EMG signals to investigate the connectivity of motor neuron pools. However, the method has not been used to determine muscle connectivity by the use of MMG. In this chapter, MMG activity is used for the first time to assess the functional connectivity between four superficial muscles in the forearm during various hand gesture tasks. This study is motivated by evidence in the literature demonstrating that the frequency spectrum of MMG contains critical information regarding motor unit recruitment and firing rate [158][26], which provides the neurophysiological basis for their use in coherence analysis.

Muscle network analysis is performed during sustained hand gesture tasks in amputee and able-bodied human participants. Muscle networks generated from MMG signals are expected to be task-dependent while showing synchronized behaviour at multiple distinct frequency bands, reflecting the spectral fingerprints of the motor unit pool activation. This study also aims to determine muscle network characteristic differences between tasks and demographics. Furthermore, functional connectivity networks derived from MMG are not only expected to show significant changes across different hand gestures but also identifiable variations across the two understudied demographics of amputee and able-bodied participants. Graph theoretical analysis is implemented to quantify characteristics of the network topologies and statistically compare muscle networks across four hand-gesture tasks and between demographics. The topology and spectral characteristics of the muscle networks provide novel insights into the neural basis of muscle synergies. Also, the characterization of MMG-based functional muscle networks can offer a new tool to examine the neural circuitry involved in the motor function.

4.2 Introduction

Congruous coactivation and coordination of groups of muscles are centrally controlled by the nervous system for the execution of functional motor tasks. A theory strongly investigated in the last decade is that the central nervous system (CNS) simplifies this complex task by controlling coordinative neural functions, or synergies, as opposed to individual muscles [29]. Neurophysiological studies have shown that the musculoskeletal system and the nervous system work collectively to coordinate the activation of muscle synergies to execute complex functional motor behaviours [47, 65, 188]. The functional synergistic synchronization implies a common neural drive identified using intermuscular coherence (IMC) [32]. This method seeks to characterize the spectral synchronization of the common neural drive to groups of muscles. While classical analysis of synergies (e.g., those achieved by applying non-negative matrix factorization to EMG signals) represents the low-frequency basis of coordination in neuromuscular control, coherence analysis captures the full spectrum of functional connectivity and synchronous control between muscle pairs, which can be summarized using metrics rooted in graph theory. Historically, coherence analysis has been implemented to process electroencephalography (EEG) brain activity to correlate functional connectivity between different regions of the brain [43]. More recently, it has been proposed to investigate functional connectivity between brain and muscle activity (i.e., corticomuscular coherence (CMC)), through mapping of synchronization between EEG and EMG recordings [54, 90, 206]. Furthermore, modulations of neural input to muscle groups in broader frequencies have been investigated using intermuscular coherence and the concept of muscle networks [32, 33, 87–89]. Muscle network analysis is a novel toolset proposed to estimate functional connectivity between muscles. This is accomplished through the isolation of key characteristics of the neural drive of muscle synergies which enable the CNS to simplify functional control via synchronous muscle activation. Boonstra [33], for example, investigated lower-limb connectivity (synchronous activation) of muscles over a range of frequency bands during various postural tasks. In another study, Laine [101] isolated coherence between three-hand muscles (first dorsal interosseous, abductor pollicis brevis, and flexor digitorum superficialis) through analysis of muscle activation during two precision pinch tasks. Both of these studies found systematic task-specific changes and widespread connectivity of muscles at multiple frequency bands. While conventional muscle synergy analysis seeks to identify low-frequency coactivation bases of muscles, functional muscle networks seek to group muscles based on their collective spectral response, observed as the co-modulation of multiple frequencies in EMG signals. Studies have further demonstrated that conventional synergy analysis and functional coherence-based muscle network analysis elucidate disparate, complementary features of muscle activation, both of which are essential for understanding neuromuscular motor control [33, 87]. Muscle network analysis has also been studied in able-bodied individuals using EMG for hand gesture recognition [107], and in stroke survivors for the analysis of functional intermuscular connectivity alterations [72]. However, its role in compensation for neural trauma has

not been extensively explored. In particular, functional connectivity variations linked to limb loss and how surgical amputation alters the behavior of muscle networks during motor tasks have not been investigated.

4.2.1 Contributions

In summary, the main contributions of the study carried out in this chapter are:

1. Identification of functional intermuscular connectivity between superficial upper-limb muscles, in various spectral bands, by the use of MMG across a cohort of amputee and able-bodied participants.
2. Identification of different muscle network topologies for different hand gestures.
3. Comparison of muscle network characteristics patterns across both demographics.
4. Identification of alterations in muscle network characteristics associated with amputation.

Beyond the first implementation of MMG in muscle network analysis, this study is the first contrasting functional co-modulation of amputee and able-bodied subjects. While MMG has been studied as an alternative means of prosthetic control surmounting well-documented challenges involved in EMG use out-of-clinic [63, 201], aspects of its neurophysiological basis remain unknown.

4.3 Related Works

4.3.1 Modalities of Muscle Activity Measure

All investigations of muscle networks to date have exclusively focused on the analysis of activity through EMG. While the obvious gold standard for muscle activity mapping, EMG signal acquisition can be challenging for isolating specific muscle activation in amputees due to variations in skin impedance (e.g., sweat, scar tissue caused by surgery, etc.) and robustness of signal acquisition in sockets. Mechanomyography is a myographic activity measure that detects mechanical oscillations produced by the dimensional changes of the active muscle fibres during a contraction [76]. MMG has been demonstrated to contain imperative information regarding neuromuscular parameters associated with motor function [135]. Investigations of this modality have revealed that spectrotemporal parameters of MMG can correlate strongly with the motor unit activation [24]. MMG has also been demonstrated to be a useful tool to assess muscle weakness characteristics and muscle performance in healthy individuals and patients [137, 191, 204]. Furthermore, MMG has been reliably described as the mechanical counterpart giving complementary information to EMG [176]. The combination of the two signals has been shown to provide unique information about the electromechanical characteristics of the muscles [46]. The benefit of MMG over EMG signal acquisition relates to the robustness to electromagnetic noises, in addition to skin sweating and sensor-skin impedance changes, as well as its response correlating to direct muscle movement [203]. However, MMG also suffers from a lack of established sensors and can demand complementary motion sensing to reject mechanical interference [113]. It should be noted that while MMG contains a lower information rate and less linear behaviour when compared with EMG, in the literature, MMG has attracted a great deal of interest for practical uses where EMG may not function properly due to the electromagnetic artefacts and sensitivity to sensor-skin conditions.

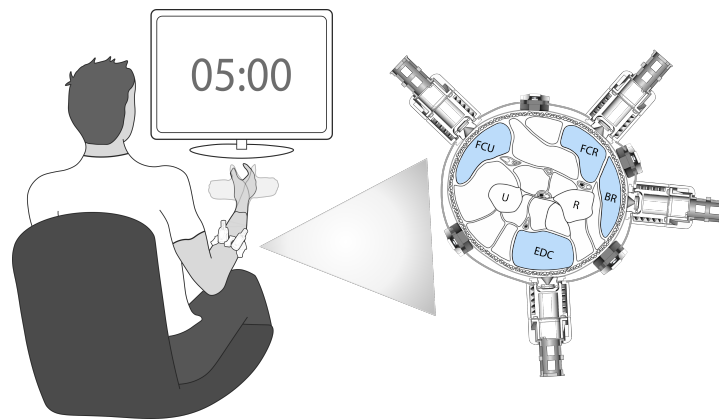


Figure 4.1: Left-side, experimental layout. While seating, participants were asked to perform four hand-gesture tasks. Hand gestures were sustained for a period of five seconds with a five-second resting period between each contraction. A digital clock was presented to the participants to keep track of the duration of each contraction. Right-side, the cross-section view of MMG sensor placement. Four MMG sensors were placed over the flexor carpi radialis (FCR), brachioradialis (BRD), extensor digitorum communis (EDC), and flexor carpi ulnaris (FCU) muscles. © 2022 IEEE. Reprinted, with permission, from [116].

4.4 Materials and Methods

4.4.1 Participants

Ten able-bodied individuals (6 males, 4 females, mean age 26 ± 7 years old) and three trans-radial amputees (2 males, 1 female, mean age 38 ± 8 years old) participated in this experiment. All participants provided their signed informed consent before taking part in the study. All experiments were approved by the Imperial College Research Ethics Committee (ICREC reference: 15IC3068).

4.4.2 Experimental Design

Data collection was performed by the use of a custom-made wearable acoustic MMG armband, described in the previous chapter. Thanks to the low effect that crosstalk has on the MMG signal in the transverse direction of propagation of the mechanical waves [79], the use of microphone-based MMG sensors, as used in the present study, results in a robust tool for the assessment of muscle activity. In addition, the level of crosstalk in the MMG signal has shown to be dependent on the level of muscle effort [78]; therefore, low-level contractions of a short span (5 seconds) resembling activities of daily living (ADLs) were applied in this study.

Experiments involved the detection of MMG activity while participants were asked to perform four different hand gestures, namely wrist Flexion, Extension, Pronation, and Supination. Four MMG sensors were placed around the forearm over the target muscles: flexor carpi radialis (FCR), brachioradialis (BRD), extensor digitorum communis (EDC), and flexor carpi ulnaris (FCU). The participants were asked to position their dominant arm in a resting position while seated. Resting

position is defined as placing the arm midway in supination at the forearm with the elbow in contact with the torso and the forearm at 90 degrees with respect to the arm. Participants were asked to stay still for the duration of the experiment. Prior to the experiment, all participants underwent a training trial which consisted of performing sustained contractions for two randomly selected gestures. Participants performed 5 repetitions of the first selected gesture, and similar to the existing literature in gesture detection [83, 152], and in motor unit activity decoding [84], intervals of 5 seconds of rest between each contraction were applied. After the last resting period, following the repetitions of the first gesture, participants performed 5 repetitions of the second gesture with similar resting intervals between each contraction. A 10-second interval was applied at the beginning and at the end of the trial. The training trial took 2 minutes per participant. Participants were asked to follow a digital clock presented on a monitor in front of them to keep track of the timing of each contraction. Fig 4.1 shows an illustration of the experimental layout.

The experiment consisted of two groups of 2 randomly selected gestures. Similar to the training trial, performing each group of gestures lasted for 2 minutes. One minute of rest was applied between the two groups to prevent fatigue of the muscles. The order and grouping of the gestures were randomized. Both able-bodied and amputee groups followed the same experimental protocol. The experiment took 5 minutes per participant. Fig 4.1 shows an illustration of the cross-section view of the forearm and the positioning of the sensors. The non-symmetry of the sensor location illustrates the anatomical differences between participants. Muscles were palpated, and sensors were positioned over the target muscles. All amputee participants are quadruple amputees and needed to undergo amputation after sepsis. The first participant had the amputation 8 years prior to this study and has a high-level trans-radial amputation on the tested limb. The participant makes regular use of a body-powered prosthesis on a day-to-day basis and maintains a high level of activity, including regular exercise and ADLs. The second and third amputee participants had the amputation 6 and 7 years prior to this study, respectively, and have distal trans-radial amputations. Both participants use a Mitt prosthesis on average every 3-4 days for ADLs, maintaining a medium level of activity.

4.4.3 Data Processing

The raw acoustic signals of the MMG channels were analyzed to identify the onset and the offset of each contraction. In this study, and similar to the existing literature on gesture detection for electromyography [185], and mechanomyography [4], the signal was analyzed during the steady-state phase of the contraction in order to minimize the high degree of stochastic non-stationarity present in the transient phases. The transient state was discarded by removing the one-second post-onset and one-second pre-offset of the signal recorded for each contraction. The duration of the extracted signal was validated to ensure at least 3 seconds of a steady-state contraction.

In this work, MMG information was recorded using a sampling frequency of 1 kHz. The literature

shows that the MMG power information resides in frequencies as high as 120 Hz [76]. Numerous investigations have demonstrated that the dominant frequencies of muscle sound are found in the range of frequencies below 30 Hz [130][128], and there is evidence showing MMG power information at frequencies as low as 2 Hz and as high as 118 Hz [27]. Thus, the raw MMG signal was filtered using a fourth-order band-pass Butterworth filter in the range of 1 - 150 Hz.

Mechanomyography can be categorized as a signal with time-varying properties with power information at multiple frequencies. Therefore, a time-variant, frequency-selective approach is required for its analysis. A method widely investigated in the literature for time-frequency analysis is the Hilbert transform, a transform-based approach used for spectral analysis of time-varying signals which has shown to be equivalent to Fourier and wavelet analysis and from which coupling measures such as coherence can be derived [34]. In this way, the Hilbert transform was applied to the filtered MMG signal to obtain the analytic representation of the signal which was further used for the estimation of the cross-spectrum and the power spectral density, both necessary measures for the evaluation of intermuscular coherence.

4.4.4 Intermuscular Coherence

Intermuscular coherence is derived based on the magnitude square of the cross-spectrum between two signals normalized by the product of the power spectrum of the two signals (4.1). Because of the normalization, IMC is confined to be between the values 0 to 1. The closer the value of IMC to 1, the more linearly dependent (correlated) the two signals in the frequency domain. A common problem in the estimation of coherence is the presence of spurious coherence due to spatial and spectral leakages [161]. In this study, in order to minimize the presence of spurious coherence caused by the filtering process and by the frequencies at which the spectral power information is critically close to zero, we implement a modified magnitude squared coherence (MMSC) method which includes a conditional statement based on the value of the product between the power spectrum of the two signals. The MMSC algorithm specifically avoids spurious coherence when the spectral information context of the signals has the least power. MMSC and IMC are used interchangeably for the rest of this thesis.

The mathematical derivation of MMSC can be found here:

$$MMSC_{xy} = \begin{cases} \frac{|S_{xy}|^2}{S_x * S_y}, & \text{if } S_x * S_y \geq 1 \\ \frac{|S_{xy}|^2}{1}, & \text{if } S_x * S_y < 1 \end{cases} \quad (4.1)$$

where,

$MMSC_{xy}$ is the modified magnitude-squared coherence between signals x and y ,
 S_{xy} is the cross-spectrum between the signals,

S_x is the power spectral density of x , and
 S_y is the power spectral density of y .

In this analysis, a method based on segment overlapping and tapering was applied in order to improve frequency resolution and reduce variance, as described in [187]. Coherence was evaluated using the following parameters: a segment of 1024 samples to obtain a frequency resolution of 0.98 Hz, a Nuttall window which helps reduce spectral leakage thanks to its significant side-lobe suppression, and 50% of overlap to account for the spectral resolution of the Nuttall window. To prevent non-stationarities and spurious coherence resulting from edge effects caused by the concatenation of trials, each 3-second trial of information was multiplied by a Tukey window using a cosine-tapered section of 0.05 [30]. Following this tapering process, the five trials of each gesture were concatenated to form a signal of 15 s duration. MMSC was calculated for all muscle pairs, gestures, and participants, resulting in a matrix of $(f_x m_x g_x s)$, denoting f coherence values, m muscle pairs, g number of gestures, and s number of subjects.

4.4.5 Non-negative Matrix Factorization

A common method for deeper analysis of muscle networks is to decompose the full-spectrum coherence between different muscle groups into frequency-based connectivity using mathematical factorization methods (such as non-negative matrix factorization (NNMF), principal component analysis (PCA), or independent component analysis (ICA)). This allows identifying the common frequency space at which muscles are co-modulated by the neural drive. Non-negative matrix factorization is a multivariate method which is characteristic for its non-negative constraints [103]. NNMF has been widely used in the literature to identify the coactivation of groups of muscles that contribute to a particular task, also known as muscle synergies [104]. In this respect, muscle synergies are extracted by applying NNMF to the EMG envelopes [143, 150]. NNMF has also been used to identify unique spectral patterns shared by groups of muscles from the estimated coherence between pairs of muscles [33, 87, 89]. However, NNMF has not been applied for the analysis of MMG activity; in particular, for the spectral decomposition of the signal. In this section, NNMF is used for the first time to decompose the MMG spectral space into frequency band components to study the spectral characteristics of the signal and to identify the common spectral patterns shared by the target muscles when performing different hand gestures.

It is established in the literature that mechanomyography includes three main processes: (i) the gross lateral movement of the muscles caused by the asynchronous activation of muscle fibres, (ii) lateral oscillations occurring at the resonant frequency of the muscles, and (iii) dimensional changes of the active muscle fibres as well as gross limb displacements [78, 114]. Dimensional changes of the muscle and gross limb displacement account for the lowest frequencies of the signal [199], tremor contributions reflecting the oscillations of the motor system have been reported over a broad frequency band, typically below 12 Hz [91, 121], and muscle inner-vibrations account

for the higher frequencies, falling in the range of 10-40 Hz due to intrinsic muscle fibres oscillations [18, 131]. As reported in the aforementioned studies, the components comprising the MMG signal have been found to occur at different frequency ranges, with some level of overlapping. In this analysis, frequency bands are defined as follows: 1-5 Hz for low-frequency information due to the bulk movement and dimensional changes of the muscles, 5-12 Hz for oscillations due to tremor produced during isometric contractions, and 12-40 Hz to capture the mechanical inner-vibrations due to intrinsic muscle fibre oscillations. In this way, non-negative matrix factorization is applied, according to (4.2), to extract three components in order to determine the common spectral patterns in the delta band for component 1, theta and alpha bands for component 2, and beta and gamma bands for component 3.

Using NMF, the original data-set regarded as an $f \times m$ matrix X , where each row contains f non-negative coherence values evaluated at each discrete frequency of the m muscle pairs, is factorized into two low-rank non-negative matrices: W , an $f \times k$ matrix with the activation patterns (common spectral patterns) of k components, and H , a $k \times m$ matrix denoting the weight coefficients (strength of muscle-pair connection) of each muscle pair for every component.

$$X \approx W.H \quad (4.2)$$

Non-negative matrix factorization was used to decompose the full-spectrum of the signal into frequency band components with their corresponding coupling strength across all muscle pairs for all gestures and subjects. In this way, NMF was applied to each coherence matrix $f \times m$ (513 coherence values $\times$ 6 muscle pairs) corresponding to each gesture for all participants. A multiplicative update rule was applied for NMF to minimize the objective function, as described in [28]. Different initialization methods for NMF have been investigated in the literature to achieve a smaller error in the approximation and faster convergence [172, 218]. A similar initialization method to that proposed in [172] is introduced in this section; however, instead of imposing a sparse structure in the spatial organization of the vectors, the scope of each component is constrained by initializing the columns of the W matrix. Each column of the W matrix representing a frequency band component (k_1 : frequency band 1-5 Hz, k_2 : frequency band 5-12 Hz, k_3 : frequency band 12-40 Hz) was initialized with a uniform random amplitude distribution in the range [0.9, 1] only for their respective active frequency band. As expected, this initialization method results in a delineated segregation of frequency bands for the common spectral patterns extracted (see Fig 4.4 top-row).

4.4.6 Connectivity Analysis

Coherence muscle networks were constructed after identifying the common spectral response of the muscle pairs at different frequencies by using NMF. The spectral activation patterns represent the unique frequencies shared by the muscles during the hand gesture tasks. The weight coefficients produced from the factorization were used to construct the adjacency matrices. Task-

and frequency-specific matrices were obtained, as NMF extracted three components from the coherence spectra for each gesture and participant. These adjacency matrices were then used to construct the undirected weighted functional connectivity networks.

The clustering coefficient (CC) is a measure of functional segregation and is denoted by the extent to which neighbours of each node are connected to each other [198]. The mean of the clustering coefficient reflects the average of the clustered connectivity across nodes [157], with highly functional segregated networks indicated by higher values of averaged CC and vice versa. Based on the generalization of the algorithm to weighted undirected networks [127], the clustering coefficient was computed at all frequency bands for each of the connectivity networks for all gestures and participants. The average of CC across nodes was subsequently calculated to obtain a value of CC for each component, gesture, and participant.

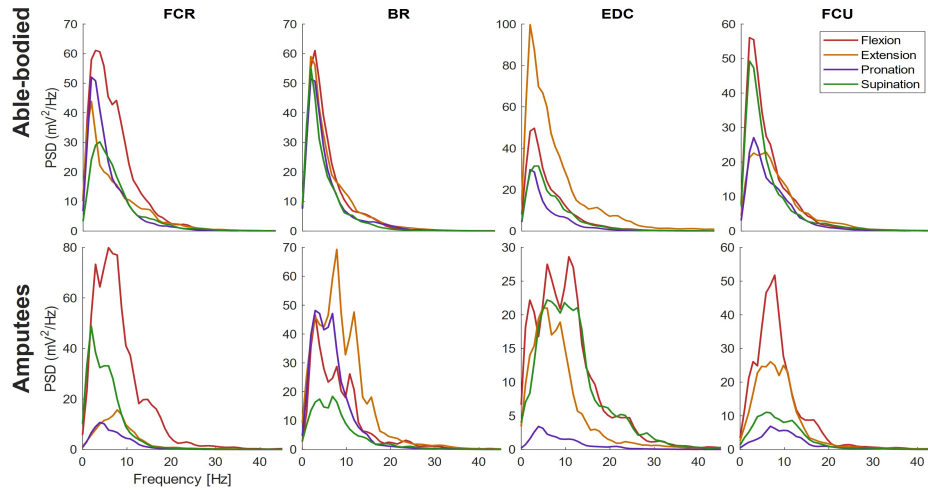


Figure 4.2: Power spectral density shown for the different muscles (FCR, BRD, EDC, and FCU) for all gestures (red: Flexion, yellow: Extension, purple: Pronation, and green: Supination). Power spectra were averaged across homologous muscles, trials, and subjects for able-bodied (top-row) and amputee (bottom-row) participants. © 2022 IEEE. Reprinted, with permission, from [116].

4.5 Results

In this work, we analyzed muscle networks based on MMG activity recorded from four superficial muscles of the forearm while participants performed four different hand gestures. The power spectral density (PSD) was generated to analyze the spectral content of the MMG signal. PSD was averaged across homologous muscles, trials, and subjects. Fig 4.2 shows the different PSD profiles of all muscles across gestures for able-bodied and amputee participants. PSD for able-bodied participants shows a broad spectrum with peaks between 2-4 Hz and similar frequency profiles across muscles with differences in scaling depending on the gesture (Fig. 4.2). PSD for amputee participants reveals distinctively different profiles across muscles with peaks found between 2-12 Hz depending on the hand gesture. PSD profiles for amputees show a shift of peaks towards higher frequencies compared to the PSD generated from able-bodied participants. PSD for both demographics showed power information at frequencies no higher than 40 Hz.

4.5.1 Statistical Analysis

The clustering coefficient of the networks was compared between gestures for all participants to obtain statistical significance at each of the frequency band components. The data passed the Shapiro–Wilk normality test. Thus, a t-test was applied to determine significance of CC between gestures. CC at each frequency component was considered significantly different between gestures for $p\text{-values} < 0.05$. Bonferroni-adjusted significance level was calculated to account for the increased possibility of type-I error. The adjusted significance level is $\text{adjusted-}p\text{-value} = 0.0028$.

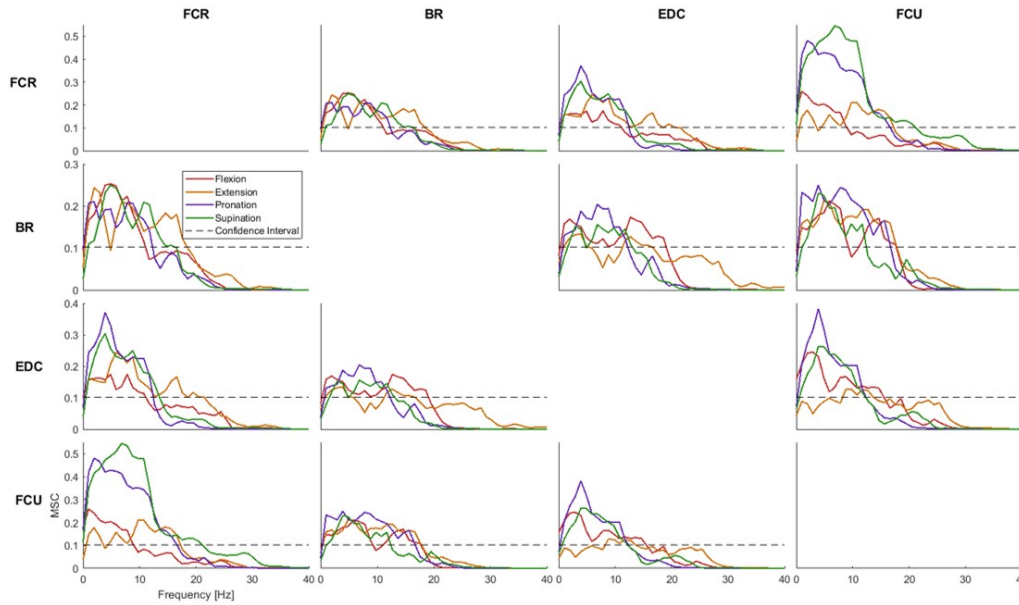


Figure 4.3: Intermuscular coherence between all muscle pairs. Coherence is shown between all muscles (FCR, BRD, EDC, and FCU) for all gestures (red: Flexion, yellow: Extension, purple: Pronation, and green: Supination). © 2022 IEEE. Reprinted, with permission, from [116].

4.5.2 Coherence Matrix

Functional muscle networks were defined by mapping the correlated spectral response of different muscles for each gesture for able-bodied and amputee participants. The nodes of the networks represent the target muscles, and the edges of the networks represent the strength of functional connections between muscles. Fig 4.3 shows the intermuscular coherence between all muscle pairs for able-bodied subjects along with the confidence interval generated according to the method described in [187]. The common frequency components across all muscle pairs, hand gestures, and subjects for both demographics were extracted. Coherence for all muscle pairs were averaged across subjects to obtain coherence profiles for each gesture. The results show distinct functional organization for different hand gestures. Coherence is observed over a range of frequencies below 40 Hz, and distinctive frequency profiles were found depending on the muscle pair and hand gesture. Negligible values of coherence were found at frequencies higher than 40 Hz. The IMC results in Fig. 4.3 imply a dense connectivity matrix for all muscle pairs, showing high levels of common spectral patterns across different frequency bands. In the case of Flexion, different levels of IMC were found at frequencies below 12 Hz across all muscle pairs. The highest level of IMC for this gesture was found at 2 Hz for muscle pair FCR-FCU. Similar coherence profiles were found for Extension, with most of the IMC found at frequencies below 12 Hz and some level of IMC present at frequencies higher than 12 Hz for the muscle pairs BRD-EDC and FCU-EDC. Pronation showed the highest levels of IMC for all the muscles connected to FCU, with peaks just below 5 Hz for muscle pairs FCU-EDC and FCU-BRD and high IMC for all frequencies below 12 Hz for muscle pair FCU-FCR. A closely similar IMC profile was observed for Supination for FCU-FCR. Regarding

Table 4.1: Statistical Results of Clustering Coefficients

	comp.	Flexion	Extension	Pronation	Supination
Flexion	k1		$t:-0.892$ $p:0.38$	$t:0.385$ $p:0.7$	$t:3.53$ $p:0.00068^{**}$ $\Delta:-18.4\%$ ↓
	k2		$t:-1.11$ $p:0.27$	$t:-0.356$ $p:0.72$	$t:0.779$ $p:0.44$
	k3		$t:-2.51$ $p:0.014^{*}$ $\Delta:16.7\%$ ↑	$t:1.78$ $p:0.079$	$t:-0.227$ $p:0.82$
Extension	k1	$t:-0.892$ $p:0.38$		$t:1.31$ $p:0.2$	$t:5.27$ $p:1.1e-06^{**}$ $\Delta:-21.6\%$ ↓
	k2	$t:-1.11$ $p:0.27$		$t:0.869$ $p:0.39$	$t:2.34$ $p:0.022^{*}$ $\Delta:-8.73\%$ ↓
	k3	$t:-2.51$ $p:0.014^{*}$ $\Delta:-16.7\%$ ↓		$t:4.13$ $p:9.1e-05^{**}$ $\Delta:-25.4\%$ ↓	$t:2.03$ $p:0.045^{*}$ $\Delta:-12.5\%$ ↓
Pronation	k1	$t:0.385$ $p:0.7$	$t:1.31$ $p:0.2$		$t:3.01$ $p:0.0036^{*}$ $\Delta:-16.6\%$ ↓
	k2	$t:-0.356$ $p:0.72$	$t:0.869$ $p:0.39$		$t:1.39$ $p:0.17$
	k3	$t:1.78$ $p:0.079$	$t:4.13$ $p:9.1e-05^{**}$ $\Delta:25.4\%$ ↑		$t:-1.85$ $p:0.067$
Supination	k1	$t:3.53$ $p:0.00068^{**}$ $\Delta:18.4\%$ ↑	$t:5.27$ $p:1.1e-06^{**}$ $\Delta:21.6\%$ ↑	$t:3.01$ $p:0.0036^{*}$ $\Delta:16.6\%$ ↑	
	k2	$t:0.779$ $p:0.44$	$t:2.34$ $p:0.022^{*}$ $\Delta:8.73\%$ ↑	$t:1.39$ $p:0.17$	
	k3	$t:-0.227$ $p:0.82$	$t:2.03$ $p:0.045^{*}$ $\Delta:12.5\%$ ↑	$t:-1.85$ $p:0.067$	

Frequency band components are represented as, k1: component 1-5 Hz, k2: component 5-12 Hz, and k3: component 12-40 Hz.

Significance is shown in orange color $*$ for $p\text{-value}<0.05$, Bonferroni-adjusted significance is shown in red color $**$ for adjusted- $p\text{-value}<0.0028$, $df=18$.

the IMC pattern of FCU-FCR, it can be highlighted that two distinct behaviours are observed, one of which relates to similar patterns for Flexion and Extension (red and yellow lines), and the other one relates to a similar behaviour comparing Pronation and Supination (purple and green lines).

4.5.3 Muscle Connectivity Networks

In order to evaluate the coherence over specific frequency ranges, intermuscular coherence was decomposed into three frequency bands using non-negative matrix factorization [103]. The number of components extracted evaluates the functional connection between muscles at low (1-5 Hz), medium (5-12 Hz), and high frequencies (12-40 Hz).

4.5.3.1 Able-bodied

The common spectral patterns for the three frequency components for each gesture were extracted using NMF. The corresponding weightings for each component yield the functional connectivity matrices of the muscle networks for each gesture. Fig 4.4 shows the functional connectivity networks for able-bodied participants, generated for all gestures at each one of the frequency components.

The first component captures coherence at low frequencies and shows relatively high connectivity between all muscle pairs for Flexion and Extension. Pronation and Supination appear to have a lower level of connectivity for muscle pairs EDC-BRD and FCR-BRD.

The second component shows a similar topology to that of the first component for all gestures. High connectivity between FCR-FCU is shown for both components for Pronation and Supination.

The third component shows a distinctly different functional organization of the networks compared to the first two spectral components. Flexion shows high connectivity for all vertices connected to the BRD muscle. Weaker connectivity is shown for the muscle triplet FCR-FCU-EDC compared to the first two spectral components. In the case of Extension, muscle triplet FCR-BRD-EDC main-

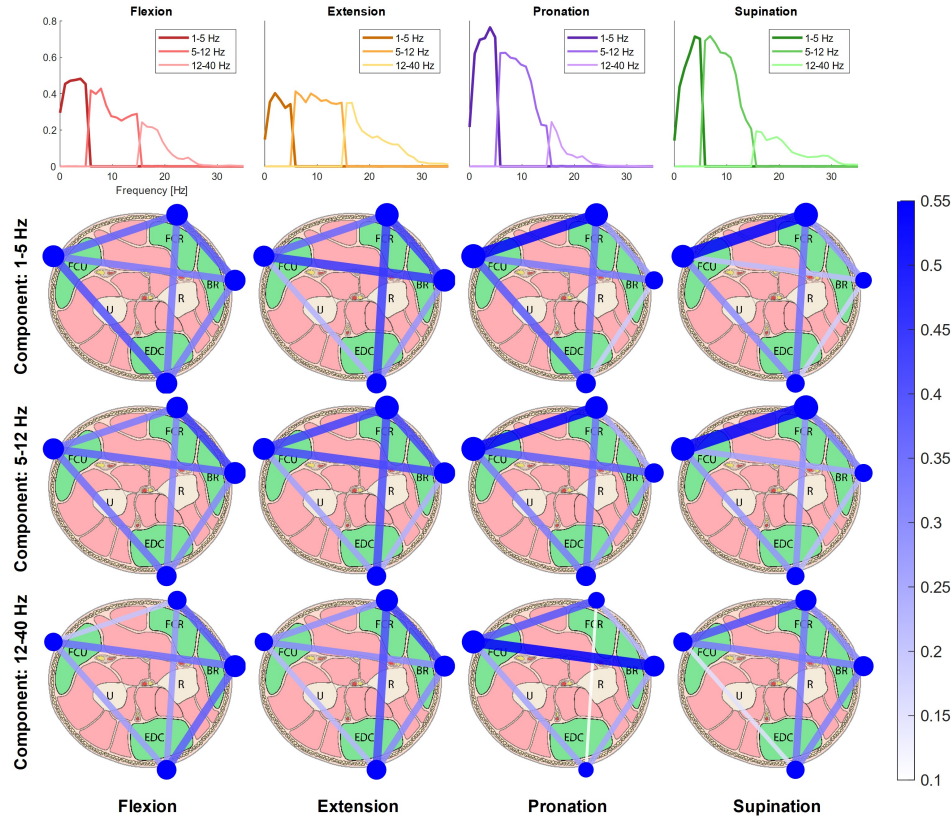


Figure 4.4: The frequency content of the coherence spectra of all muscle combinations was averaged across subjects and decomposed into three components using non-negative matrix factorization. The three frequency components were defined as follows: component 1: 1-5 Hz, component 2: 5-12 Hz, and component 3: 12-40 Hz. Top-row, common spectral patterns extracted for each gesture at every frequency component. Different shadings of colour show the frequency ranges. Gestures are colour-coded (red: Flexion, yellow: Extension, purple: Pronation, and green: Supination). Functional muscle networks were extracted for each gesture at each of the frequency components. Muscle networks were characterized by the extracted common frequency patterns and the weightings of those patterns in the original spectra. The weightings give the strength of the edges between the four muscles (nodes). The mapping of the colour bar and the thickness of the edges show the strength of the connections between all muscle pairs. The size of the nodes denotes the degree of each connectivity for each muscle. Functional connectivity networks of all components (rows) are shown for each gesture (columns) for able-bodied participants. © 2022 IEEE. Reprinted, with permission, from [116].

tained a high level of connectivity while FCR-FCU and FCU-BRD show reduced connectivity. As opposed to Flexion and Extension, Pronation shows evidently strong connectivity for all muscle pairs connected to FCU. connectivity between FCR-BRD and EDC-BRD shows similar connectivity to that shown in the other two spectral components. Lastly, Supination shows a distinct topology related to the third spectral component, showing lower connectivity between the muscle pair FCR-FCU and FCU-EDC but higher connectivity between the rest of the muscle pairs. FCR-BRD shows a similar level of connectivity compared to the first two spectral components. Muscle networks in Fig 4.4 indicate a gradual transition from widespread connectivity between all muscle pairs for the lowest

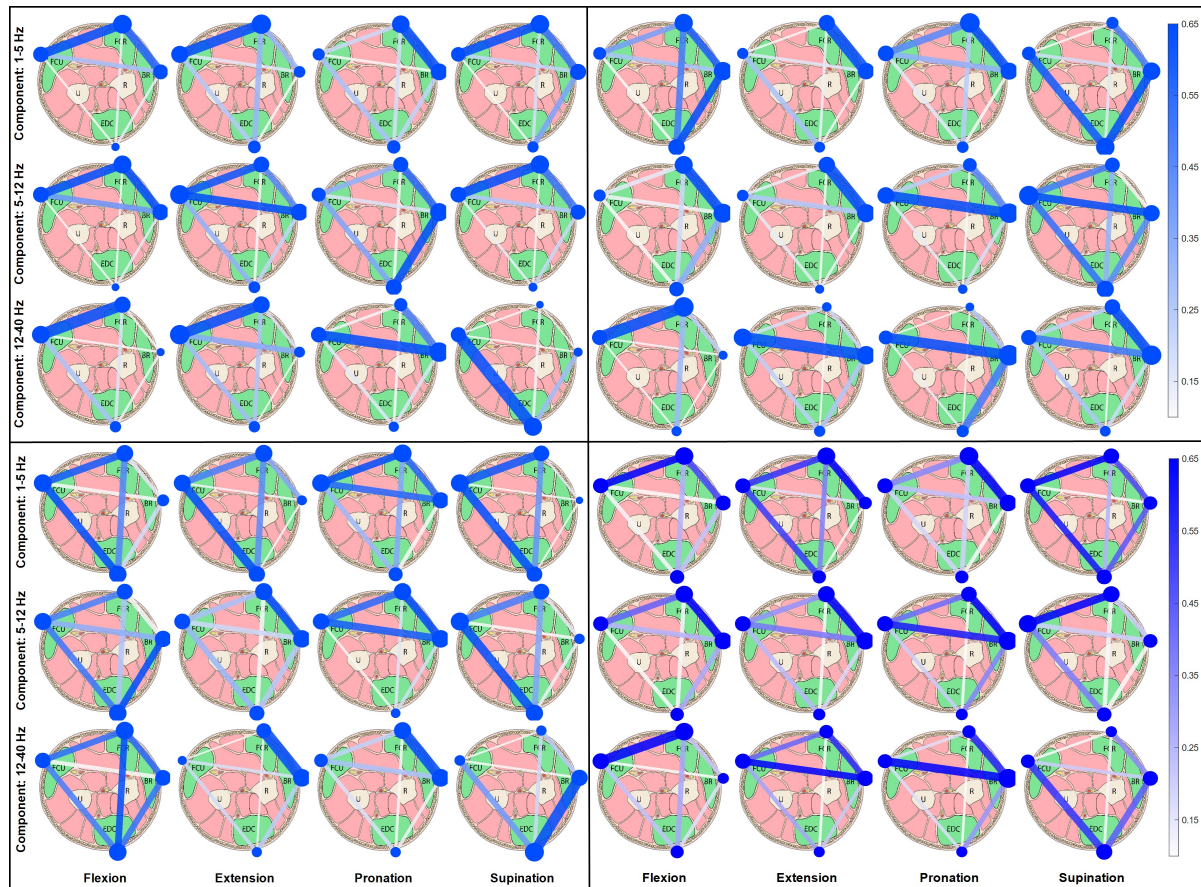


Figure 4.5: The common spectral patterns of the coherence responses of all muscle combinations were decomposed into three components. Functional muscle networks were generated for each gesture at each of the frequency components. Muscle networks are generated from weightings of the common frequency patterns. The weightings give the strength of the edges between the four muscles (nodes). The thickness and colour code of the edges shows the strength of the connections between muscles. The size of the node denotes the degree of connectivity of muscles. Functional connectivity networks are shown for all components (rows) for each gesture (columns) for all amputee participants (amputee 1: top-left, amputee 2: top-right, amputee 3: bottom-left, and the average of amputees: bottom-right). © 2022 IEEE. Reprinted, with permission, from [116].

frequency component to strong localized connections for the third frequency band. This analysis also suggests a distinct signature of MMG-based connectivity for different gestures.

4.5.3.2 Amputees

Fig 4.5 illustrates the functional connectivity networks for each amputee participant and the mean of the participants for all gestures at each frequency component.

For each amputee participant, the first component shows high connectivity between muscle pair FCR-FCU for Flexion, medium to high levels of connectivity between FCR-BRD for Extension, and low levels of connectivity for both gestures between FCU-BRD. Pronation shows high connectivity between FCR-BRD, medium levels of connectivity between EDC-FCR, and medium to low connectivity between FCU-EDC and EDC-BRD. Supination shows low connectivity between FCU-BRD and

heterogeneous connectivity for the rest of the muscle pairs across participants.

The second component shows widespread connectivity between all muscle pairs for Flexion and Extension for two of the amputee participants, and a strong connection between FCR-BRD for Flexion, Extension and Pronation for all participants. Strong connections were also found for all vertices connected to BRD for Pronation, with low connectivity between EDC-BRD. Interestingly, a similar topology to that of the first component was shown for Supination across all participants.

The third component shows a decrease in connectivity in muscle pair BRD-FCU and high connectivity between FCR-FCU for Flexion for all participants. Heterogeneous connectivity between all muscle pairs across participants was found for Extension with medium levels of connectivity between EDC-BRD and FCU-EDC and low connectivity for FCR-EDC. A similar topology was found for Pronation with higher connectivity between FCU-BRD. For Supination, all participants showed high and medium levels of connectivity for FCU-EDC and EDC-BRD, respectively, while medium to low connectivity was found for the rest of the muscle pairs.

4.5.3.3 Able-bodied vs Amputees

The first component shows a similar network topology to that of the second component across all gestures for able-bodied and for each of the amputee participants. The third component shows different topologies and lower connectivity compared to the first two components for both demographics. These results suggest overlapping frequency information for the bulk movement of the muscles and the tremor produced during the contractions. The distinct topologies at higher frequencies suggest that muscle fibre oscillations produce localized spectral activity for specific muscle pairs depending on the gesture.

It is important to mention that opposite gestures reflect a similar topology of connectivity for the first two frequency components for all amputee participants and, more evidently, for able-bodied participants. In other words, Flexion and Extension show a similar connectivity topology, and Pronation and Supination present the same phenomena. This could be a result of the fact that MMG captures not only the contraction of the agonist muscles but also the relaxation of the antagonist muscles, both simultaneously occurring during the task and found to be present at low frequencies [93]. Interestingly, similar topologies were found between Extension and Pronation across all frequency components for each amputee participant. The third component showed a different topology between able-bodied and amputees for all gestures, with some similarity in connectivity strength for BRD muscle pairs for Extension and Pronation

Regarding the role of each muscle during the gestures, all four muscles are involved when performing wrist Flexion and Extension. Able-bodied participants showed widespread connectivity between muscles for the first two components with some localized connectivity in the FCR and BRD muscles for the third component. Similarly, high connectivity was found for FCR and BRD muscles for two of the amputee participants across the same gestures in the first two compo-

nents, with also high connectivity present in the FCU muscle for both participants. In general, for each amputee participant, EDC appeared to be the least active muscle for Flexion and Extension for the first two components.

The brachioradialis muscle is responsible for bringing the pronated, or supinated forearm into a neutral position. Thus, in the case of Pronation and Supination, it is expected to find a higher level of connectivity for vertices connected to BRD due to its role in both actions. Interestingly, similar topologies were found between Extension and Pronation across all frequency components for each amputee participant. The third component showed a different topology between able-bodied and amputees for all gestures, with some similarity in connectivity strength for some muscle pairs for Extension and Pronation.

A low level of connectivity is expected for the EDC muscle during Pronation and Supination due to the role that the EDC muscle has during these gestures. The extensor digitorum communis muscle is a multi-compartment muscle that is responsible for extending digits 2–5. Given that extension of the fingers occurred only during Flexion and Extension, the connectivity of the muscle is expected to be higher for these gestures than for Pronation and Supination. This is evident for able-bodied participants, particularly for the third frequency component. However, this is not the case for amputee participants, where a low level of connectivity is found for the EDC muscle compared to the rest of the muscles across all frequency components for all gestures. These differences in muscle pair connectivity strengths, and therefore in the topology of the networks between demographics might be present because of the anatomical differences caused by amputation, variations of remaining muscle, and level of muscle activity. These functional (re)organization differences between able-bodied and amputees could show not only how the anatomy has changed after amputation but also how the neural drive adapts to those anatomical changes when performing the same gestures.

4.5.4 Network Analysis

Complex network analysis was used to compare the muscle networks between hand gestures for the different frequency components. In order to analyze network segregation, the clustering coefficient (CC) was derived from all networks. In this work, a t-test was used to evaluate the statistical significance of the network behaviours. Fig 4.6 shows the results of the t-test for the CC of all the undirected networks. Significant differences between gestures are shown in orange for ($p < 0.05$) and in red after applying Bonferroni correction for ($p < 0.0028$). For able-bodied participants, the first frequency component showed that CC for Flexion and Extension were significantly higher than CC for Supination ($p < 0.0028$). CC for Pronation was also found to be significantly higher than CC for Supination ($p < 0.05$). The second frequency component shows a significant difference in CC between Extension and Supination only ($p < 0.05$). On average, similar values of CC were found between the rest of the gestures. Similar to the first component, Supination showed the

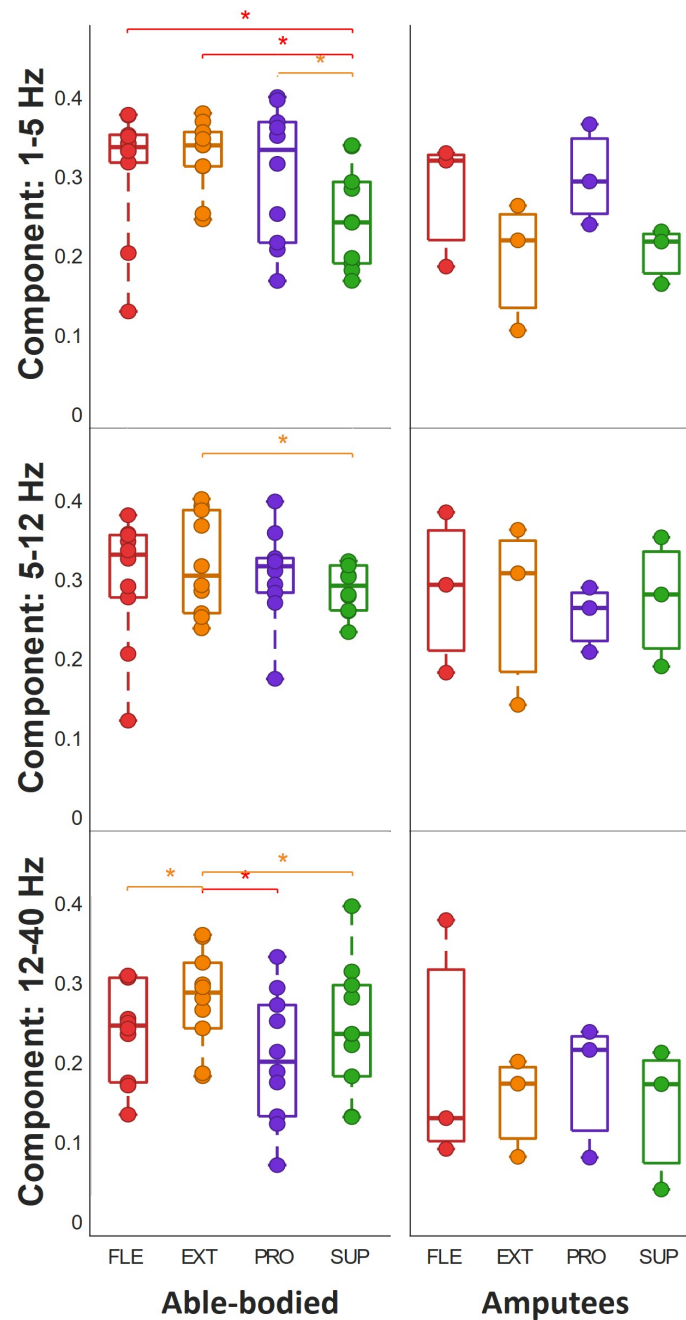


Figure 4.6: Clustering coefficient (CC) was used to statistically compare the functional muscle networks across gestures (red: Flexion, yellow: Extension, purple: Pronation, and green: Supination) and frequency components (from top to bottom: 1-5 Hz, 5-12 Hz, and 12-40 Hz). The clustering coefficient was evaluated for each undirected weighted network for able-bodied (left column) and amputees (right column). A two-sample t-test was used to statistically compare the CC between gestures for able-bodied participants. Significance is shown in orange color for $p\text{-value} < 0.05$, Bonferroni-adjusted significance is shown in red color for $\text{adjusted-}p\text{-value} < 0.0028$. © 2022 IEEE. Reprinted, with permission, from [116].

lowest values of CC across all gestures. The third frequency component shows that CC for Extension is significantly higher than CC for Flexion, and CC for Supination is significantly higher than

CC for Extension ($p < 0.05$). Pronation showed a significantly lower value of CC compared to Extension ($p < 0.0028$). Table 4.1 summarizes the statistical results of the clustering coefficient for all frequency bands and gestures for able-bodied participants. For amputee participants, the first component showed distinct distributions of CC values for all gestures. The individual contributions of each amputee participant can be seen in Fig 4.6. Similar to able-bodied participants, the second frequency component showed the least variability of CC between gestures compared to the other frequency components. The third frequency component showed a distinctively wider distribution for Flexion compared to the other gestures which showed similar distributions of CC.

4.5.5 Discussion

Results show distinct muscle connectivity topologies depending on the frequency component, gesture, and demographic. Significant differences in functionally segregated networks for specific gestures at low and high frequencies were found. The differences in CC between Supination and the rest of the muscles for the first frequency component for able-bodied participants suggest a characteristic spectral profile for the muscle displacement that occurs during Supination. The differences in CC between Extension and the rest of the muscles for the third component suggest common spectral characteristics between muscles at higher frequencies for this particular gesture compared to the other gestures. The above-mentioned analysis and the results given in Table 4.1 show a clear distinction of functional muscle networks registered using MMG and calculated by intermuscular coherence at different frequency bands. The results also highlight potential differences in the MMG frequency spectra between able-bodied and amputees. This analysis provides for the first time a strong bio-marker of synergistic muscle functionality using the clustering coefficient of the network using MMG activity. Different types of time and frequency analysis methods have been suggested to analyze the MMG signal features and their role in motor control [38, 76]. MMG power spectrum has been reported to contain information regarding the firing rate of motor units, with increases in the global firing rate of motor units resulting in higher frequencies of the MMG signal [3]. The results found regarding differences in muscle connectivity networks across frequency components and clustering coefficient distributions may support the application of MMG signal parameters as indicators of motor unit activation patterns and firing rates during muscle activity. The outcome of this analysis can further be used for the conduction of classifiers to find the motor intention of the user based on functional connectivity, with potential for real-time implementation of the MMG-based approach [5]. The results can also be used to track the changes in functional synergistic behaviour of healthy and impaired muscles.

The present results show evidence that mechanomyography can be used as a tool to perform analysis of functional muscle networks for able-bodied and amputee users, however, the following limitations must be considered. Miniaturization of the device is proposed to translate the technology into a wearable system to be able to utilize the proposed novel MMG-based muscle network analysis in the control of prostheses. This study did not consider complex dynamic activities which

have shown to provide relevant information regarding muscle function [76]. So far, muscle network analysis has been done only by the use of EMG. This study did not include the simultaneous acquisition of EMG activity for the comparison of muscle networks obtained using each type of myographic signal. Previous research indicates that the motor unit recruitment and firing rate affect the MMG and EMG equally for contractions up to 80% MVC [131]. Therefore, it is expected that muscle networks derived from both of these myographic modalities will reflect similarities in their topologies for low and medium levels of contraction. Future perspectives of the work presented in this chapter include (a) miniaturization of the device for translation of the proposed system into wearable technology to be used in clinical settings, (b) evaluation of static and dynamic tasks for a deeper analysis of the neural circuitry involved in different types of motor tasks, and (c) simultaneous acquisition of electromyography and mechanomyography activity during different gestures for analysis and comparison of muscle networks derived from each myographic modality.

4.6 Conclusions

In this chapter, the analysis of functional muscle networks using MMG and mapping of its variance between able-bodied and amputee participants is introduced for the first time in the literature. Inter-muscular coherence was derived from the frequency response of all the muscle pairs for all gestures and participants. Coherence was decomposed into three frequency components using non-negative matrix factorization. Muscle networks were generated for all gestures and all spectral components. Complex network analysis was conducted to extract the clustering coefficient of each network, which was used for statistical comparisons between gestures for able-bodied participants. Results showed significant differences between gestures across multiple frequency bands for able-bodied participants. These findings support the hypothesis that mechanomyography can be used for muscle network analysis and that it can be further exploited for the analysis of functional muscle connectivity for able-bodied and amputees. The findings of this investigation offer the concomitant outcomes of supporting the usability of MMG to map muscle coherence from a neurophysiological perspective as well as providing a mechanistic basis for its translation into human-robot interfaces (e.g., prosthetic hand control). It is important to mention that further analysis including the simultaneous acquisition of MMG and EMG activity is expected as the next step to continue this line of research in order to analyze muscle networks derived from each myographic signal and study the contributions of each modality in the analysis of functional muscle connectivity. In addition, the results presented here motivate the investigation of a wider range of research questions, including MMG spectral analysis of a bigger range of activities requiring different sets of muscles in the upper and lower limbs.

Chapter 5

Analysing three-dimensional muscle networks using MMG

This chapter introduces the study of multi-dimensional muscle networks based on MMG activity. Using the MMG sensing technology in Chapter 3, the sensing armband was re-adapted to house 3-axis accelerometers as the transducers used to acquire the MMG signal. The analysis discussed in this chapter is built in the context of evaluating the feasibility of MMG information collected from the multi-directional sensor to build muscle networks along the different spatial dimensions with respect to the muscle fibres.

The contents of this chapter including materials, methods, analysis, and results have been submitted for publication and are currently (October 2022) under review in IEEE Transactions on Biomedical Engineering.

5.1 Overview

Network analysis has been extended from neural architectures built for the purpose of studying synchronous activity between brain regions during the execution of cognitive and motor tasks [52] to the analysis of muscle synergies and functional muscle connectivity [33]. As such, this novel method has proved to be able to group muscles based on their common input by the use of muscle synergies [29] and has been further investigated to create functional muscle connectivity networks based on the common spectral content of the neural drive [87]. The previous chapter introduced the analysis of the later analysis on functional muscle connectivity by the use of acoustic/microphone MMG. This chapter aims to exploit the potential of the mechanical nature of the MMG signal captured from multiple directions by the use of accelerometers. There are a number of studies in the literature suggesting the propagation of the MMG signal along multiple directions with respect to the muscle fibres' alignment. By the use of an accelerometer, MMG activity can be quantified along these directions in order to perform muscle connectivity analysis based on intermuscular coherence in the three orthogonal directions of the muscle fibres.

In this chapter, accelerometer-based MMG activity is used for the first time to generate three-dimensional muscle networks and evaluate the different topologies along with the information content of each direction of the MMG. This functional connectivity analysis is performed for four superficial muscles in the forearm during the execution of hand gesture tasks. Similar to the analysis carried out in the previous chapter, network analysis is performed during sustained contractions in a cohort of 20 able-bodied participants. Muscle network topologies are expected to be distinct not only between gestures and frequency bands but also between axis, showing unique characteristics for each axis as the signal propagates in multiple directions. In this way, this study aims to find characteristic network topologies and differences between tasks, frequency bands, and axis. In addition, the study presented here also aims to investigate the effects of normal force on the quality and discriminative power of the accelerometer MMG signal when different levels of contact force are applied. Multiple spectrotemporal metrics are evaluated and statistically compared to quantify the effect of normal force variations on the features of the signal which are reflected in the performance of a gesture classification model. This characterization of MMG-based functional muscle networks and the effect that normal force has on accelerometer-based MMG offer a new toolset with potential for the examination of the neurophysiology behind the motor function and the application of the methodology for its use in rehabilitation and human-machine interfaces.

5.2 Introduction

5.2.1 Functional Muscle Networks

In the last decade, research on neural synchronization has been extended from neuron pairs coupling [61] to the analysis of coherent neural organization [43, 123]. One example of this is the study of the neural circuitry involved in the motor system as it facilitates the execution of complex motor activities [200] by coactivating coordinative groups of muscles to be able to integrate movements into a functional task [125, 193]. This coordinative activation of collective groups of muscles is governed by the central nervous system (CNS) [29] and is possible by the synchronization of the neuronal activity which plays a primordial role in the neurophysiological drive to the muscles [120]. Intermuscular coherence (IMC) is a method used to investigate this oscillatory common input to the muscles by characterizing the spectral synchronization of the neural drive to the groups of muscles [33, 101]. This method is extended using network analysis which describes characteristics of complex neurophysiological network structures by determining their topological representations and quantifying their properties [157], an analysis that has proven crucial for understanding neural connectivity during the execution of motor actions [35]. In this way, network analysis is used to unravel interactions between the CNS and the musculoskeletal system [89].

These methodologies, intermuscular coherence and muscle networks analysis, allow for the isolation of key spectral characteristics of the neural drive to groups of muscles which enable the CNS to simplify functional control via synchronous muscle activation [32, 33, 87–89]. For example, in [33], the analysis was used to show distinct patterns of connectivity between muscles not only across the different postural tasks but also across constituent frequency bands. More recently, in [87] the analysis of muscle networks was extended to different stages of gait cycle, showing how network characteristics vary according to the gait cycle, how the neuromuscular system couples anatomical and functional linked muscles during locomotion, and how this information is encoded into different frequency band components. These studies show task-specific changes with localized and widespread connectivity between muscles at multiple frequency bands depending on the motor task.

5.2.2 MMG Muscle Activity

Electromyography (EMG) remains the gold standard in myographic sensing employed in the analysis of muscle networks. While the source of nearly all muscle connectivity validation studies, EMG suffers from well-documented limitations imposed by skin-related impedance (sweat, scar tissue, etc.), specialized equipment requirements, and electromagnetic interference susceptibility which can hamper use out-of-clinic [1, 100]. Mechanomyography (MMG) offers a simple alternative to tackle these limitations as a myographic modality that traces the mechanical response of active muscle fibres during a contraction as opposed to the electrical innervation of the muscles

[76]. Muscle network analysis by the use of MMG was previously introduced in [116] for the analysis of functional intermuscular connectivity alterations linked to upper-limb loss and differences in muscle network topologies derived from different hand gesture tasks. The results showed evidence that the spectral features of the MMG signal can be used to construct muscle connectivity networks, reflecting the common spectral space shared by specific muscles when performing different motor tasks. However, based on the literature on the directional propagation of MMG [79], analysis of the multi-directional space of MMG is necessary to further elucidate the characteristics of the MMG signal as it propagates along the different directions with respect to the muscle fibres alignment.

5.2.3 Research Focus

One of the main characteristics of MMG is the directional propagation of information. In this study, for the first time, we propose the concept of three-dimensional (3D) muscle networks based on vibrational MMG (vMMG). Four superficial muscles are considered to formulate the functional muscle networks during various hand gesture tasks. Based on the evidence in the literature around the multi-directional propagation of MMG, we hypothesize that the multi-dimensional muscle networks will reflect the degree to which the signal propagates along the different directions of the muscle fibres' alignment. This manner of spatial mapping lends itself to MMG since EMG, due to the nature of the signal, cannot show propagation across muscle fibres. As such, we expect these three-dimensional muscle networks to show not only distinct topological characteristics between hand gestures at multiple frequency bands but also between the longitudinal, lateral, and transverse directions of the muscle fibres. Furthermore, we hypothesize that the coherent activation of muscles, showing the common spectral patterns of muscle activity, are distinct enough between gestures and directions, and can be further exploited to build discriminative models for hand gesture prediction. As a result, intermuscular coherence generated from all muscle pairs from the vMMG armband is proposed as the input to train a classifier for the prediction of hand gestures.

The main objectives of this study are:

- Derivation of functional intermuscular connectivity between forearm muscle pairs at low, medium, and high-frequency bands by the use of multi-axis MMG transducers during the execution of different hand gesture tasks.
- Identification of multi-dimensional muscle networks, based on intermuscular coherence extracted from each axis of vMMG, during the execution of different hand gesture tasks.
- Identification of distinctive characteristics in muscle network topologies based on the gesture performed, frequency band, and the direction of propagation.
- Implementation of a classification model based on intermuscular coherence derived from ac-

celerometer MMG to explore the gradient of discriminative information distributed along the different directions of propagation of muscle fibres.

5.3 Materials

5.3.1 Sensor Design

The sensor introduced in this section follows a similar design to that discussed in Chapter 3. The design has been adapted to house a printed circuit board (PCB) containing a 3-axis accelerometer (m-cube MC3635), a piece of mylar film onto which the sensor is glued to ensure direct contact with the skin, a cover to isolate and protect the wiring, and a stabilizing ring used to maintain tension on the film at the same time as it stabilizes the sensor. Different from the previous design, this sensor's case has been adapted such that the dimensions and shape of the main (previously 'acoustic') chamber fit the diameter and an added tolerance of the PCB with the accelerometer, which has a dimension of 5 mm. Fig. 5.1 shows a schematic of the custom-made accelerometer MMG sensor developed for the study carried out in this chapter.

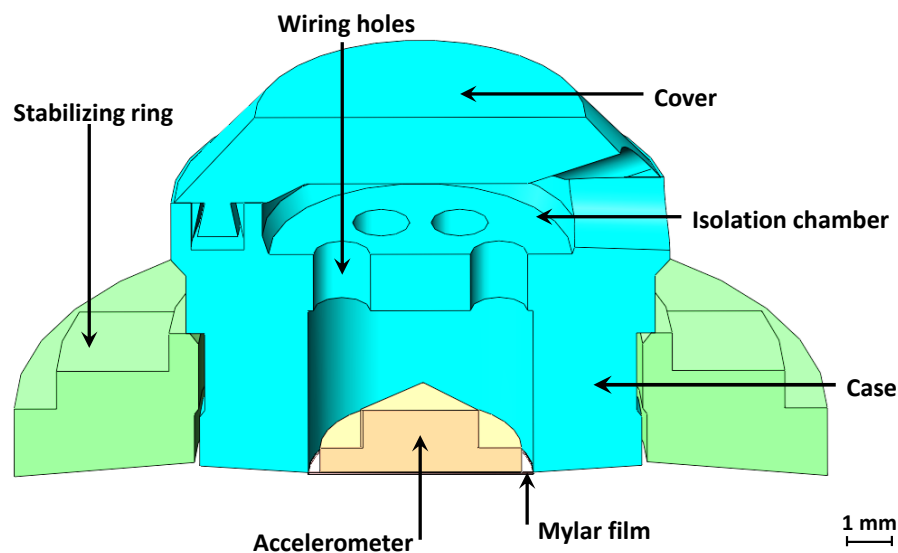


Figure 5.1: Cross-section view of custom-made accelerometer MMG. The device is comprised of five parts: a case that encloses all the components together, an accelerometer, mylar film onto which the accelerometer is glued to securely position the sensor and ensure direct contact with the skin, a cover to seal and protect the wiring, and a stabilizing ring, which is used to keep tension on the film and prevent the case from shifting or tilting. The isolation chamber is sealed using hot glue in order to reduce noise artifacts and ensure secure connections.

5.3.2 Graphical User Interface

In order to carry out the experiments intended for the study proposed in this chapter, a graphical user interface (GUI) was developed to effectively gather and store data. The GUI consists of three buttons, participant-information, start-recording, and stop-application. Fig. 5.2 shows a schematic of the options in the GUI. Each of these functions has different functionality. Participant information is used to save participant data prior to commencing the experiment. Start recording is used

once the sensors have been put in place and the participant is ready to start the experiment. Stop application is used once the experiment has culminated.

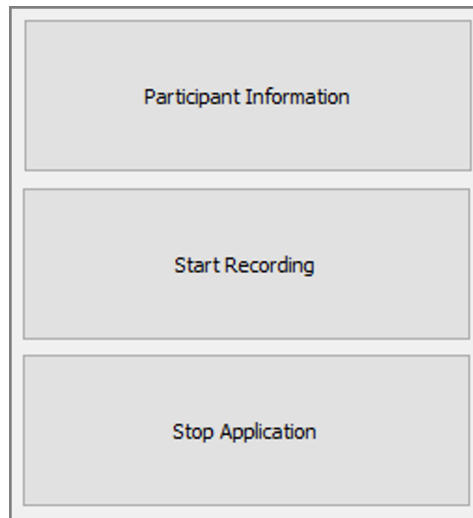


Figure 5.2: Graphical User Interface (GUI) designed for data collection. The GUI has three options: participant-information, start-recording, and stop-application. Each option includes different functionality.

5.3.2.1 Participant Information

This option opens a window in which participant details are introduced. Fig. 5.3 shows a schematic of the options when the window participant information is opened. ID is generated according to the numeric identifier for each participant in the experiments. Additional information includes age, gender, dominant arm, skinfold thickness measured by the use of a skinfold calliper, and finally arm diameter.

5.3.2.2 Start Recording

This option opens a new window running two parallel lines of commands (threads). The first line of execution operates in the background collecting the information sent from the wearable armband device and storing it into a binary file for post-processing. The second line of execution takes care of the front end and displays a square wave with a 10 s period on a plot to direct the participants during the experiment. Both threads are initialized once the 'Start' button is selected and they end once the 'Stop' button is pressed. The 'Clear' button initializes the plot from zero. A display text box is shown at the bottom to indicate the correct execution of the program or flag any errors. Fig. 5.4 shows a schematic of the options when the option 'Start Recording' is selected.

Participant Information

Start Recording

Stop Application

Participant Information

ID (completed by investigator):

Age:

Gender: ☐ Male ☐ Female

Predominant Arm: ☐ Right ☐ Left

Skinfold Thickness:

Arm Diameter:

Save

Cancel

Figure 5.3: Participant Information. This option is used to open a new window in which participant details are saved. Information includes ID, generated based on the participant number, age, gender, predominant arm, skinfold thickness, and arm diameter. The information is gathered prior to the participant starting the experiment and saved in a secured comma-separated file (csv).

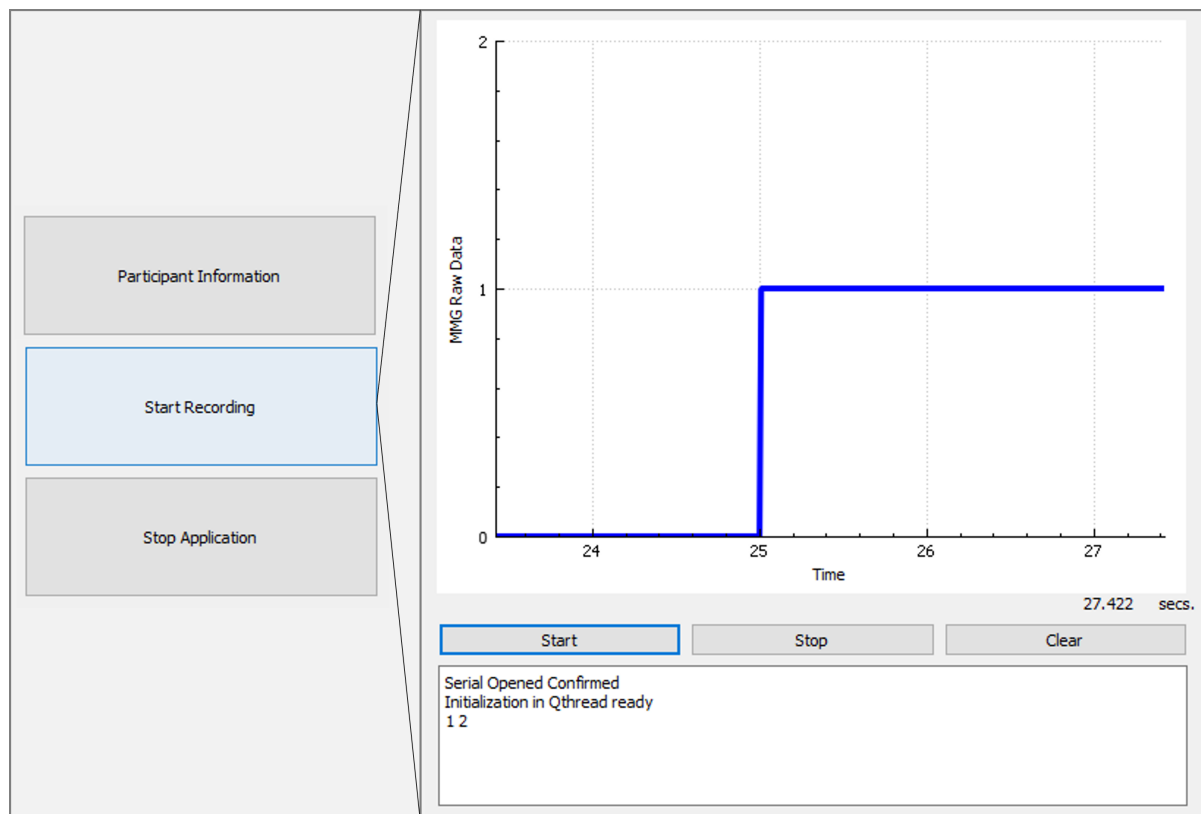


Figure 5.4: Start Recording. This option of the graphical user interface enables the data acquisition mode. Two parallel threads are run in order to store information and to show visual cues to the participants during the experiment. The first thread is run in the background and it is responsible for acquiring and storing the MMG information sent from the wearable armband device. The second thread is used for the front end and it is used to show a square wave signal with a period of 10 s to guide the participants during the experiments.

5.4 Methods

5.4.1 Participants

Twenty individuals (12 males, 8 females, mean age 25 ± 7 years old) participated in this study. See table 7.1 for additional participant information. Participants provided their signed informed consent before taking part in the experiments. All experiments were approved by the Imperial College Research Ethics Committee (ICREC reference: 15IC3068).

5.4.2 Experimental Design

For this study, a four-channel accelerometer-based MMG armband was assembled following the design described in [36]. Data was collected using the custom-made MMG armband comprised of four MC3635 3-axis accelerometer sensors configured with a resolution of ± 2 g. Accelerometers were positioned such that the axes were aligned with respect to the muscle fibers. The x-axis was aligned with the longitudinal direction, the y-axis was aligned with the lateral direction, and the z-axis was aligned with the transverse direction of the muscle fibers. Information was recorded while participants performed different hand gesture tasks. The experimental protocol followed the one described in [116]. For this study, gestures and target muscles were maintained. Namely wrist Flexion, Extension, Pronation, and Supination for gestures and flexor carpi radialis (FCR), brachioradialis (BRD), extensor digitorum communis (EDC), and flexor carpi ulnaris (FCU) for target muscles. Each participant was asked to follow a square wave presented on a monitor in front of them to keep track of the timing of the contractions (see 5.5 for an illustration of the experimental layout). Participants were asked to stay still for the duration of the experiment to minimize motion-induced artifacts. All participants performed a training trial which consisted of performing a series of sustained contractions of two randomly selected gestures. Each participant performed 7 repetitions of each gesture with intervals of 5 seconds of rest between each contraction. The experiment consisted of the same process as that of the training trial with gestures divided into two groups, each of two randomly ordered gestures. Intervals of 10 s of duration were applied at the beginning and the end of each of the two groups of recordings. The order of the gestures was randomized for each participant. The full duration of the experiment took less than 10 minutes for each participant.

5.4.3 Data Processing

The raw MMG signal of each channel was analyzed to extract the steady-state phase of the contraction. Three seconds of information were extracted for each contraction. MMG data was collected using a sampling frequency of 1 kHz. The raw signal of each MMG transducer was filtered using a fourth-order band-pass Butterworth filter in the range of 1 - 150 Hz. A Hilbert transform was applied to the filtered data in order to obtain the analytic representation of the signal to be further used in

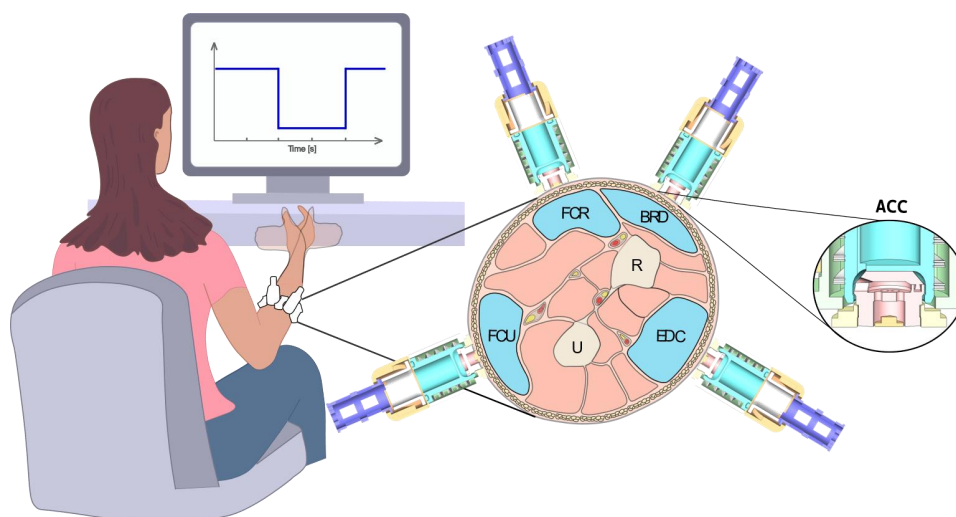


Figure 5.5: Experimental Layout. Participants were asked to perform four different hand gestures by following a square wave with a 10 s period displayed on a monitor in front of them to keep track of the duration of the contractions. Each contraction was sustained for a period of five seconds with five seconds of rest between contractions. The cross-section view of the forearm is presented to illustrate the muscles of interest and sensor placement. Sensors were positioned over the flexor carpi radialis (FCR), brachioradialis (BRD), extensor digitorum communis (EDC), and flexor carpi ulnaris (FCU) muscles. A detailed view of the cross-section view of the sensor is shown on the right side to illustrate the accelerometer positioning in contact with the skin.

the calculation of the power spectral densities of the signals. These same data processing steps were applied for information collected along the three directions of the sensors.

5.4.4 Intermuscular Coherence

Intermuscular coherence was extracted between each muscle pair following the method described in [116] for the calculation of modified magnitude squared coherence (MMS). In this study, we used a method based on the average of trials to estimate IMC instead of the concatenation of trials to minimize the presence of spurious coherence. Each 3-second trial of data was zero-padded at both ends by a number of samples equal to half of the segment samples needed to account for the full 1024 segments for the calculation of coherence. Coherence was then evaluated using a segment of 1024 samples, a Nuttall window, and 50% of overlap. To prevent spurious coherence resulting from edge effects caused by the zero-padding process, each 3-second trial of information was multiplied by a Tukey window using a cosine-tapered section of 0.05 [30]. IMC was extracted from each of the seven trials, then averaged across trials and subsequently averaged across participants. This process was applied for each accelerometer direction. In this way, IMC was generated for all muscle pairs, all gestures, for all directions, resulting in a matrix of $(c_x m_x g_x d)$, denoting c coherence values, m muscle pairs, g number of gestures and d number of directions.

5.4.5 Spectral Decomposition

Non-negative matrix factorization (NNMF) was used to decompose the MMG spectral space into frequency band components to identify the common frequency space at which the target muscles are co-modulated by the neural drive when performing different hand gestures and utilize the spectral characteristics of the signal to subsequently generate the corresponding muscle networks. Frequency band components were defined as 1–5 Hz for low-frequency information, 5–12 Hz for medium-frequency oscillations caused by tremor, and 12–40 Hz to capture high-frequency information produced by the inner muscle fibres oscillations, all of which constitute the MMG spectral space [121, 131, 199]. NNMF was used to decompose the spectral space of the signal into frequency band components with their corresponding coupling strength across all muscle pairs for all gestures along each direction. In this way, NNMF was applied to all coherence matrices $c_x m$ corresponding to each gesture for each direction. A multiplicative update rule was used to minimize the objective function and constraint the scope of each component to that of the frequency bands, as described in [116]. IMC of all muscle pairs was decomposed over the intervals specified above into non-negative factors using an alternating least squares algorithm, thus resulting in two non-negative matrices reflecting the spectral signatures (basis vectors) and the corresponding coupling strengths between all muscle pairs for each gesture and each direction.

5.4.6 Muscle Networks

Basis vectors along with the coupling strengths generated for each frequency band component were used to extract task- and frequency-specific matrices for each gesture and each direction. The resulting adjacency matrices were then used to generate the undirected weighted functional connectivity networks. Muscle networks are constructed so that each target muscle represents a node in the network and the edges of the network are defined by the connections between the nodes, denoted by the basis vectors obtained from the NNMF process. Fig 5.8 shows the muscle networks for each gesture (columns) and frequency component (rows) for each direction.

5.4.7 Feature Extraction

For the purpose of training a multi-class classification model based on IMC, information from each trial was segmented into windows of 0.97 ms (1024 samples) with 50% of overlap. IMC was calculated following the same process mentioned above for each one of the generated segments. In order to improve computational speed, the feature space was reduced to discard IMC information at frequencies higher than 256 Hz as they have a negligible effect on classification performance. IMC data from all muscle pairs for the entire frequency domain were concatenated to generate the feature space. The feature space was subsequently segmented using a hold-out validation method consisting of 80% of the data used for training and 20% of data used for testing. A multi-class support vector machine (SVM) model was trained and tested for each participant using the feature space generated.

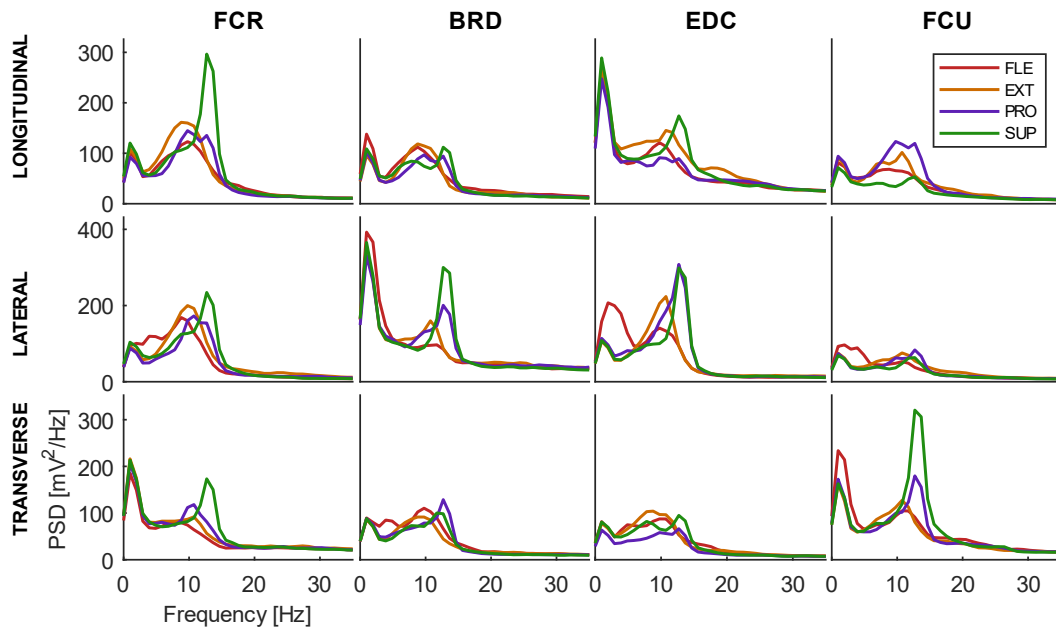


Figure 5.6: Power spectral densities shown for the different muscles (columns: FCR, BRD, EDC, and FCU) for all gestures (red: Flexion, yellow: Extension, purple: Pronation, and green: Supination) for each direction of propagation (rows: Longitudinal, Lateral, and Transverse). Power spectral densities were averaged across trials, muscles, and participants.

5.5 Results & Discussion

In this chapter, the intermuscular coherence between muscle pairs from four superficial muscles in the forearm was extracted for the generation of task-specific muscle networks and the evaluation of a classification model for the detection of hand gestures. Following the signal processing steps and after obtaining the analytic representation of the signal, the power spectral densities (PSDs) for each channel along each direction were extracted for each trial and all gestures. PSDs were averaged across all trials and subsequently across participants in order to obtain the mean power spectral response of each muscle when performing different gestures. Fig 5.6 show the PSDs for all gestures for each muscle (columns) and each direction/axis (rows). PSDs of all directions showed power information at frequencies no higher than 40 Hz, with minimal power found at higher frequencies. Interestingly, the PSDs across directions show similar profiles with distinct power information depending on the gesture, muscle, and direction.

5.5.1 Muscle-Pairs Coherence

Intermuscular coherence was calculated for each muscle pair for all gestures, participants and directions. Fig 5.7 shows the IMC activity for all muscle pairs (columns) for each direction/axis (rows). The confidence interval is calculated following the method described in [187] for overlapped segments. IMC show functional activation at multiple frequencies with distinct profiles

across muscle pairs and similar spectral common response across gestures with different scaling factors. Coherent activation across muscles is observed at multiple frequencies below 40 Hz. IMC results show high levels of connectivity for FCR-BDR, FCR-EDC, and EDC-FCU muscle pairs along the longitudinal direction (longitudinal), widespread common spectral activity across the lateral direction (lateral), and high connectivity for FCR-EDC, FCR-FCU and BDR-FCU muscle pairs for the transverse direction (transverse). For the transverse direction, and different from the other two directions, low levels of IMC were found for FCR-BDR, BDR-EDC, and EDC-FCU muscle pairs. IMC for the different hand gestures shows common frequency information across directions with distinct profiles for specific muscle pairs. Flexion shows the highest IMC for FCR-BDR and EDC-FCU muscle pairs along the longitudinal and lateral directions, with low IMC along the transverse direction. Extension shows a distinct higher activity of IMC in the lateral direction across muscle pairs BDR-EDC, BDR-FCU, and EDC-FCU. Higher coherent activity compared to Flexion was found along the transverse direction for Extension. Pronation shows the highest IMC in the longitudinal direction for FCR-BDR muscle pair. Supination shows distinctively higher levels of IMC compared to the other gestures across all muscle pairs in the transverse direction. The highest peak of IMC for Supination was found for FCR-EDC.

5.5.2 Muscle Networks

Intermuscular coherence found across the frequency spectra were decomposed into frequency ranges according to the spectral bands of interest (i.e., 1-5, 5-12, 12-40 Hz). Basis vectors and coupling strengths resulting from the spectral decomposition were used to generate muscle connectivity networks for each gesture at each frequency component for every direction. Fig 5.8 shows

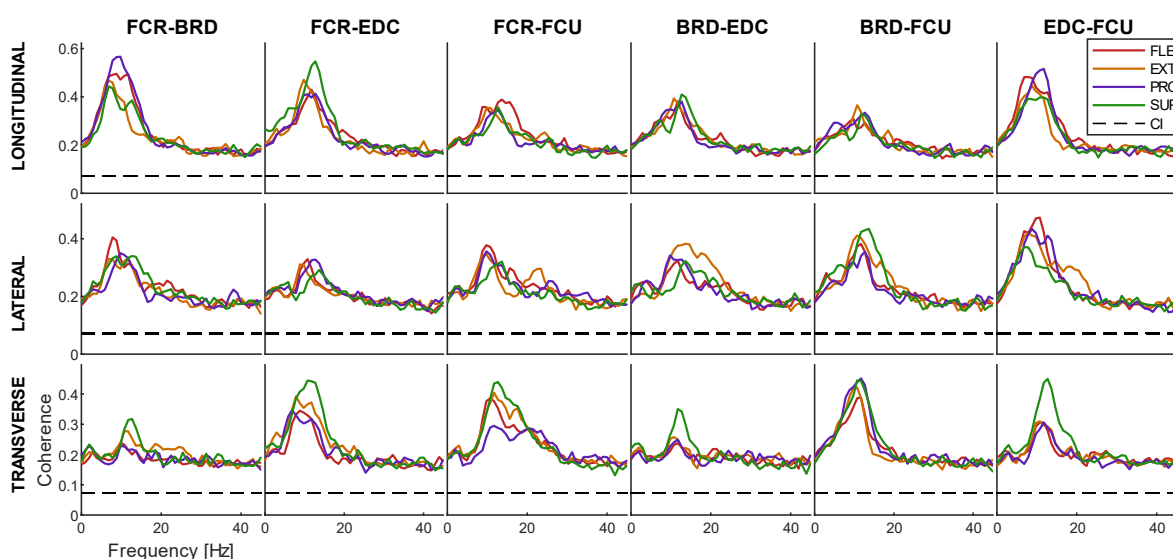


Figure 5.7: Intermuscular coherence between all muscle pairs (columns). Coherence is shown between all muscles for each gesture across every direction of propagation captured by the accelerometer (rows).

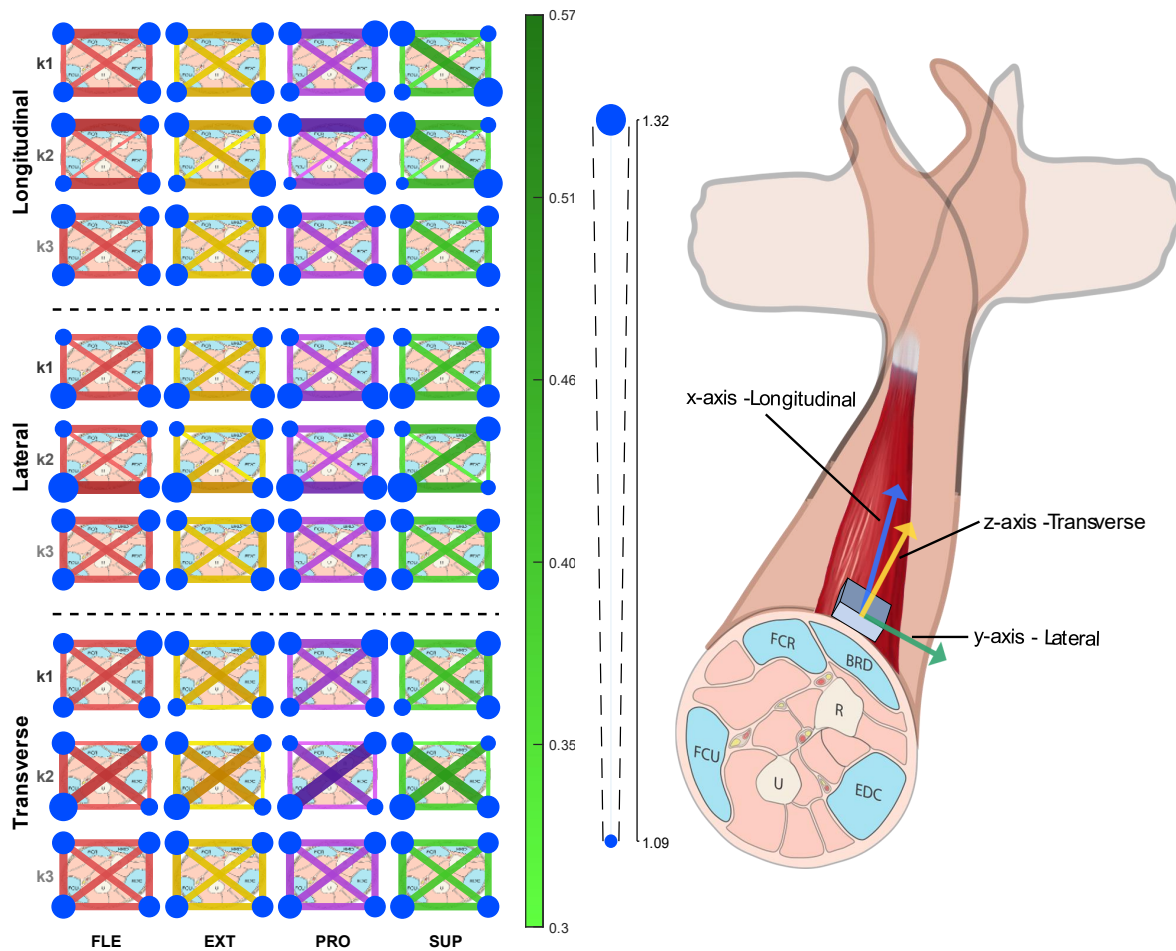


Figure 5.8: Intermuscular coherence between muscle pairs was decomposed into three frequency bands using non-negative matrix factorization. The three frequency components were defined as: k1: 1-5 Hz, k2: 5-12 Hz, and k3: 12-40 Hz. Left-side, muscle connectivity networks were extracted for each gesture (columns) at each of the frequency components (rows) for all axes (groups of rows). Functional networks were generated using the common spectral patterns and the corresponding weightings across frequency bands. Weightings were used to define the strength of the connections (edges) between muscles (nodes). Connectivity strength is illustrated by the gradient of colour defined by the colour bar and the thickness of the connection. Node strength is illustrated by the size of the node and it is defined by the weightings of the edges connected to the muscle. Right-side, cross-section view of the forearm for illustration of the positioning of a single accelerometer sensor over a target muscle. Each accelerometer was aligned such that the x-axis was co-linear with the longitudinal direction of the muscle fibre, the y-axis was co-linear with the lateral direction of the muscle fibres, and the z-axis was aligned with the normal direction of the muscle fibres.

the functional connectivity networks for all gestures (columns) at each frequency band component (rows) for the three directions of the accelerometers (groups of rows). Symmetric networks are illustrated for better identification of connectivity distinctions between muscle pairs.

5.5.2.1 Longitudinal networks

The first component yields distinct connectivity topologies between gestures. Flexion shows strong connections between medial forearm muscles (FCR-BRD) and lateral muscles (FCU-EDC). Extension shows a similar topology with higher connectivity compared to flexion between FCR-EDC muscles. Pronation shows strong connectivity between FCR-BRD. Supination shows a strong connection between FCR-EDC muscles. The second frequency component yielded similar topologies to those of the first frequency component with stronger and more evident distinctions in connections between muscle pairs. In this component, Flexion shows stronger connectivity between FCR-BRD. High connectivity is also found between FCU-EDC. Similarly, Extension shows strong connectivity between FCR-BRD and FCU-EDC, with a stronger connection between FCR-EDC muscles. Pronation shows a similar topology to that of Flexion, with strong connections between FCR-BRD and FCU-EDC. Supination presents a similar topology to Extension, with strong connections between FCR-BRD, FCU-EDC, and even stronger connectivity for FCR-EDC. The lowest levels of connectivity across gestures and components were found between FCU-BRD. The third frequency component shows widespread medium levels of connectivity across muscles for all gestures. This component shows stronger connectivity for all gestures between anterior and posterior muscle pair connections compared to the first two components. Fig 5.8 indicates a transition from localized connectivity between muscle pairs at low frequencies (i.e., 1-5 Hz) to stronger localized connections at medium frequencies and widespread connectivity at high frequencies.

5.5.2.2 Lateral networks

The first component shows medium-to-high connectivity between the FCU-BRD-EDC triplet for Flexion. High connectivity between FCU-EDC and medium connectivity for FCU-BRD and FCR-BRD was found for Extension. Pronation shows strong connectivity for FCU-EDC muscle pair. Supination shows strong connectivity for FCU-EDC with medium to high levels of connectivity for FCU-BRD and FCR-EDC. In general, the muscle pair FCU-EDC shows strong levels of connectivity across gestures, with FCU-BRD showing a similar characteristic with medium levels of connectivity. For the second component, a phenomenon similar to the longitudinal direction was found, where the connectivity between muscles shows a higher level of connectivity compared to those of the first component. Flexion shows strong connectivity between FCR-BRD muscles. Extension shows a similar topology to Flexion with medium levels of connectivity between FCU-BRD. Pronation shows high connectivity between FCU-EDC with low levels of connectivity between the rest of the muscles. Supination shows strong connectivity between FCR-BRD, FCU-BRD, and FCU-EDC. Interestingly, the second component for the lateral direction shows low connectivity between FCU-BRD muscles across all gestures and medium to low connectivity between anterior and posterior muscle pair connections. The third component shows medium levels of connectivity across muscles and gestures. This component shows an increase in connectivity for FCU-BRD across all gestures compared to the previous component and a similar behaviour for FCU-FCR and BRD-EDC.

Table 5.1: Statistical Comparison for Classification Performance

Force Levels	Direction	*	Probability	% Variation
Force Level 1 vs Force Level 2	Longitudinal		$p: 0.25$	2.86% ↑
	Lateral		$p: 0.38$	2.51% ↓
	Transverse		$p: 0.23$	3.93% ↓
	All-Directions		$p: 0.88$	0.36% ↓
Force Level 1	Longitudinal vs. All	*	$p: 4.1e-10$	26.61% ↑
	Lateral vs. All	*	$p: 2.6e-07$	16.24% ↑
	Transverse vs. All	*	$p: 6.7e-09$	18.93% ↑
Force Level 2	Longitudinal vs. All	*	$p: 8.4e-09$	23.39% ↑
	Lateral vs. All	*	$p: 7.2e-07$	18.39% ↑
	Transverse vs. All	*	$p: 5.2e-08$	22.50% ↑

Significance is shown in red color for the Bonferroni-adjusted significance $adjusted-p-value < 0.0166$, $df=3$ for the statistical comparison between uni-directional and multi-directional trained classification models.

5.5.2.3 Transverse networks

The first component for the transverse direction shows widespread connectivity for most muscle pairs across gestures with distinctive low connectivity between FCR-FCU and FCU-EDC. Medium to high levels of connectivity are found between FCU-BRD and FCR-EDC and medium to low levels of connectivity are found between FCU-EDC and FCR-FCU across gestures. The second component shows topologies similar to the first component with more evident differences in connectivity strength between muscle pairs. Flexion shows strong connectivity between FCU-BRD and FCR-EDC and heterogeneous connectivity between the rest of the muscle pairs. Extension shows distinctively strong connectivity between the same muscles (FCU-BRD and FCR-EDC). Pronation shows the highest connectivity across gestures, components, and directions between FCU-BRD. Medium to high connectivity is found between FCR-EDC and a characteristic low connectivity strength is found between the peripheral connections. Supination shows a similar topology to those of Flexion and Extension. For this component, characteristic low connectivity between FCR-BRD and BRD-EDC is found across gestures. In the third component, similar topologies to those of the first two directions are found with widespread connectivity between all muscle pairs across gestures. Muscle connectivity strength increased for muscle pairs FCR-BRD and BRD-EDC compared to the second component.

The longitudinal direction shows strong connectivity between FCR-BRD and FCU-EDC across gestures and low connectivity between FCU-BRD. The lateral direction shows high connectivity between FCU-EDC and low connectivity between the diagonal connection FCR-EDC across gestures. Interestingly, the transverse direction shows strong connectivity between the diagonal muscle connections FCU-BRD and FCR-EDC. The distinct differences in the topology of the networks between

directions suggest unique spectral characteristics of the mechanomyography along the three directions of muscle fibre alignment. The functional strengthening of muscle connectivity from the first to the second frequency component seen across directions suggests overlapping spectral responses between low-frequency oscillations caused by movement and tremor, respectively, with tremor accounting for the majority of the common spectral power between muscles. This common characteristic for the first two components across directions along with the similar topological signatures for the different directions in the third component suggests a multi-directional propagation of the mechanomyography activity along the longitudinal, lateral, and transverse directions.

Regarding the role of each muscle during the gestures, both flexor muscles and the extensor digitorum communis play a role in wrist Flexion and Extension, therefore it is to expect a high functional activation of the FCR-FCU-EDC muscles. FCU shows high connectivity with the EDC muscle across directions. FCR-EDC shows high connectivity along the transverse direction only. Interestingly, the BRD muscle shows high connectivity with the FCR along the longitudinal direction. Similarly, high connectivity was found for FCU and EDC muscles for Extension along the longitudinal and lateral dimensions, and a strong connection between FCR-EDC muscles for the lateral and transverse direction. The brachioradialis muscle is in its majority responsible for gestures Pronation and Supination; therefore, a higher level of connectivity is expected for vertices connected to the BRD muscle during those gestures. High connectivity between FCU-BRD is found for the lateral direction and more evidently for the transverse direction. Interestingly, similar topologies were found between Extension and Supination across directions for the second frequency component. The highest levels of connectivity were found along the longitudinal and transverse directions, suggesting a higher propagation of the MMG signal in these directions in line with the directional propagation of mechanomyography activity longitudinally and normal with respect to the muscle fibers according to previous findings [41].

5.5.3 Contact Force

Different myographic transducers have been applied in MMG investigations to successfully capture the signal. Typically, MMG modalities have been found to be affected by different factors, such as the length of the muscle being tested, external artefacts, cross-talk, and skin thickness [76]. Particularly, all MMG sensing modalities have been shown to be influenced by the pressure with which the sensor is secured to the skin [31, 178, 197]. A recent study regarding the association of anthropometric parameters and the temporal features of accelerometer MMG [180] found that the signal remains invariant and robust to changes in arm diameter, muscle length, and skin-fold thickness, with also minimal crosstalk between arm and forearm muscles. However, there is minimal investigation on the effect of changes in contact force between the sensor and the skin on not only the temporal but also the spectral features of the accelerometer MMG signal.

In [36], the authors demonstrated how different levels of contact force affect the temporal and

spectral properties of the acoustic MMG signal, evident in changes in the signal-to-noise ratio and bandwidth, resulting in alterations in the discriminative power of the signal when discerning multiple hand gesture tasks. Results of the study indicate that increasing the normal force between the MMG sensor and the skin causes subject-specific variations in the quality and discriminative power information for the classification of gestures. Previous studies on the effect of contact force on MMG activity indicate that higher levels of contact force result in an increase in the amplitude of the signal [31, 178]. However, in the case of the MMG detected using accelerometers, there is only a small number of investigations on the effect of contact force. In [197] the authors showed that progressively adding higher loads to the sensor (from 2 g to 50 g), thereof increasing the level of contact force, results in gradual signal distortion. The lack of systematic investigation and understanding of this phenomenon on MMG captured using accelerometers motivates the analysis of the quality and discriminative power of the signal under different levels of contact force. Making use of the sensor design described in [36] adapted for accelerometer sensors, the experimental protocol described above was also performed using a second level of contact force. To ensure consistency, during the first part of the experiment described above the first level of contact force was determined by matching the length of the armband with the arm diameter of each participant. The second level of contact force consisted of protruding each sensor 3 mm onto the skin while maintaining the same length of the armband and without removing it, effectively increasing the level of contact force between the sensor and the skin and ensuring the same sensor location.

5.5.4 Spectrotemporal Features variations

Temporal and spectral features of the MMG signal have shown to contain essential information regarding neuromuscular control of muscles, providing important insights into the strategies of motor unit recruitment and firing rate [2, 23]. Gaining a better understating of how changes in contact force alter the features of accelerometer MMG could improve the usability of the signal for the analysis of the neuromuscular function of the muscles. In order to evaluate the spectrotemporal changes between the levels of contact force for the MMG response, three temporal metrics and three spectral metrics were extracted for each channel/muscle, gesture, and level of force in all directions. Temporal features include the following:

5.5.4.1 Root Mean Square (RMS)

RMS is a widely used feature in MMG activity commonly used for the analysis of fatigue, force production, toque [191], and has also been used for hand gesture classification [8]. The mathematical derivation can be expressed as:

$$RMS = \sqrt{\frac{1}{N} \sum_{i=1}^N x_i^2} \quad (5.1)$$

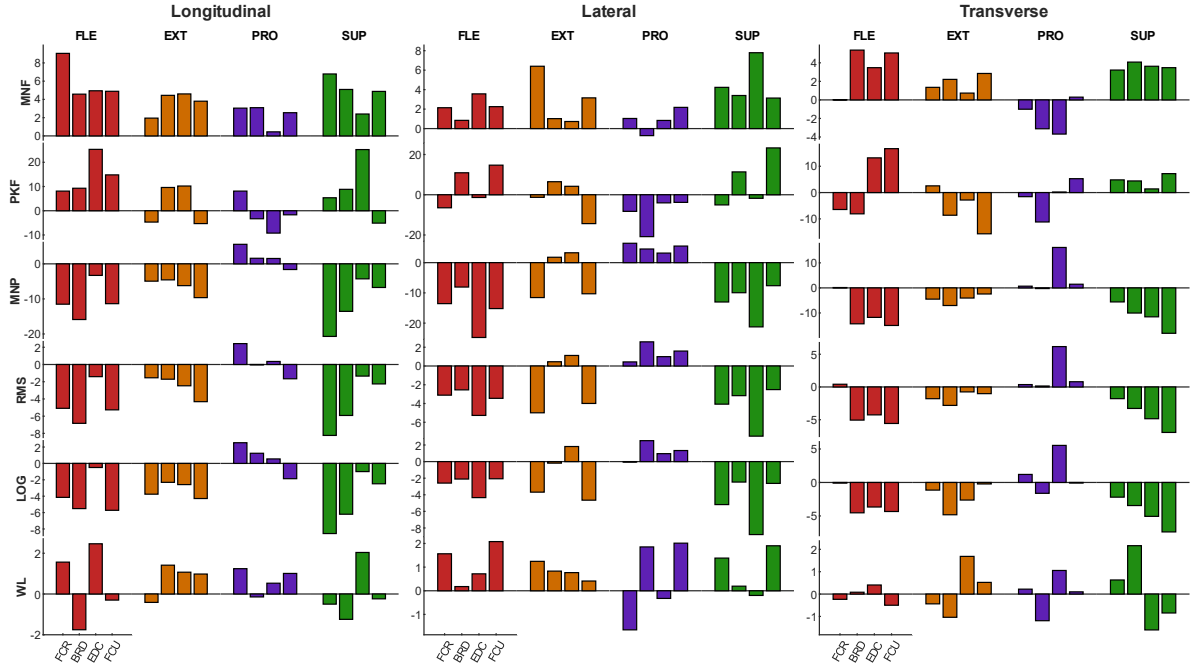


Figure 5.9: To analyze the effect of contact force in the time and frequency domain of the MMG signal, three temporal (MNF, PKF, MNP) and three spectral (RMS, LOG, WL) features of the MMG activity were extracted for all muscles, gestures, directions and averaged across trials and participants. The percentile variations of the features from the first level of contact force to the second level of contact force are shown for each spectrotemporal feature (rows) for every muscle (bars), gesture (colour-coded groups of bars), and for all directions (columns).

5.5.4.2 Log Detector (LOG)

LOG is a feature commonly used in EMG to obtain an estimate of muscle contraction [189] and it has recently been used in MMG for estimation of muscle strength [208]. It can be defined as:

$$LOG = \exp \left(\frac{1}{N} \sum_{i=1}^N \log(|x_i|) \right) \quad (5.2)$$

5.5.4.3 Waveform Length (WL)

WL is defined as the cumulative length of the signal over time segments and it is a measure of the complexity of the signal. It can be calculated by:

$$WL = \sum_{i=1}^N |x_i - x_{i-1}| \quad (5.3)$$

Frequency domain features include:

5.5.4.4 Mean Frequency (MNF)

MNF is a spectral feature that is calculated as the summation of the product between the frequency and the power present at each frequency divided by the total power spectrum. It can be calculated as:

$$MNF = \frac{\sum_{j=1}^M f_j P_j}{\sum_{j=1}^M P_j} \quad (5.4)$$

where,

f_j is frequency of the spectrum at frequency bin j ,

P_j is the EMG power spectrum at frequency bin j , and

M is length of the frequency bin

5.5.4.5 Peak Frequency (PKF)

PKF is known as the frequency at which the maximum power occurs. It is defined as:

$$PKF = f_j \text{ such that } \max(P_j) \quad (5.5)$$

with, $j = 1, \dots, M$

5.5.4.6 Mean Power (MNP)

MNP is defined as the average power of the spectral response of the MMG signal. Similar to RMS, this feature has been used in the literature for the analysis of torque [23]. The calculation is defined as:

$$MNP = \frac{1}{M} \sum_{j=1}^M P_j \quad (5.6)$$

Fig 5.9 shows the percentage change of each spectrotemporal feature between force level one and force level two for each direction. Features were averaged across participants. Results from the longitudinal direction show in general an increase in the MNF across gestures, suggesting an increase in the power across frequencies. A similar characteristic is also found for the PKF with increases across the majority of the gestures and a general small decrease for the FCU muscle for most gestures except for Flexion. However, results from MNP show a general decrease in values across gestures, with the exception of Pronation. RMS and LOG showed a general decrease across gestures with the exception of Pronation, which showed minimal increase in both features. The

decrease in RMS indicates a lower average amplitude of the signal for the second level of force, in line with results in MNP. The decrease in LOG, implying a decrease in muscle contraction could be explained as a result of limited mobility of the muscles at higher levels of contact force. WL showed heterogeneous variations across muscles and gestures between levels of contact force.

Results from the lateral direction show a less pronounced increase in the MNF compared to the longitudinal direction, showing in general small increases across gestures. Heterogeneous variations were found for the PKF across gestures with small variations of this feature between contact force levels. Results from the MNP show a decrease across muscles for Flexion and Supination, small increases across muscles for Pronation, and small variations for Extension. These results, similar to the longitudinal direction, showing a decrease in the MNP and increase in MNF indicate lower power information is found in the second level of contact force with a shift of the active frequencies in the first level towards higher frequencies at the second level of contact force, resulting also in increases for the PKF. Interestingly, Pronation showed the opposite characteristic for both directions, showing an increase for both MNP and MNF with a decrease in PKF. These results suggest a shift of the power information of the active frequencies in the first level of force towards lower frequencies at the second level of contact force, hence producing lower PKF at the second level of force. RMS and LOG show a decrease across gestures except for Pronation which, as expected from the spectral features, shows the opposite characteristic compared to the rest of the gestures. WL shows an increase across muscles for Flexion, Extension, and Supination, and for anterior muscles for Pronation. A decrease in WL was found for posterior muscles during Pronation.

Results from the transverse direction show increase in MNF for Flexion, Extension, and Supination, and a decrease in Pronation. Heterogeneous variations were found across muscles and gestures for the PKF with Supination showing an increase across all muscles. MNP present a decrease in the mean power information for Flexion, Extension, and Supination. Minimal changes were found for Supination across muscles with a characteristic increase for EDC muscle. Similar characteristic variations across muscles and gestures were found for RMS and LOG. WL show the lowest variations across directions and heterogeneous variations across muscles depending on the gesture. Results of WL across directions show that the characteristic complexity of the signal for each muscle and gesture is detected in all directions of the accelerometer. Interestingly, the lowest variations across temporal and spectral features were found for Pronation across all directions.

5.5.5 Gesture Classification

Fig 5.10 shows the confusion matrices and the distribution of the accuracies for the gesture classification models trained using IMC from individual directions and from the combination of all directions. For the longitudinal direction, Extension and Pronation were classified correctly more generally than Flexion and Supination. Extension shows the highest rate of classification across

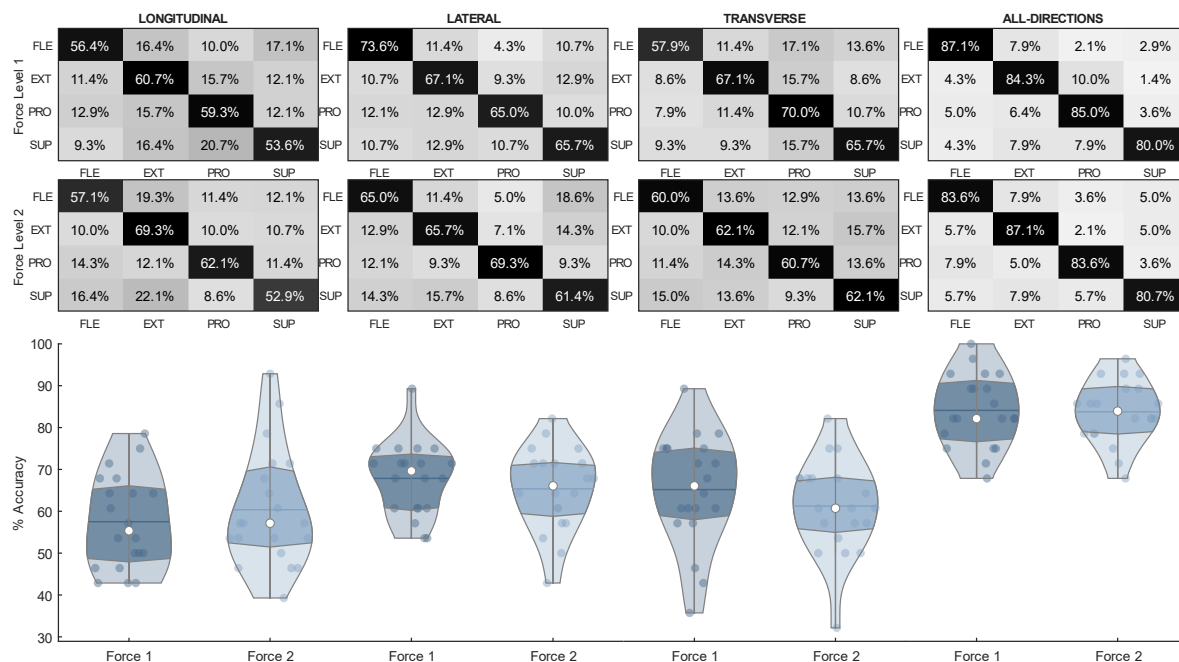


Figure 5.10: Top. Confusion matrices of the performance of the classification models based on a single axis and the combination of axes (last column) of the accelerometer for each level of contact force. Bottom. Violin plots that illustrate the distribution of the classification accuracies of the models across participants for single- and multi-axis-based models for each level of contact force.

gestures for both levels of contact force. Supination shows the lowest classification rate across gestures for both contact force levels, with the majority of miss-classifications being identified as Pronation for the first level of contact force and as Extension for the second level of contact force. In the lateral direction, Flexion showed the highest rate of classification for the first level of force, with Pronation and Supination showing the lowest rates. In the second level of force, Pronation yielded the highest classification rate and Supination showed the lowest. In general, classification rates decreased in performance between the first and second levels of contact force with the exception of Pronation, which showed an increase in the classification rate. For the transverse direction, the highest classification rate was found for Pronation and the lowest accuracy was found for Flexion in the first level of contact force, with the majority of miss-classifications identified as Pronation. The second level of contact force showed in general a decrease in classification performance compared to the first level of force and similar levels of classification accuracies across gestures. In the case of the multi-directional trained model, the highest classification rate was found for Flexion for the first level of contact force and Extension for the second level of contact force. The lowest classification performance was found for Supination for both force levels.

The lowest accuracies were found for the models trained using longitudinal direction IMC features. Models trained using IMC features along the lateral direction yielded the highest performance between directions. Interestingly, model performance for the second level of force shows higher variance compared to the first level of force across directions. However, the opposite results are

found for the model trained using features from all directions, showing less variance in accuracy distribution for both levels of force. The classification accuracy of the models shows similar performance between the two levels of force across directions. As expected, similar behaviour is found for the model trained using all directions. The mean accuracy of classification for the first level of force in the longitudinal direction is 57.5%, which increased to 60.3% for the second level of force with standard deviation 0.112 and 0.139, respectively. The accuracy of classification for the lateral direction and transverse direction decreased between the first and the second level of force. Classification for the lateral direction yielded 67.87% and 65.36% for the first and second levels of force, respectively, with standard deviation 0.087 and 0.099, respectively. Classification accuracy for the transverse direction shows a decrease from 65.1% for the first level of force to 61.2% for the second level of force with standard deviation 0.132 and 0.111, respectively. As expected, the mean classification accuracy of the multi-directional trained model showed a substantial increase in accuracy with similar performances between levels of force, yielding 84.11% and 83.75% for the first and second levels of contact force, respectively, with standard deviation 0.087 and 0.074, respectively.

5.5.6 Statistical Analysis

In this study, three statistical comparisons were performed. The first consisted of comparing the temporal and spectral features between levels of force for each muscle, gesture and direction to evaluate statistical significant changes in the quality of the signal when different levels of contact force are applied. The second statistical comparison consisted of comparing the performance accuracy of the classification models between levels of force for each classification model. The third statistic was performed to compare the performance accuracy of classification models between the single-direction vs multi-direction trained models. All statistically compared data passed the Shapiro–Wilk normality test. Statistical comparisons were performed using a t-test to determine significance. Statistical significance was considered for values of $p\text{-values} < 0.05$. Bonferroni-adjusted significance was computed to minimize type-I errors. The adjusted significance level for the first statistical comparison was $adjusted\text{-}p\text{-value} = 0.0031$. Adjusted significance level for the second statistical comparison was $adjusted\text{-}p\text{-value} = 0.0125$. The adjusted significance level for the third statistical comparison was $adjusted\text{-}p\text{-value} = 0.0166$.

There have only been a few investigations related to the analysis of the effect on the MMG signal quality when using different levels of contact force. The study and analysis performed in Chapter 3 showed how different levels of contact force on two demographics, able-bodied and amputees, effectively alter the quality and discriminative power information of acoustic MMG, resulting in alterations in the SNR, bandwidth, and classification performance of various hand gesture tasks. Results showed user-specific behaviour of features when evaluating different levels of contact force, suggesting an optimal level of contact force attachment which could be related to physiological factors. In this study, results of the different levels of contact force on accelerometer MMG show

that both temporal and spectral features of the signal are affected in a multi-directional manner and these changes are captured along the different directions of the accelerometer MMG. However, statistical comparison between forces for the spectrotemporal feature changes showed no significant differences ($p > 0.05$) of features between the first and the second level of contact force. In terms of classification of gestures, accuracies were statistically compared between levels of force for each direction and the combination of directions. No significant differences ($p > 0.05$) were found between the classification performance of force level one and force level two for all trained models. Statistical comparison between classification models trained using features from each individual direction vs the combination of directions show statistical significance ($p < 0.0166$) for all models for both levels of contact force. Table 5.1 summarizes the statistical results of the comparison between levels of force and between classification models. Significant differences between gestures are shown in red.

This study is motivated by findings in the literature demonstrating the relevance of MMG for the analysis of neurophysiological parameters involved during motor function [26, 158], by the recent studies in muscle connectivity networks [72, 87] and by the recent investigation on the feasibility of using MMG for muscle connectivity analysis [116]. The present results show further evidence that mechanomyography can be used as a tool for functional muscle connectivity analysis. Muscle connectivity results show distinct topologies depending on the frequency, gesture, and direction. The differences in connectivity strength between muscles for the multiple gestures suggest a characteristic spectral profile at the different frequency ranges driven by muscle activity during gestures. The analysis of muscle connectivity as shown in Fig 5.8 shows a clear distinction of functional activity of muscles based on the gesture, which can be registered by MMG. This study also shows for the first time the use of intermuscular coherence derived from MMG for the classification of motor tasks. As shown, the use of IMC obtained from each individual direction yields a relatively high classification accuracy which can be enhanced by the combination of IMC across directions, providing a more robust framework for the classification of gestures. Furthermore, this study also provides additional evidence of spectrotemporal feature variations based on the level of contact force between the sensor and the skin for accelerometer MMG. Results show that the temporal and spectral space of MMG detected using accelerometer transducers vary minimally when increasing the level of contact force. It is worth mentioning that the design of the sensor allows for the increase in contact pressure on the muscle while adding no extra weight to the sensor, which could explain the different findings reported in [94, 197].

5.6 Conclusion

The investigation introduced in this chapter shows for the first time the analysis of multi-dimensional muscle networks extracted using 3-axis accelerometers. The sensors were aligned according to the directions of muscle fibre alignment. For each direction/axis, intermuscular coherence was extracted for all muscle pairs, gestures and participants. The resulting IMC profiles were decomposed using non-negative matrix factorization into frequency components containing the different spectral elements of the MMG signal. Muscle connectivity networks were generated for each frequency component, gesture, and direction. The resulting muscle networks showed distinct topologies across frequency components, gestures, and directions. To evaluate the effect of contact force on the quality of the MMG accelerometer signal and the discriminability power of classification algorithms based on IMC information, temporal and spectral characteristics of the signal were extracted for each muscle, gesture, and direction for each level of contact force for further comparison. Results show variations for both temporal and spectral features between contact force levels, however, these variations were found to be non-significant. In order to evaluate the effect of contact force on the discriminative power of IMC-based classification models, a statistical comparison of classification accuracies between levels of contact force was performed. As expected from the spectrotemporal features results, no significant changes were found in classification accuracy between contact force levels. In order to evaluate the classification performance between uni-directional and multi-directional trained models, a statistical comparison between models trained using IMC from each direction and from the combination of directions was performed. Results showed significant differences between all uni-directional trained models vs the model trained using the combination of all directions for both levels of contact force.

The findings of this investigation further support the usability of MMG as a tool for functional muscle connectivity analysis and provide evidence of the unique spectral characteristics of the MMG signal detected along the different directions of propagation of the MMG when performing different motor tasks, enabling the applicability of classification models based on IMC. Lastly, as a future perspective of this work, the results presented in this study motivate the investigation of muscle network analysis based on MMG during complex dynamic motor tasks involving a higher number of muscles.

Chapter 6

Conclusions

This chapter recounts the main conclusions of the work presented in this doctoral thesis. This includes a summary of the results obtained contrasted with the hypotheses set out in Section 1.1. An outline of the future work derived from the findings of the studies conducted in this thesis is described here. The immediate next steps to further investigate the paradigms described in this thesis and the future perspectives of MMG as a tool for the analysis of muscle activity towards its establishment as a reliable clinical assessment tool are also discussed.

6.1 Main Conclusions

6.1.1 Chapter 3 - Effect of contact force on acoustic MMG

In this chapter, a novel mechanomyography signal capture technology is introduced. This new design enables another spatial dimension on the MMG signal capture with the ultimate goal of enhancing the performance of human-machine interfaces through the selection of optimal sensor-to-skin pressure. The study carried out in this chapter focuses on analysing the relationship between contact force and the properties of the acoustic MMG signal. By the use of a custom wearable MMG armband, the analysis included the study of different levels of contact between the sensor and the skin from four superficial muscles in the forearm while participants were asked to perform sustained isometric contractions. The study also included the evaluation of a gesture classification model based on the spectrotemporal properties of the MMG signal under different levels of contact force.

The design of the new sensing device is motivated by the nonlinear viscoelasticity of the tissue, which increases with the normal surface pressure. According to the theory, an increase in the sensor-to-skin contact force results in higher conductivity of mechanical waves and hypothetically facilitates the acquisition of deeper muscle information, thus enhancing the signal content. Utilizing this novel approach, increased MMG signal quality is achieved by this added degree of freedom normal to the sensor-skin contact area. Results show that the SNR increased with the higher levels of contact force and the occupied bandwidth increased for the second level of contact force and decreased by a higher degree for the third level of contact force. These results suggest a better signal quality with respect to the presence of noise when the level of contact force is increased. It also shows an increase in the occupied spectral content of the signal when a firm (2nd) level of contact force is applied; however, this frequency information bandwidth decreases as the contact force is further applied. Furthermore, the results of the classification performance of the different trained models show a heterogeneous response between subjects when the different levels of contact force were applied, suggesting subject-specific behaviour to the changes in contact force which could be associated with the anthropomorphic and physiological differences between participants, which have shown to play an important role in the MMG signal acquisition.

These results have significant implications for the sensing apparatus employed in human-machine interfaces and particularly in prosthetic devices, which require the embedding of myographic sensors in sockets for prosthetic limb control.

6.1.2 Chapter 4 - Muscle connectivity network analysis using MMG

In this chapter, the methodology for intermuscular coherence and functional muscle connectivity analysis based on MMG activity is introduced. Both of these analyses are implemented from MMG information collected from a cohort of able-bodied and amputee participants with the interest of

evaluating functional connectivity information in healthy and impaired muscles. The study consists of the collection of MMG activity from four superficial muscles of the forearm while participants are asked to perform isometric contractions. Intermuscular coherence is extracted from each pair of muscles while subjects perform different hand gestures. This coherence information is further decomposed into the frequency components of the MMG signal, dividing the coherence spectra into three frequency bands to evaluate the muscle activity at low, medium, and high-frequency ranges. The resulting common spectral patterns and corresponding weights are used for the construction of functional muscle networks, which are analysed based on their topological characteristics.

Results show distinct topological characteristics not only between the different hand gestures but also across frequency bands. Muscle networks show characteristic relationships between muscles based on their specific function during each gesture. Muscle connectivity analysis at multiple frequency bands for able-bodied subjects showed significant topological differences across gestures for low (i.e., $< 5\text{Hz}$) and high (i.e., $> 12\text{Hz}$) activation frequencies. The comparison between network characteristics between able-bodied and amputee subjects shows different topological characteristics and shapes, suggesting different levels of muscle activity which could be associated with the physiological changes caused by amputation. Furthermore, noticeably different topographies between able-bodied and amputees were also found between frequency bands which could be a result of the neural adaptation following amputation. Results demonstrate the feasibility of MMG as a tool for the analysis of functional muscle connectivity and mapping of synergistic functional synchronization of upper-limb muscles in complex movement tasks. A functional muscle network is a critical concept in describing the functional synergistic muscle synchronization and functional connectivity needed for the execution of complex motor tasks. The methodologies presented here open a large new area of investigation for MMG, from the analysis of the neurophysiological properties of motor activity to the evaluation of muscle condition in clinical applications.

6.1.3 Chapter 5 - Analysing three-dimensional muscle networks using MMG

In this chapter, the methodology for the analysis of multi-dimensional muscle networks is introduced based on multi-channel multi-directional accelerometer MMG sensors. In addition, the study presented in this chapter analyses the effect of normal force on the signal properties of accelerometer MMG and its evaluation for the classification of motor tasks based on intermuscular coherence. This classification of hand gestures is compared between models trained using individual axes of the accelerometer vs a model trained using the combination of axes in order to assess the contributions of discriminative information from all the directions captured by accelerometer MMG.

The study entails the development of a custom-made wearable MMG armband to house multi-axis accelerometers for the collection of MMG activity from four superficial muscles in the forearm while participants performed a series of sustained hand gestures. For the first part of this study, and similar to the analysis of functional connectivity networks based on acoustic MMG, intermuscular coherence is extracted from the common spectral response between each muscle pair and functional muscle networks are generated from the resulting weights and basis vectors. Muscle connectivity networks are generated not only for the decomposed frequency spectrum bands but also across the different axis of the accelerometers. The directionality of the sensors is aligned with respect to the muscle fibres. Results show distinct topographies between gestures, frequency bands, and axes. Based on the findings from the previous study, distinct topographical characteristics between gestures and frequency bands were expected. In addition to these findings, the comparison of muscle networks between axes also showed unique characteristics for dimension. These results show further evidence of the signal propagation of the MMG activity.

For the second part of this study, the level of contact force was increased to a second level, and participants were asked to perform the series of isometric contractions a second time. Analysis of temporal and spectral characteristics of the signal was performed for both levels of contact force. Subsequently, intermuscular coherence information was utilized for training a gesture classification model for both levels of contact force, and the evaluation of the model classification performance was computed. A final comparison between all single-axis-based models vs the combined axes model was carried out. Results of this analysis show different spectrotemporal variations across axes between levels of normal force; however, these variations were not statistically significant. These different degrees of the effect of normal force across axes could be a result of altered propagation of the signal MMG signal along the different directions. Results on the performance of classification models based on intermuscular coherence showed relatively high accuracy and similar performance between axes. This similarity in accuracy indicates a similar discriminative content between the different directions, which could be a result of the multi-directional propagation of the signal and overlapping information. Finally, the model trained using the combination of axes surpasses the performance of all individual axis models, indicating a clear contribution of information from the different dimensions.

The methodology presented in this study and the findings of the analysis supports the feasibility of using MMG technology for the extraction and analysis of functional muscle networks and show evidence of the unique multi-directional spectral content of the MMG signal. This characteristic enables the application of novel classification models based on the common spectral information between muscles in the context of multi-dimensional space and demonstrates the benefits of using a multi-directional feature space for the classification of motor tasks. The results presented here also provide more insights into the relationship between the temporal and spectral information of accelerometer MMG and the level of contact force. All of these findings motivate the future application of the methodology for the analysis of complex dynamic tasks and show

the potential to provide further insights into the neurophysiological phenomenon underlying MMG generation.

It is worth mentioning that in general there was a higher number of male participants in the studies conducted in this thesis. For comparative purposes it is important to take this into consideration as the characteristics of the MMG signal may vary due to gender differences in muscle fibre composition [124]. In the interest of advancing the technology to improve experimental efficiency it is important to consider the number of male and female participants in future studies [183].

6.2 Future Perspectives

This thesis highlights the pressing need to establish an optimal set of steps to be able to overcome the technical and physiological factors commonly affecting the MMG signal. A great deal of progress has been made with the rapid development of technological advancements, which in the last two decades have provided the opportunity to overcome many of the original limitations preventing MMG from becoming an established tool in clinical and non-clinical muscle function assessments. Promising applications have been made possible from the realisation of the advantages that MMG holds compared to other myographic modalities, thanks to its nature and versatility, as described here in chapter 2.

The pursuit of establishing MMG as a conventional technique in muscle physiology and clinical assessment continues and invites newer applications for the signal. The need for further technical developments to enable MMG to realise its full potential continues and has been highlighted in the previous chapters. In this respect, I propose new sensing modalities of MMG to advance the investigation of the signal in different fields and overcome its current limitations.

6.2.1 Advancements in MMG Sensing Technology

As a future direction of research for the work presented in the thesis, it can be mentioned that a multi-sensory approach can be designed to make the technique more robust to the intrinsic limitations of the individual sensing modalities of MMG, namely accelerometer, microphone, and pressure. For example, the combination of accelerometer and microphone sensing can achieve a more reliable assessment of the motor function, less prone to motion-induced artefacts. The reliability of MMG needs to be established not only for the variety of conditions imposed by the particular applications in which the technology is used, but it also needs to be robust against potential non-desired effects caused by physiological and anthropomorphic factors. In this thesis, the results show strong evidence of the effect of contact force on the usefulness of the MMG signal.

6.2.1.1 Multi-modal MMG

Motivated by the above-mentioned note, as a future line of research, I propose the concept of a multi-modal sensor approach which includes a form of force resistive or capacitive sensor embedded in a sensing unit along with the main transducer (i.e., accelerometer/microphone) such that contact force information is collected simultaneously with MMG. The first prototype design of this proposed module of MMG with simultaneous acquisition of contact force can be seen in Fig 6.1. Furthermore, an extension of this proposed sensor is the dual acquisition of accelerometer and acoustic MMG along with the pressure information. Simultaneous acquisition of contact force, acceleration, and acoustic MMG result in a multi-modal sensing unit comprised of an accelerometer, a microphone, and a force-resistive sensor, which could provide the long-awaited holistic MMG unit

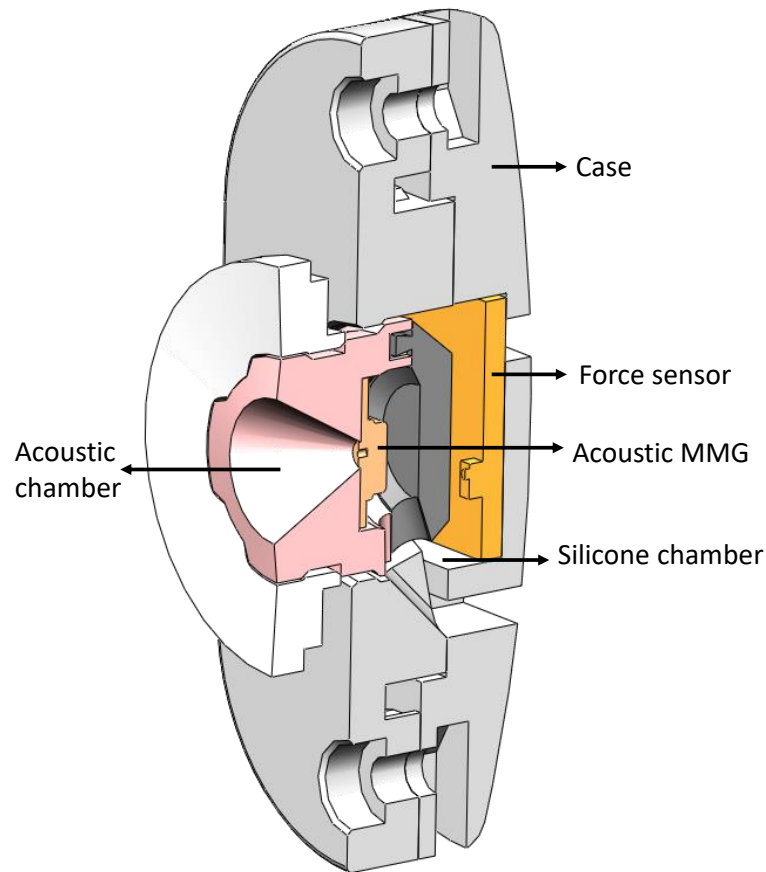


Figure 6.1: Multi-modal MMG sensor. The sensor includes an acoustic MMG transducer and a pressure (barometric) sensor. The space between the back plate of the acoustic section and the pressure sensor is filled with silicone to transmit the amount of force applied at the level of the skin.

capable of separating the different components of the MMG signal from its acquisition while also being robust to the limitations and caveats of each individual MMG sub-modality. A combination of signals would enable the separate detection of (a) tremor oscillations of the motor system detected mainly by accelerometry, (b) the inner vibrations of the muscle fibres detected mainly by acoustic MMG, and (c) the dimensional changes of the muscles detected by the force sensor, all of which provide a more suitable tool to study the nature and origin of MMG activity as it enables the separation of the signal from its source.

6.2.1.2 High-Density MMG

Besides the acquisition of the constituent modalities of the MMG activity, it is also imperative to further develop technology for MMG which could allow us to study the propagation characteristics of the signal by not only acquiring the temporal activity of MMG from a single location on the muscle but instead by allowing the acquisition of spatial information in the form of a grid of MMG transducers, analogous to high-density electromyography (HD-EMG). This grid of equidistant MMG transducers will allow the spatial MMG activity to be recorded from multiple locations along

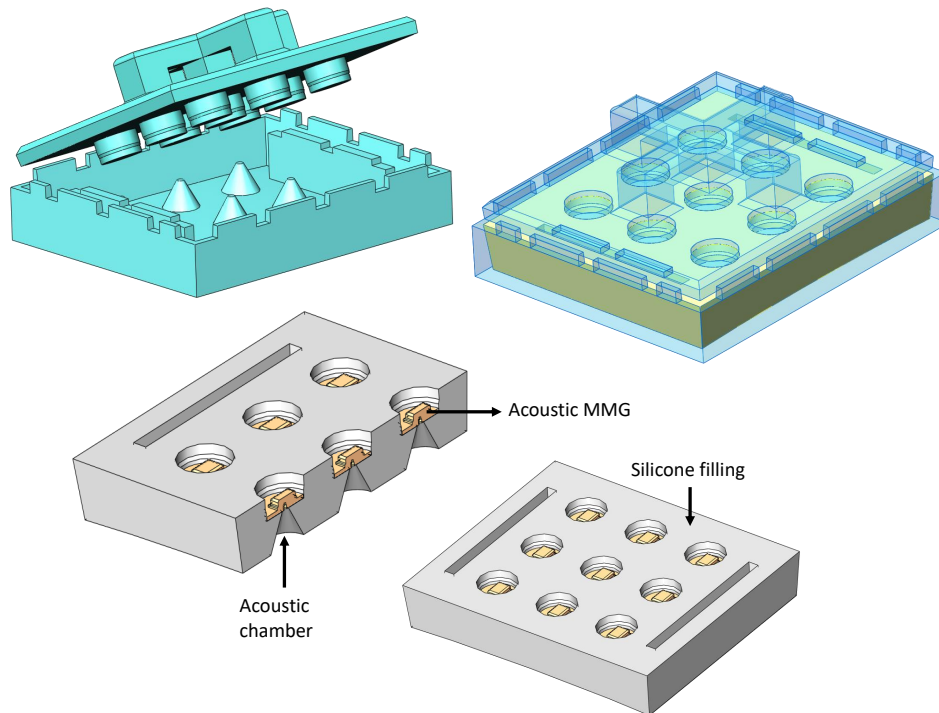


Figure 6.2: High-density MMG. The mould is comprised of two components which fit together such that the resulting silicone piece from the internal cavity is formed for n number of MMG acoustic sensors. The sensor is comprised of nine acoustic MMG transducers separated by 6.5 mm. The enlarged space on each side allows for the moulding of the hangers for the sensor.

the muscle, thus expanding the possibilities to detect new muscle characteristics based on the collective properties of the MMG signals. Especially the analysis of motor unit contractile properties and the spatial dependency of these to MMG sensor location. HD-MMG would therefore be a method for recording both spatial and temporal characteristics of MMG, unlike traditional MMG, thus allowing a broader assessment of the muscle function. Due to the different morphology and size of the muscles, it is necessary to utilize a material which could easily adapt to the skin while being comfortable and causing minimal changes to the skin condition. In order to achieve this while maintaining the geometric characteristics of the current technology, I propose a method to develop HD-MMG sensors by casting a soft material with the properties described above into a pre-formed mould. Fig 6.2 illustrates the assembly and casting process to produce a 3x3 HD-MMG sensor.

This sensing modality could provide a better tool for the quantification of muscle performance based on the spatial location and spatiotemporal features of HD-MMG. Furthermore, HD-MMG could enable the extraction of features that depend on the spatial distribution of the motor units and on the anthropomorphic factors of the muscles. Fig 6.3 shows the first prototype of the mould and cast to create an HD-MMG sensor.

One of the most important advantages of MMG is the ability to detect the mechanical response of muscles in which the direct measurement of force is not possible, such as muscles in the back,

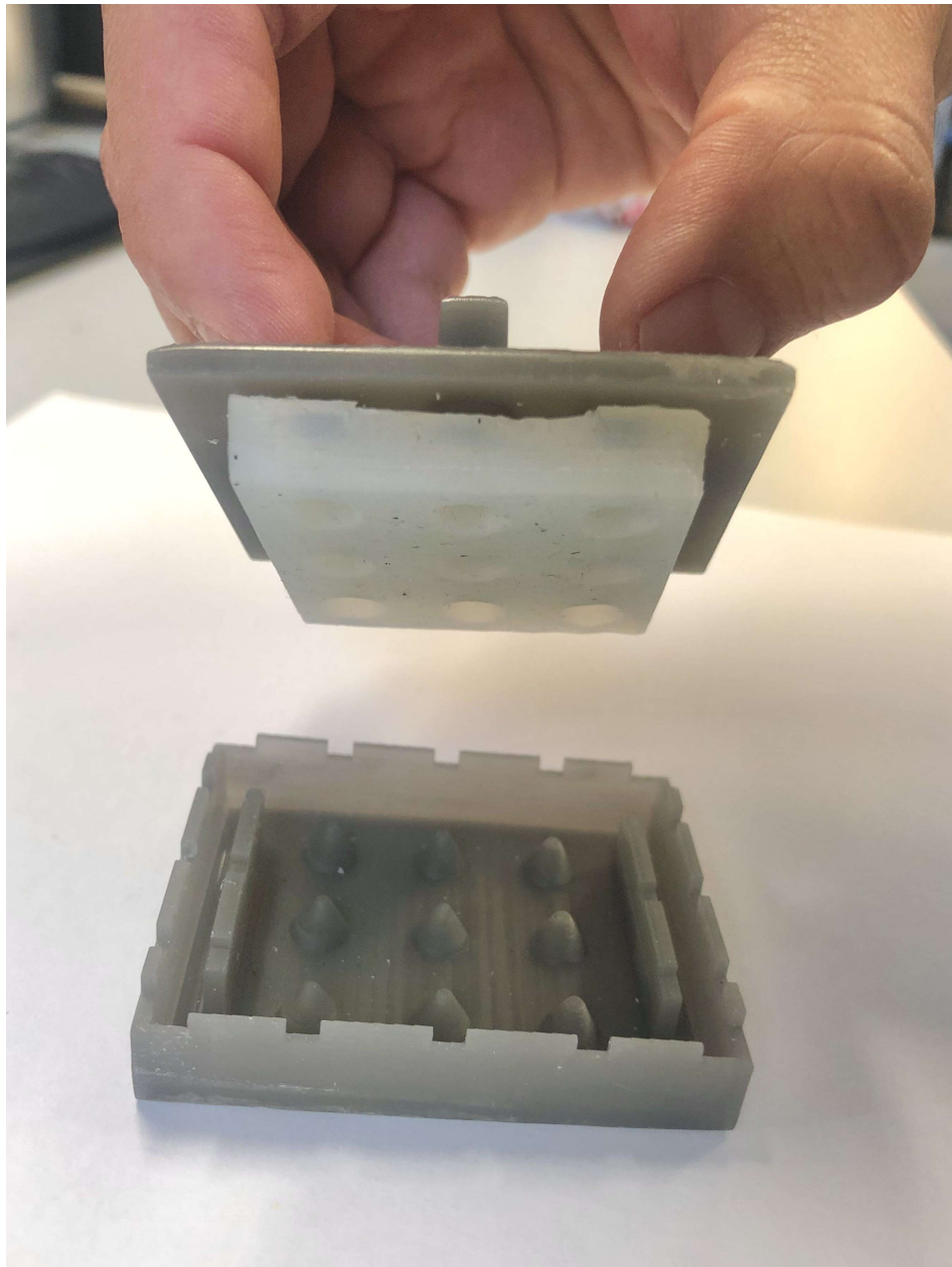


Figure 6.3: The HD-MMG sensor is built following a series of steps, which include pouring silicone for the lower section of the sensor, the addition of the MMG transducers, and a second pouring of silicone to seal the sensor chambers.

abdomen, face, etc. The relationship between force and MMG requires further investigation to provide a better understanding of how the spectrotemporal properties of the signal are related to force production. In this respect, the proposed multi-sensor modality and the HD-MMG offer a new tool to analyse motor control strategies underlying different stages of force production. As such, these technologies offer the potential to expand into new areas of study, including superficial and non-superficial muscles not yet investigated by the use of MMG.

In order to establish the MMG signal as a standard modality for muscle function assessment, first, the technology has to evolve in such a way that its usability is not limited by physical and exter-

nal factors, but instead, its use can be easily adapted to different applications, some being more straightforward than others, without the need to redesign the technology. A holistic MMG sensing unit capable of acquiring all the components of the MMG signal independently and a high-density sensing unit capable of acquiring the spatial and spectrotemporal characteristics of MMG are imperative towards this endeavour in the establishment of MMG as a standard muscle assessment tool.

6.2.2 Future Applicability of Muscle Networks by MMG

At the same time that the technology for the detection and acquisition of MMG activity evolves, the applications of MMG can be expanded with the development and use of novel methods for signal processing and analysis. In this thesis, I introduced the use of MMG as a tool for functional muscle connectivity analysis. As discussed in chapter 4, this analysis has attracted particular attention in the last decade as it provides a tool to analyse the neural circuitry involved in muscle activity from a full-spectral perspective, complementing current methodologies, which so far have focused only on the temporal characteristics, such as muscle synergy analysis.

Muscle network analysis by the use of MMG can be applied in the investigation of muscle connectivity during muscular exercise by analysing the topographical characteristics and the changes following training. By studying the characteristics of the muscle networks as they relate to different levels of strength, endurance training, or force production, all of which have been found to hold a relationship to MMG frequency, new areas of study open for the sensing modality. It is, therefore, to expect that at the same time as technological improvements of the MMG signal capture overcome some of the intrinsic and extrinsic limitations of the signal, the scope and applicability of MMG expand deeper into current applications of myographic studies and further into new avenues of research.

6.2.3 Clinical Relevance

Over the years, the applicability of the MMG signal has gradually evolved as a tool for clinical diagnosis. Changes in amplitude [16] and frequency [162] of the MMG signal have been associated with muscle function deterioration in neuromuscular disorders, also including Parkinson's and Huntington's disease, myopathy, dysphagia, fibromyalgia, and muscular dystrophy, among others (see [38, 64, 76]). In this thesis, muscle network analysis of motor tasks performed by amputees showed distinctly different topologies of networks between subjects across multiple frequency bands, reflecting the physiological changes in the muscles caused by amputation and an indication of changes in the neural drive to the muscles following amputation. All of these findings reflect reductions in motor unit recruitment, size and number of motor units, and firing rate, all linked to injury or impaired muscle and all of which have been shown to correlate with different features of the MMG signal. Here, muscle network analysis using MMG offers a potential tool to dive deeper into the analysis of the physical and neurophysiological changes of muscles when investigating different

motor dysfunctions.

Furthermore, the relationship between electroencephalography activity (EEG) and MMG has been previously studied by examining the coherence of the two signals [86]. The findings of the investigations indicate that such an approach would be of clinical value for patients with neurological disorders. Despite the promising findings of their investigation, the study of synchronous information between EEG and MMG has not been continued. Coherence analysis and network analysis open this possibility once again to analyse cortical activity and the mechanical output of the muscles from a renewed perspective.

In this way, contractile mechanisms have been explored in healthy muscles as well as in pathological conditions. MMG findings continue to emerge in areas related to different physiological conditions, such as fatigue, muscle length variations, force production, strength training, and muscle dysfunction. Therefore, the main potential of MMG in the context of novel spectrotemporal signal processing techniques lies in the extended analysis in fields such as sports science, physiotherapy, and neurophysiology and opportunities to improve diagnostic abilities and clinical assessment.

The studies presented in this thesis and the findings discussed call for further exploration of the neural circuitry involved in motor function and a better understanding of how the signal features vary with different physiological conditions, all of which are necessary to increase the use of MMG towards its translation into an established and reliable technique for studying the contractile mechanisms of the motor function. There are many potential applications for MMG, but the success of the technique will depend on careful application and consideration of its limitations. At present, the most successful use is in physiological studies, where the recording conditions can be controlled well. Further refinements of MMG technology and signal processing methods would make it more robust for routine clinical use and other non-clinical applications.

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Appendix

The GitHub repository at <https://github.com/CSM116/Coherence> contains all the code developed in this doctoral thesis as well as additional images and other materials.

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The following table shows further participant information for reference.

Table 7.1: Participant General Information

Age	Gender	Predominant Arm	Skinfold Thickness [cm]	Arm Diameter [cm]
31	M	Right	3-4	24.7
25	F	Right	4-6	21.8
25	M	Left	3-4	23
22	M	Right	2-3	25
23	F	Right	6-7	24
24	F	Right	8-10	26
30	M	Right	4-5	28
23	M	Right	3-4	24.5
31	M	Right	3-5	28
23	F	Right	5-7	23.3
25	M	Right	4-7	26.2
26	M	Right	4-6	27
22	M	Right	4-5	26
31	M	Right	11-12	28
27	F	Right	6-8	25
28	F	Right	4.5-5.5	23.5
32	M	Right	6-7	28.5
29	M	Right	7-8	28.5
21	F	Right	5-6	22.1
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