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EQUIPO DE BIORROBÓTICA, CAR-UPM, CSIC

Use of Discrete and Continuous Wavelet Transform in Surface Electromyographic signals for human gait characterization

TRABAJO FIN DE MÁSTER

Autor: Álvaro Mellado Ibáñez

Tutor Externo: Juan C. Moreno, PhD.

Tutor Académico: Bojan Mihaljévic, PhD.

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Abstract

This research presents a comprehensive validation exercise of two signal processing methodologies in the context of assessing neuromuscular control through the non-invasive technique of surface electromyography (sEMG): the Discrete Wavelet Transform (DWT) and the Continuous Wavelet Transform (CWT). The primary objective of this study was to validate the performance of these two methodologies, which were developed from scratch, in the analysis of sEMG signals. Validating these methodologies would enable their application in the description of muscle activity and its correlation with the neuromuscular mechanisms underlying pathological gait across different neurological populations. The core of this work involved conducting two rigorous replication studies designed to mimic the ones described in two open access scientific papers.

The DWT methodology was evaluated through replication of the study conducted by Zhang Y. *et al*. This process included several steps: data preparation, conversion to the Eurobench format, data processing and the application of the DWT to the sEMG signals of an existing database of patients with altered gait due to neurological disorders (i.e. Parkinson's disease, stroke, spinal cord injury). The accuracy of the implemented DWT was assessed by performing an identical analysis, which involved extracting the same features from the coefficients obtained as output from DWT using the same dataset, and comparing our results with those reported in the original study.

Likewise, the CWT methodology was tested similarly by reproducing the steps given by Di Nardo F. *et al*. The data used in this study was obtained from a public database created by the authors themselves. The CWT method was then applied to the raw data and a Donoho thresholding was performed to clean the noise from the signal. Both original signals were reconstructed using the Inverse Discrete Wavelet Transform (IDWT) and Inverse Continuous Wavelet Transform (ICWT) methodology to verify the quality of the transformation.

In order to assess the accuracy of the methodologies, published papers were replicated, using the same raw data and procedures, so that the only variables under comparison were the proposed methodologies. Since no significant differences were observed between the results presented in the original papers and those obtained in this research (p-value > 0.05), both methodologies demonstrated to be accurate and reliable.

This study contributes to the existing body of knowledge by providing empirical evidence of the effectiveness of the DWT and CWT in characterizing sEMG data and highlight the importance of rigorous validation exercises to ensure the reliability and accuracy of methodologies used in scientific research. Once both have proven to be valid, future research will explore their application in other contexts, such as gait analysis in neuromotor disorders patients, gait asymmetry characterization, development of new rehabilitation treatments, etc. This would further enhance our understanding of the potential advantages and limitations of the DWT and CWT methodologies, promoting their application in clinical settings as potential tools for the study and classification of different neuromotor disorders through their application to sEMG signals.

Acronyms

CWT – Continuous Wavelet Transform

DWT – Discrete Wavelet Transform

EMG – Electromyography

FFT – Fast Fourier Transformation

iEMG – Intramuscular Electromyography

ICWT – Inverse Continuous Wavelet Transform

IDWT – Inverse Discrete Wavelet Transform

MDF – Median Frequency

MNF – Mean Frequency

MUs – Motor Units

PIs – Performance Indicators

PSD – Power Spectral Density

sEMG – Surface Electromyography

SNR – Signal-to-Noise Ratio

1. Introduction

1.1. Motivation

It has been previously shown that the application of Discrete Wavelet Transform (DWT) [1] and Continuous Wavelet Transform (CWT) [2] to Electromyographic (EMG) signals is crucial for detailed time-frequency domain analysis. These techniques allow for the examination of non-stationary signals, capturing changes in muscle frequency of activation over time. DWT provides multi-resolution analysis, ideal for detecting event-related desynchronization/synchronization. The event in this case entails muscle contraction/relaxation, and the analysis would reflect the activation/deactivation pattern of the muscle under study. It has been reported that CWT offers superior resolution for both time and frequency, useful for identifying more subtle muscle activation patterns. However, both approaches seem to be valuable to elucidate neuromuscular mechanisms underlying muscle activation. Utilizing these methods enhances the scope of the studies analysing EMG signals, contributing to the development of more effective rehabilitation protocols and assistive technologies.

These methodologies have been widely employed in research, yet they are rarely published and made openly accessible for others to use the codes. For this reason, the main motivation of this research is to develop these two methodologies ourselves and validate them using previous research works on the field with open access associated data.

1.2. Research Context

Walking is a vital part on everyday life. Keeping that in mind, the scientific community has tried to explain the mechanics of physiological gait and how those normative patterns are disturbed in pathological gait (such as neurodegenerative diseases and other kind of motor disorders). Throughout these years of research, numerous methodologies for gait analysis have been proposed, each tailored for specific applications.

As the variety of methodologies that could be used for the analysis of human gait is very vast (such as cinematic analysis, spatiotemporal parameters, etc.), it was decided after some deep bibliography review that the use of electromyographic (EMG) signals was the preferred approach for studying muscle activity and neuromuscular mechanisms underlying gait disturbance that will be carried out during this research.

EMG measures the electrical activity of the muscles under study. Prior to movement, when there is an intention or preparation for movement, the brain's motor cortex is activated and an electrical signal, called action potential, is transmitted through the spinal cord to the motor neurons. The union of a single motor neuron and all the muscle fibres it innervates is known as motor units (MUs). Those MUs are the basic functional unit of muscle contraction responsible of initiating the contraction – and consequently the movement – of the muscle, by electrical stimulation of muscle fibres. If the electrical signal that reaches the motor neuron surpasses the required threshold, they will transmit the signal to the muscle fibres, leading to muscle contraction.

By measuring muscles' electrical activity, insight into muscle function and its abnormalities can be gained. This was the main reason why the EMG method was chosen for this research.

While EMG signals can offer valuable information about muscle activation/relaxation patterns, they have significant drawbacks, being this kind of signal very susceptible to noise, complex to interpret/analyse and non-stationary. Overcoming these challenges requires meticulous and involves time-consuming procedures, including robust signal processing, and a detailed time-frequency domain characterization.

While reviewing the currently available literature on the field, it was clear that the most used methodology for analysing complex and non-stationary signals was the Continuous Wavelet Transform (CWT) [2], followed by the Discrete Wavelet Transform (DWT) [1].

1.3. Objectives and hypothesis of the project

The primary objective of this research project was the validation of our own developed DWT and CWT methods compared to previously published investigations and open access data, in the context of EMG analysis, for studying the muscle activation patterns throughout the gait cycle.

The hypothesis of this project stated that both DWT and CWT methodologies can have an accuracy and effectiveness enough for explaining specific events occurred during muscle activation while performing a pathological gait cycle.

Also, this hypothesis assumed that the DWT and CWT methods are effective tools for analysing EMG signals and that their validation will confirm their utility in the context of gait analysis. Having a robust and reliable methodology to apply to our own signals in further investigations could have significant implications in clinical and neurorehabilitation settings.

1.4. Structure of the thesis

The first part of the thesis will consist of an introduction to the theoretical concepts that must be known beforehand, as they will provide the reader the necessary background to fully understand the work conducted in this research. To begin with, a brief introduction to the basic concepts of human gait will be provided, followed by a more extended explanation of electromyographic signals and its uses in neurorehabilitation. Afterwards, we will delve into the nature of wavelets and its use in electromyographic signals, commenting in detail specifically both DWT and CWT.

After the introduction, the methodology will be meticulously described. Firstly, the required pre-processing of data will be explained, including a detailed account of how the data were converted to Eurobench format. Secondly, the procedure for conducting various wavelet analyses will be outlined, as well as some additional methods that had to be applied for the replication of the original papers and wrap up the section with the presentation of the statistical methods used for the interpretation of the results.

In the results section the findings will be presented, starting with the validation of the DWT methodology and continuing with the assessment of the CWT.

Next, there will be a discussion section. In this part, the results will be interpreted in the context of the existing literature in the field and the limitations of the study will be outlined. The importance of the findings will be critically exposed, as well as the contribution of this work to the current body of knowledge. Also, comments on future research lines will also be highlighted.

Finally, the research will be summarized, its implications and potential future directions.

2. State of the art

2.1. Human gait

Gait refers to the way a person walks or runs. It is a complex, whole-body movement that requires the coordinated action of many joints and muscles of the musculoskeletal system. When brain damage occurs, gait and balance are often impaired. Therefore, the evaluation of the gait cycle plays a vital role during the rehabilitation process of subjects who suffer from neuromuscular disorders [3].

A single cycle of gait (see *Figure 1*) starts when the heel of one foot strikes the ground and ends when that same heel touches the floor again. It consists of two main phases: stance and swing [4].

The stance phase occupies 60% of the total gait cycle, during which part of the foot is in contact with the ground. It starts when the heel first impacts (heel strike) and ends when the toe leaves the ground (toe off).

At that precise moment, the swing phase begins. It occupies 40% of the total gait cycle, during which the foot is in the air and the body weight is borne by the other leg and foot.

The whole process can be divided into eight sub-phases, which can be observed in *Figure 1*.

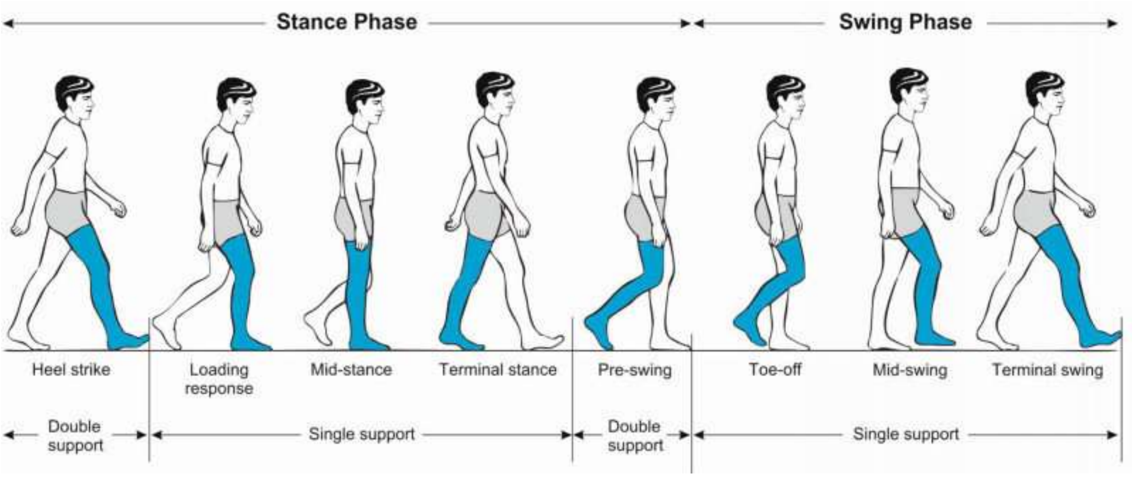

Figure 1. Phases and sub-phases of human gait cycle for the right leg [4].

Gait analysis needs an efficient segmentation into its different phases, as the descriptors and parameters are usually extracted from each stride or phase. Furthermore, understanding the gait cycle and its subphases is crucial for the study and treatment of various neurological and musculoskeletal conditions, as changes in muscular activity at each phase of the gait cycle may be directly related to the biomechanical function.

2.2. Electromyography signals and its use in neurorehabilitation

The process of muscle movement is initiated by the brain sending an electrical impulse. This action potential travels through the spinal cord and nerves until it reaches the motor neurons. These neurons are vital in initiating muscle contraction by stimulating the muscle fibres. If the strength of the electrical impulse surpasses the action potential needed to activate the motor neuron, it will transmit this signal to the muscle fibres, leading to its contraction and subsequent movement.

Electromyography (EMG) is an electrodiagnostic technique that records electrical signals generated by muscle activations, providing insight into neuromuscular control mechanisms [5]. These signals are crucial for monitoring medical abnormalities and for assessing the intensity of muscle activation [6, 7]. Therefore, any alteration in the contraction of a muscle due to an injury, nerve damage or neuromuscular disorder may be identified through the analysis of EMG signals [8].

Muscle patterns underlying movement, traditionally recorded with invasive electrodes, can be used to detect movement and gait disturbance. Various EMG signal processing techniques have been applied for diagnosing gait disorders, ranging from traditional statistical tests to complex machine learning algorithms [9]. These techniques have promising clinical applications and they may serve as a potential tool to assist in advanced diagnostic procedures and in the design of personalized rehabilitation strategies.

Surface electromyography (sEMG), a non-invasive variant of intramuscular EMG (iEMG), is a prevalent tool particularly in the field of physical medicine and rehabilitation [10] (both the method of signal acquisition and raw signal example are depicted in *Figure 2*). It is a technique with a lot of potential, but very delicate and complex to analyse, which requires a lot of attention on cleaning the skin where the sensors will be placed, trying to minimize noise sources and carefully selecting the sensor placement locations.

One of the problems that this technique shows is its high sensitivity to noise – as other electrical signals can interfere – and physical factors (e.g., thickness of the human tissue, movement artifacts, etc.). This contributes to the difficulty of obtaining high-quality and reliable signals. As a result, despite its significant potential, this technique is not widely utilized in clinical settings due to limited understanding of the relationship between these electrical signals and their biological functionality.

Gait asymmetry is another aspect that can be studied through EMG [11]. Its study can be crucial as this symptom is usually manifested in initial stages of several neuromotor disorders or neurodegenerative disease, such as stroke, Parkinson's disease or spinal cord injury. This lateral asymmetry would be of great interest for the neurorehabilitation field, as it can be used as a biomarker to characterize the degree of affectation and to assess the evolution of a patient undergoing rehabilitation therapy.

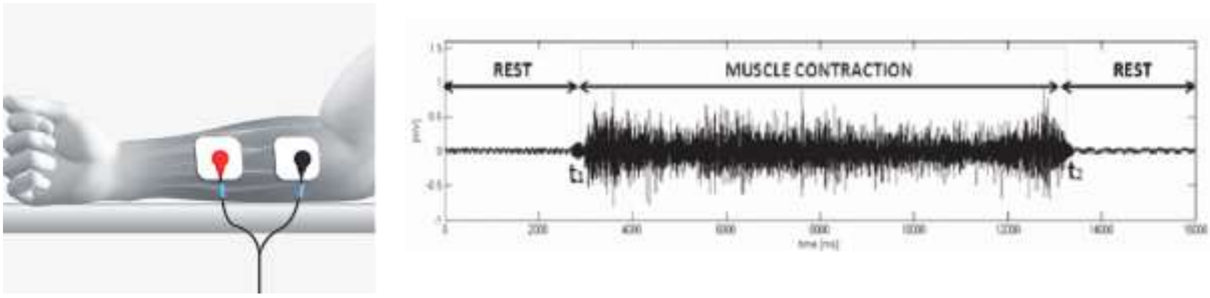

Figure 2. Typical bipolar sEMG signal acquisition (left) [12] and signal example (right) [13].

The use of EMG in neurorehabilitation has shown new possibilities for integrating and supporting these two clinical disciplines: treatment and neurorehabilitation. By providing an outlook into neuromuscular activity, EMG allows for a more precise and objective assessment of a patient's motor function in a non-invasive way. This can guide the design of individualized therapy programs and track progress over time [14].

Moreover, EMG measurements can be used to control assistive devices such as prosthetics or exoskeletons. This provides a tangible way for patients to regain lost function, thereby improving their physical capabilities [15]. But the benefits are not just physical. The ability to control these devices can also have significant psychological benefits, enhancing motivation and engagement in therapy. This is particularly important in neurorehabilitation, where long-term engagement is often necessary for meaningful recovery [16].

EMG has also been used in sports medicine to optimize performance and prevent injuries. By analysing the activation patterns of different muscle groups during various sports activities, researchers can develop targeted training programs to improve performance and reduce the risk of injury [17].

Furthermore, EMG has been applied to design more comfortable and efficient workstations. By studying muscle activation patterns of workers, ergonomists can identify sources of strain and fatigue and adjust the workstation layout, equipment design, and work procedures to reduce these issues [18].

In gait analysis, several techniques have been developed to obtain and interpret muscle activation patterns of patients showing altered locomotion. EMG signals can complement traditional gait analysis approaches (that use the study of spatiotemporal, kinematics and kinetics parameters) by providing indirect insight into how the nervous system performs motor control, especially by elucidating altered neuromuscular mechanisms underlying pathological gait [19]. Currently, the usage of sEMG signals is limited to the scientific research rather than clinical practice. The validation of this methodology could help to extend the use of this technology in clinical settings, leveraging its considerable potential as a support tool.

2.3. The Eurobench EMG data format

The Eurobench format – promoted by the European Union [20] – is designed to accommodate data from a variety of sensing devices and laboratories, making it versatile and widely applicable. It provides a comprehensive and flexible data format for a wide variety of sensor modalities, including EMG [21].

This flexibility is particularly important in the current research context, where data is collected using different equipment and methodologies. By providing a standardized format, Eurobench ensures that EMG data from various sources can be integrated and compared, thereby facilitating collaborative and comparative studies [22].

This format is also designed to ensure the automatic computation of Performance Indicators (PIs) based on recorded data [23]. PIs are quantifiable measurements that classify the performance of a system, process, or individual in relation to key objectives. In the context of Eurobench, PIs could relate to various aspects of human locomotion, such as speed, stability, or energy efficiency. This is particularly valuable in fields such as sports science or rehabilitation, where tracking progress over time is crucial [24].

Furthermore, this format is designed to maximize compatibility between PIs that are common to several protocols. This means that the same PI can be computed and interpreted in the same way, regardless of the experimental protocol that was used. This enhances the comparability of results across different studies or experiments [25].

The Eurobench data format is organized into four different classes of files (as depicted in *Figure 3*). The first class is the Bipedal system specification file, which provides specifications of the dimensions of any bipedal system (could be a human subject, a humanoid, a prosthesis or an exoskeleton). The second class is the Testbed configuration file. This file provides values for any configuration parameter needed to reproduce the conditions of an experiment. The third class is the Raw Data, which includes signals directly collected by the sensors. The fourth and final class is the Pre-processed Data. This refers to sensor-actuator agnostic data (information that can be used and interpreted regardless of the specific type of sensor that collected it) acquired during the experimentation. The structure of such a file is compliant with the format agreed in the Eurobench documentation [26].

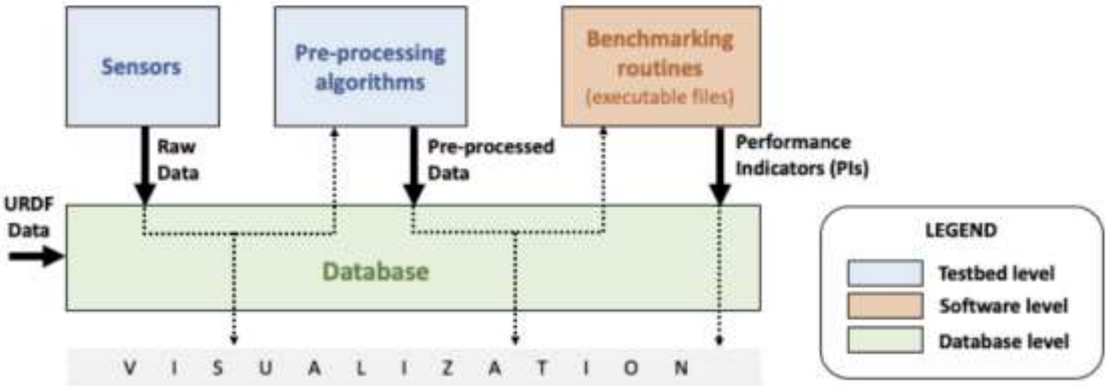

Figure 3. Workflow for Eurobench data format [25].

An experiment in Eurobench format consists of recording data files while the subject is performing a given task. This framework allows to record different runs of the same activity (repeating the same actions in the same conditions) and/or different conditions where either the activity or the setup are changed [27].

One of the main reasons why the EMG technology is underutilized in clinical settings is the lack of open access databases, containing sufficient and standardized data. This challenge complicates the validation and dissemination of results, making it difficult to confirm that they are reproducible and robust enough to provide a universal functional explanation of the meaning of EMG signals. This underscores the importance of using the Eurobench format.

2.4. Wavelets and its use for EMG signal analysis

Wavelet analysis, a mathematical technique used for signal processing, has emerged as a powerful tool in the field of EMG analysis. The electrical activity measured in EMG signals can be analysed to understand various aspects of muscle function [28].

The wavelet analysis technique is particularly effective in decomposing these EMG signals into different frequency components. This allows for a more detailed understanding of the bioprocesses taking place, as MUs fire at different frequencies according to their function. By analysing these frequencies, valuable insights can be gained into muscle activity and the strategies used for MUs recruitment [29].

MUs recruitment refers to the process by which the nervous system activates MUs to reach a specific motor threshold required to perform a specific movement or activity. The recruitment strategy can vary depending on the specific demands of the task being performed [30]. For example, during low-intensity activities, smaller MUs are typically recruited first. As the intensity of the activity increases, larger MUs are progressively recruited. This is known as the size principle [31].

Wavelet analysis can provide insights into these recruitment strategies by revealing the frequency components of the EMG signals. It is particularly useful in the analysis of EMG signals derived from lower extremity muscles during activities such as walking and running. These activities involve complex, coordinated movements that require the recruitment of multiple MUs pools. By applying wavelet analysis to the EMG signals obtained during gait, it is possible to gain a deeper understanding of the underlying muscle activity by relating changes in frequency bands with the alteration of the corresponding MUs firing at that specific rate [32].

There are two types of wavelet analysis: discrete and continuous wavelet transform.

2.4.1. Discrete Wavelet Transform

The Discrete Wavelet Transform (DWT) has been widely used in the field of signal processing, particularly in the analysis of EMG signals. As EMG signals are complex and non-stationary in nature – the spectral components change over time – DWT provides an efficient and effective method to characterize signals in both time and frequency domains with modest computational cost. The decomposition of EMG signals into different frequency components allow for a more detailed analysis than other traditional approaches (purely temporal or spectral) [33].

The DWT operates by applying a series of filters to a signal to isolate each frequency band. This process is repeated recursively, with each iteration focusing on the lower frequency components of the signal. The total number of applied iterations is known as the level of decomposition. The result is a set of coefficients that represent the signal at various scales and translations, resulting in a multi-resolution analysis [34] (see *Figure 4*).

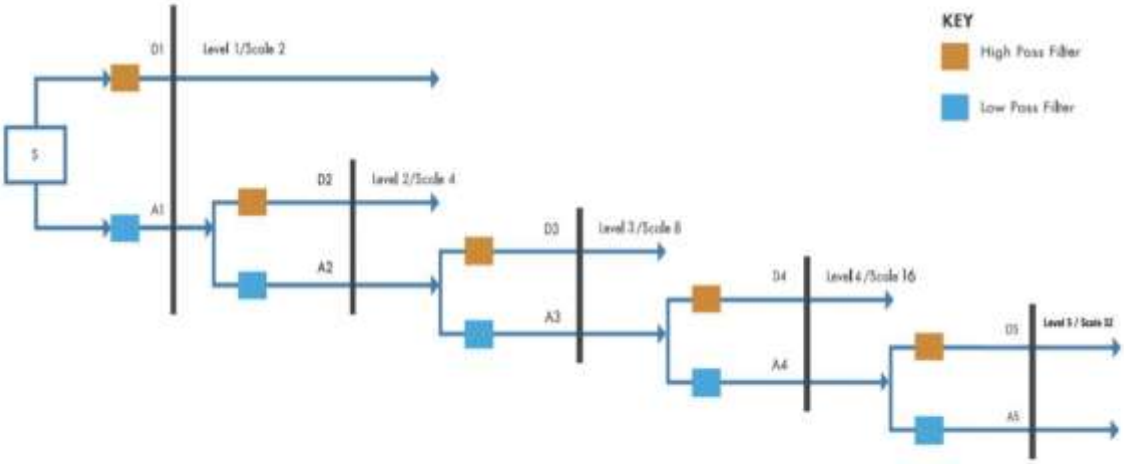

Figure 4. Discrete Wavelet Transform workflow for four levels of decomposition [35].

This multi-resolution analysis is particularly important in EMG signal analysis. Different MUs within a muscle tend to fire at different frequencies, which can change depending on the type of the recruited MU. By decomposing the EMG signal into different frequency components, the DWT allows to study these individual bands, providing valuable insights into muscle activity and MU recruitment strategies [36].

Moreover, the DWT enables the extraction of effective features to characterize the EMG signals for classification of muscle patterns during gait. These features, which include mean frequency, median frequency and wavelet coefficients, among others, can be used to distinguish between various types of muscle activation [37]. This allows to characterize and differentiate between a normal activity of the muscle in a healthy individual or a pathological one that may need therapy.

To sum up, the DWT is widely used for the analysis of complex signals, as it has little computational cost and good resolution that allows to obtain reliable results. Nevertheless, in the case of complex and non-stationary signals (as it may be the EMG) it is not the gold standard methodology, as the resolution is not high enough to proportionate an exhaustive description. In those cases, the Continuous Wavelet Transform methodology is preferred.

2.4.2. Continuous Wavelet Transform

The Continuous Wavelet Transform (CWT) is a mathematical tool used for the analysis of non-stationary signals, such as EMG. As it was previously stated, non-stationary signals are those whose frequency content changes over time.

The CWT provides a deeper time-frequency representation, which means it allows us to see how the spectral content of the signal changes in time. This is particularly useful for characterizing EMG, as the pattern of its frequency components can be modified, manifesting a possible alteration in the underlying mechanisms of motor control.

The CWT works by doing a convolution of the signal of interest to a set of wavelet functions, or “wavelets”, that are created by dilating and translating a fixed “mother wavelet”. In the context of signal processing, a wavelet is a waveform of limited duration, well-located in time and frequency domains, whose average value is zero. The term “continuous” in CWT refers to the fact that the transform operates over every possible scale and every possible position for each scale [38]. That is why CWT resolution is higher than that obtained with DWT.

According to its nature, each wavelet function captures a certain frequency component within a specific time window of the signal. The dilation parameter allows the wavelet to stretch or compress, capturing lower or higher frequency components, respectively. Meanwhile, the translation parameter allows the wavelet to move along the time axis, thereby characterizing all frequency components at each time instant [39] (see *Figure 5*).

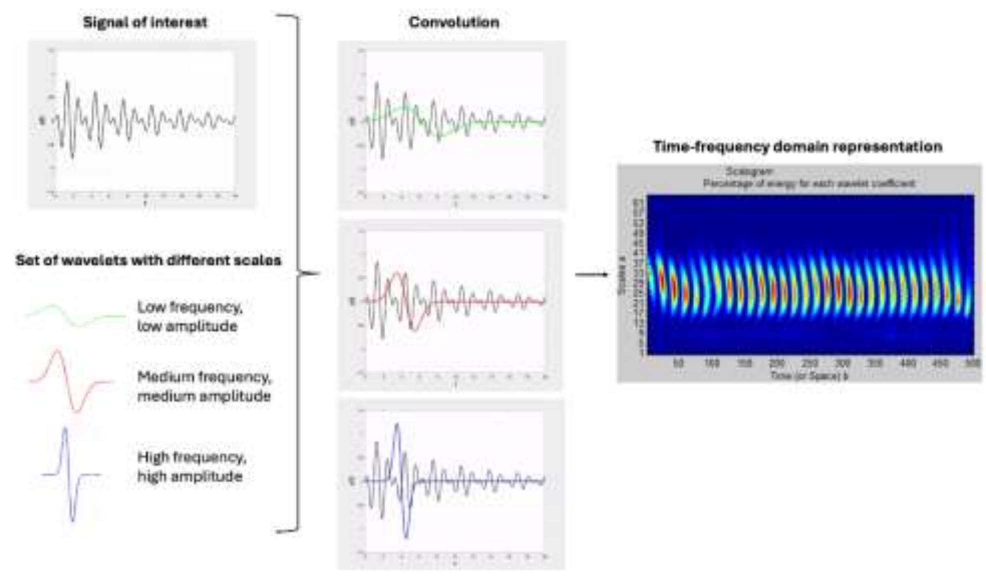

Figure 5. Continuous Wavelet Transform workflow applied for sEMG signals and Daubechies 4 wavelets for a given set of scales. Scheme of own creation.

When applied to an EMG signal, the CWT can provide a detailed view of how the spectral content of the signal changes over time, something that can be visually inspected through the scalogram. This is particularly useful in EMG analysis, as it allows for the examination of these changes in a very detailed manner, usually higher than DWT, providing valuable insights into muscle function and dysfunction [40].

3. Methodology

3.1. Data pre-processing

3.1.1. Data for Discrete Wavelet Transform validation

The raw data for this section came from a public database and the validation process was based on the work done by Zhang Y. *et al.* [41].

The original data consisted of 14 healthy volunteers (age: 28±7.82 years old, height: 174±5.88 cm, mass: 67.64±11.35 kg) from the University of Technology Sydney. The EMG data collection process was carried out with one electrode placed on the *Vastus medialis* muscle, and joint angles were registered using a goniometer placed on the knee joint. The hair and dead skin cells on the target electrode placement location were shaved from the skin surface prior to the experiment. Once shaved, the skin was cleaned with alcohol and the electrode was then placed on the skin over the muscle belly. The volunteers performed gait in flat floor surface. After the recording, the raw data was stored in *.csv files, and uploaded to a public database.

Firstly, raw data were read and pre-processed. This included assigning appropriate column names and adjusting the knee angle values based on the specific file. To perform gait segmentation, the point where knee angle was less or equal to a certain angle, based on the information provided by Ahn J. *et al*. [42]. Basically, if the individual was at the swing phase (the knee angle was decreasing, and afterwards increasing) or the stance phase (the knee angle remained the same). A schematic drawing illustrating that can be seen in *Figure 6.* As previously explained, this knee angle was vital for extracting gait events and distinguishing between subphases (stance and swing), therefore allowing an efficient and physiological gait analysis.

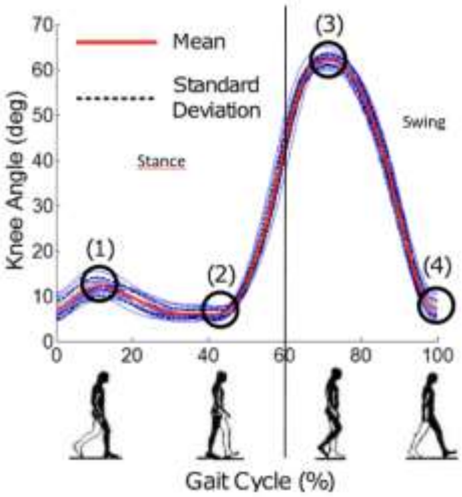

Figure 6. Representation of the evolution of knee angle at different stages of gait cycle. Obtained from the paper of Ahn J. *et al* [42].

Next, the data were grouped based on the value where the swing was suspected to begin, creating separate tables for each group based on this criterion. The tables were then segmented based on the maximum value of the knee angle. Since the knee angle is very sensitive to changes and could lead to incorrect segmentation due to sensor imprecision, the maximum knee angle was used as a threshold to determine whether a detected swing was complete or incomplete. This approach resulted in a set of accurately segmented swing tables.

Following this, stance phases were identified from the resulting swing phases. For each swing, a corresponding stance was created, which was the remaining part of the signal that went from the end of the swing to the beginning of the next one.

Finally, for each swing and stance phase, a subtable was created containing the sEMG signal for *Vastus medialis* muscle, with a new time axis. These subtables were then saved as separate files for further conversion to Eurobench format and filtering.

3.1.2. Data for Continuous Wavelet Transform validation

The data was extracted from a public database, which was published by Di Nardo F. *et al.* in [44]. For the utilization of these raw data the Waveform Database Software Package

(WFDB) for Python [48] was required, as the data was posted on PhysioNet format. Once the data were transformed to *.csv format, signal pre-processing could start.

Experimental data included the foot–floor contact and sEMG signals collected during the walking of 30 healthy young adults, which was retrospectively taken from the dataset built up at Università Politecnica delle Marche. Differential sensors were employed to measure sEMG signals bilaterally over the following two lower leg muscles during 5 minutes of ground walking: *Gastrocnemius lateralis* and *Tibialis anterior*.

Initially, the data were read from each *.csv file. The knee angle phase (either stance or swing) was determined based on whether the knee angle was below or above certain thresholds (the 25th and 75th percentiles of the knee angle data, respectively), as previously stated in [42]. A stride counter incremented each time the knee angle changed phase from swing to stance, and this step number was assigned to each row of data tables.

The processed data were then segmented into individual steps, saving each stride in a separate dataframe. All of them were saved as a new *.csv file in a patient-specific output directory.

Given that the first and last strides may not be clean and considering the large number of strides performed for each patient (nearly 250), the first and the two last strides were discarded from the future working dataset for conversion to Eurobench format and filtering.

3.2. Data pre-processing and filtering

The first step involved converting the raw data column names to the Eurobench format. As the *Vastus medialis* muscle was the one used for DWT validation, the column name had to be abbreviated to Eurobench notation for that muscle, being so *VaMe*. The same was done for *Tibialis anterior* muscle in the case of CWT validation, changing its name to *TiAn*. For the time axis, the column just remained as *time*.

Afterwards, a bandpass filter was applied to the EMG data – in the usual range of muscle activity – between 20 and 500 Hz [43]. A notch-filter was employed to remove power line interference, which is a common type of noise coming from the power grid that usually contaminates EMG signals and lays in 50 Hz in Europe [43]. Regarding DWT validation data the sampling frequency was 1000 Hz and authors applied a constrained bandpass filtered (20-90 Hz).

For the CWT validation data, the bandpass filtered was looser (10-240 Hz) being the sampling frequency 2000 Hz.

Once the data were filtered and converted to Eurobench format, they were ready for the DWT and CWT analysis.

3.3. Wavelet analysis

3.3.1. Discrete Wavelet Transform

The proposed DWT method took the sEMG signal of the *Vastus medialis* (VaMe in Eurobench format) muscle as an input and decomposed it into different frequency sub-bands using Daubechies 4 as the mother wavelet. The rationale behind choosing this mother wavelet was, as it has been previously demonstrated by Di Nardo *et al*. [44], that this kind of wavelet has the most similarity to the action potential of MUs. Also, Daubechies 4 wavelet has been used by the scientific community previously for analysing sEMG signals with the DWT method [45].

The process began by initializing an array to store the wavelet coefficients. After that, the Python function *dwt* from the library PyWavelets was used.

The outputs were then down-sampled by a factor of two. This process was iteratively applied to the approximation coefficients, decomposing the signal into different frequency bands (256 ~ 512 Hz, 128 ~ 256 Hz, 64 ~ 128 Hz, 32 ~ 64 Hz, and 16 ~ 32 Hz). The output was the wavelet coefficients.

The DWT function can be mathematically defined as it can be seen in *(1)*.

$$DWT_{sEMG}(t) = \sum sEMG[k] \cdot \psi(t-k) \qquad (1)$$

Where *sEMG[k]* represents the signal, ψ refers to the mother wavelet, and *t* is the time.

3.3.2. Inverse Discrete Wavelet Transform

The Inverse Discrete Wavelet Transform (IDWT) method involved the inversion of the DWT. The function took as input the coefficients obtained from the DWT method and applied the same sub-bands using the same mother wavelet to reconstruct the original signal.

$$sEMG(t) = \sum DWT_{sEMG}[k] \cdot \psi(t-k) \qquad (2)$$

The mathematical formula is the exact same (*2*), but instead of analysing the sEMG signal directly, the coefficients resulting from the application of the direct DWT were examined. If the transformation has been performed correctly, the output would be the original sEMG signal being reconstructed, expecting very little to no loose of signal information.

Therefore, this process helped to evaluate the accuracy of the transformation done to the sEMG signal.

3.3.3. Continuous Wavelet Transform

The CWT function took as input a signal the sEMG signal from *Tibialis anterior* (TiAn in Eurobench format) and a range of different scales.

For this methodology, it was chosen Daubechies 4 as mother wavelet, as many studies have shown to use this kind of wavelet, due to its similarity to MUs action potential [32, 45, 46, 47].

Contrary to the DWT methodology, in this case, the method had to be stablished on our own, as *PyWavelet* library still does not give support to Daubechies 4 wavelets for these calculations, because originally, Daubechies 4 is a discrete wavelet that cannot be applied in a continuous methodology. Being that so, not only the function had to be coded from scratch, but also the function that will define mathematically the Daubechies 4 mother wavelet.

To begin with, an output array of complex numbers was initialized to store the resulting wavelet coefficients. For each scale, a set of wavelets with varying frequency and amplitude according to the scale and displacement values deriving from the mother wavelet (Daubechies 4) was used. Then, the mean of the wavelet data was subtracted to centre it (this process is called demeaning), and then the signal was convolved with the wavelet performing a Fast Fourier Transformation (FFT). As output, the coefficients of the wavelet were obtained.

The CWT function can be mathematically defined as shown in *(3)*.

$$CWT_{sEMG}(t,\ a,\ b)\ =\ \int sEMG(t) \cdot \psi^{*}_{a,\,b}(t)\, dt \ \ a \neq 0 \tag{3}$$

Being $\psi^{*}_{a,\,b}(t)$, the so-called mother wavelet at scale a and displacement b (*4*).

$$\psi_{a,\,b}(t)\ =\ \frac{1}{\sqrt{a}}\psi\left(\frac{t-b}{a}\right) \tag{4}$$

It has to be noted that these operations are highly complex, and since Daubechies 4 is an orthogonal wavelet, the resulting coefficients have both real and imaginary part. For the sake of the simplification, only the real part was considered.

3.3.4. Inverse Continuous Wavelet Transform

For the Inverse Continuous Wavelet Transform (ICWT) methodology, the process was essentially the opposite of the CWT. The function accepted as input the coefficients derived from the CWT method and applied the same scales using the selected mother wavelet (Daubechies 4) to reconstruct the original signal.

$$sEMG(t,\ a,\ b)\ =\ \int CWT_{sEMG}(t)\ \cdot\ \psi^{*}_{a,\,b}(t)\, dt \ \ a \neq 0 \tag{5}$$

The mathematical formula remains the same (*5*), with the only difference being that the subject of analysis was the coefficients rather than the sEMG signal. If the transformation has been correctly applied, the outcome should be a reconstructed sEMG signal that is very similar to the original one, despite undergoing some changes during the process and losing some pieces of information.

This methodology allowed us to revert the transformed signal back to its original form, providing a comprehensive and effective indicator of the quality of the reconstruction.

3.4. Power Spectral Density

In the process of spectral analysis, it was employed Welch's method to compute the Power Spectral Density (PSD).

The first step consisted of dividing the sEMG signal into smaller segments for analysis. This is often done because the characteristics of the signal can change over time, and by dividing the signal into time windows, those changes can be captured. This is known as the Short Time Fourier Transform (STFT), an updated version of the Fourier Transform that allows to study frequency and time thanks to the use of windows of time and a sliding window method.

The data were divided into overlapping segments, with 50% overlap. Each of these segments was then subjected to a sliding window function – the Hanning window – to minimize the discontinuities at the segment's start and end. That is due to the bell shape that characterizes the Hanning window, which starts and ends at zero, thereby minimizing the discontinuities at the segment's start and end.

Following this, the Fourier Transform was then applied to each windowed segment, transforming the data from the time domain to the frequency domain, resulting in periodograms. A periodogram is a function that represents the distribution of power in the sEMG signal across different frequency domains, obtained by applying the STFT to segments of the signal. Basically, it is a visual representation of the time-frequency domain of a signal, but as a function of frequency (periods) instead of wavelet scales (which leads to the previously depicted scalogram in *Figure 5*).

The crux of Welch's method lies in averaging the periodograms. This averaging process significantly reduces the variance of the PSD estimate, providing a more reliable representation of the data.

3.5. Mean and Median Frequency calculation

The Mean Frequency (MNF) is a measure of the central tendency of a frequency distribution. In the context of signal processing, it is the average frequency of a signal. It can be calculated as shown in *(6)*.

$$MNF = \frac{\sum Frequency\ group \cdot Power_{Frequency\ group}}{Total\ Power} \qquad (6)$$

The MNF can provide information about the overall characteristics of the signal. For example, a shift in the MNF of an EMG signal might indicate muscle fatigue, or muscle malfunction.

The Median Frequency (MDF) is another measure of central tendency, but unlike the MNF, it is not affected by the values at the extreme ends of the frequency distribution (*7*). It is the frequency that divides the power spectrum into two equal halves. This means that 50% of the power is contained below the MDF, and 50% is contained above it. It is often used in the analysis of EMG signals as it is less sensitive to changes in the signal amplitude and more sensitive to changes in the shape of the power spectrum.

$$MDF = L + \frac{\frac{PSD_{total}}{2} - PSD_{acum}}{PSD} \cdot c \qquad (7)$$

Being “L” the inferior limit of the median frequency, “PSD total” the total sum of all PSDs, “PSD acum” the sum of PSDs of frequency ranges before the actual range of the median frequency, “PSD” the power spectral density for the median frequency, and “c” the size of the range of the frequency.

In the context of this research, MDF has the role of quantifying shifts in the spectrum and changes in activation power of the vastus medialis muscle. Likewise, to correlate those energy changes with their corresponding frequency, MNF was calculated, which indicates the frequency at which most of the signal power is concentrated [1].

3.6. Statistical analysis

In this study, the Jamovi tool was utilized: a user-friendly statistical software, whose analyses are performed in R programming language (despite the program interface being coded in Python), to conduct an unpaired Student’s t-test. This test was used to determine whether there was a significant difference between the means of two independent groups, being one of them the results provided by the original papers, and the other the ones obtained from our own developed methodology.

The statistical analysis provided us with a t-statistic and a p-value. The t-statistic indicated the size of the difference relative to the variation in our data, while the p-value gave us the probability of observing such a difference if the null hypothesis were true. Typically, when the p-value is lower than 0.05, this suggests that there is sufficient evidence to reject the null hypothesis, leading to consideration of the alternative one. In our case, we wanted to accept the null hypothesis, as it stated that no significance difference could be observed between groups, meaning that our methodology could be validated since we obtained the same results as in the reference works. Conversely, the alternative hypothesis asserted that both groups were statistically different and that the proposed methodology would not be giving the same results as the original, so it could not be hereby validated.

4. Results

4.1. Discrete wavelet methodology validation

The original paper by Zhang Y. *et al.* [41] aimed to characterize relevant events during gait. To achieve this, they applied a DWT to their sEMG data, then they reconstructed the original input signals based on the coefficients of the DWT applying IDWT to check the quality of the transformation and finally, they performed a spectral analysis of all the strides taken by each patient. Subsequently, they calculated the MDF and MNF.

Once replicated the steps taken by the original researchers, the general mean and standard deviation for stance and swing phases were calculated. The results of these calculations can be seen in *Table 1*.

Gait Phase	Category Data	Paper Data	Experimental Data
Stance	MNF ± STD	54.17 ± 7.72	53.20 ± 6.25
Stance	MDF ± STD	48.48 ± 13.51	51.60 ± 8.19
Swing	MNF ± STD	53.07 ± 9.37	51.40 ± 5.18
Swing	MDF ± STD	45.43 ± 11.64	49.90 ± 6.82

Table 1. Comparison among original data extracted from the Zhang Y. *et al* paper and the experimental data. The paper data were extracted from the Table 2 of the original paper [41].

In order to validate our hypothesis, both the paper data and the experimental data obtained during this research had to be comparable (i.e., no statistical differences were supposed to be found if the methodology was accurately developed). The mean and standard deviation of MNF and MDF values for each stance and swing subphases of both groups were statistically compared. The groups were assumed to be normally distributed. To ensure statistical significance, two sets of one hundred values were taken for each population. The results obtained from these statistical t-test can be seen in *Table 2* and *Figure 7*.

Group Name	p-value	Interpretation
MNF Stance	0.193	No significant differences can be observed among both populations
MNF Swing	0.545	No significant differences can be observed among both populations
MDF Stance	0.732	No significant differences can be observed among both populations
MDF Swing	0.545	No significant differences can be observed among both populations

Table 2. Results obtained from statistical t-test comparing the original paper data from Zhang Y. *et al* [41] and the experimental data.

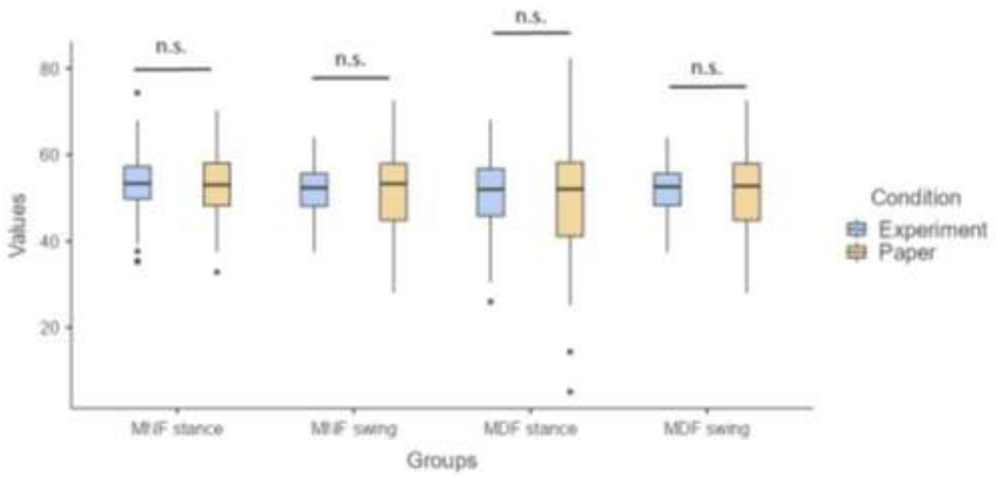

Figure 7. Graphical representation of the results obtained from statistical t-test comparing the original paper data from Zhang Y. *et al* [41] and the experimental data.

The results obtained from this test showed that the null hypothesis, having a p-value greater than 0.05, could not be rejected, meaning that our results and theirs were comparable and our methodology can be considered reliable.

4.2. Continuous wavelets methodology validation

The original paper of Di Nardo F. *et al* [44] aimed to identify muscles co-contraction in the time-frequency domain. To do so, they used the data posted on their publicly available repository at the PhysioNet network [46].

To achieve that identification, they performed a CWT for their sEMG data, a Donoho thresholding for noise-cleaning, reconstruction of those signals based on the coefficients obtained from the CWT and performed a signal-to-noise ratio (SNR) calculation of each gait cycle.

After doing all that (as it was explained in the methodology section), the general mean and standard deviation for SNR values were calculated. The results of these calculations can be seen in *Table 3*.

	Paper data	**Experimental data**
Mean SNR ± STD	14.50 ± 7.00	16.11 ± 2.39

Table 3. Comparison among raw data (before dividing by steps) extracted from the Di Nardo F. *et al* paper and the experimental data. The paper data were extracted from the Table 2 of the original paper [44].

To confirm our hypothesis, it was necessary that the data from the paper and the experimental data gathered during this study were analogous. This means that if the methodology was correctly implemented, no statistical discrepancies should be detected. The average and standard deviation of the SNR values for each stride of both groups underwent statistical comparison. The groups were assumed to follow a normal distribution. To guarantee statistical relevance, two sets of one hundred values were sampled from each population. The results obtained from this statistical analysis can be seen in *Table 4* and *Figure 8*.

	p-value	**Interpretation**
Paper population VS Experimental population	0.064	No significant differences can be observed among both populations

Table 4. Results obtained from statistical t-test comparing the original paper data from Di Nardo F. *et al* [43] and the experimental data recently generated.

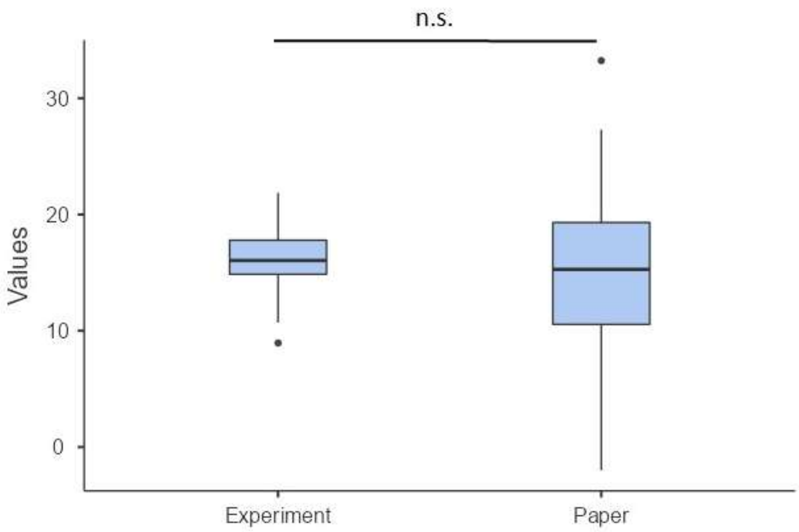

Figure 8. Graphical representation of the results obtained from statistical t-test comparing the original paper data from Di Nardo F. *et al* [43] and the experimental data.

The results obtained from this test showed that the null hypothesis, having a p-value greater than 0.05, could not be rejected, meaning that our results and theirs were comparable and our methodology can be considered reliable.

5. Discussion

5.1. Discussion of current work

The DWT and the CWT methods have been widely used for the assessment of sEMG signals, for instance, in gait cycle analysis [49, 50] and other applications (such as hand gesture recognition) [52]. Unfortunately, besides its extended use, authors refrain from sharing the codes employed for implementing these methodologies in their scientific research. That, also combined with the lack of publicly available sEMG data, makes it challenging to validate the results coming from the study of muscle activity.

The first problem that was encountered was the difficulty to comprehend the external data, as they did not share a universal format. That problem was overcome by using the Eurobench format, demonstrating its interoperability – and the need of that standard format for sharing the results among the scientific community – by being able to use such different data as the one available from the paper of Zhang Y. *et al* [41] and the data of Di Nardo F. *et al* [44].

Considering that there are not publicly verified sEMG signals, the data used by both papers had to be trusted. Even though data were considered to be correct, there is no clinical evidence of its quality, and therefore, its reliability (reinforcing the need of more open access databases with a standard format which can be used by the scientific community consistently). At the very least, using the same data removes the variability of signals from the equation, allowing us to focus solely on validating the methodology itself, which was the main goal of this thesis.

Moving on more specifically to the DWT validation, it can be concluded that the results were robust, as evidenced by the lack of statistically significant differences between the original results and those estimated by our methodology. This was confirmed by the statistical analysis, which yielded a p-value higher than 0.05, indicating no significant differences among the groups and thus validating the methodology.

Another noteworthy detail regarding the validation of DWT was the method used for stride segmentation. While in the original investigation the different stride phases were divided automatically, at this research this was not possible, so segmentation had to be approximated using the knee angle. That may carry some error, which may have affected the obtained results by increasing the difference between the results obtained at the original paper, and the current research. That remarks the accuracy of the DWT methodology proposed in this research, as no significant differences could be observed among both investigations.

One of the positive aspects of the proposed DWT methodology validated in this research lies on its dependence on the Python library PyWavelets [53]. This library is open source and it is in constant improvement managed by the scientific community and a team of experts on the field, which makes it accessible to everyone working in a Python environment.

On the counterpart, the CWT methodology has a problem concerning the use of the mother wavelet Daubechies 4. Even though it is widely used on current research [2, 32, 45, 46, 47], the PyWavelets library has not yet implemented this wavelet on their CWT function, as it is traditionally a discrete wavelet. Also, the codes for this methodology have never been published, therefore adding more difficulty to the task of programming it, as there is no reference where to base the code on. The methodology of CWT using Daubechies 4 as mother wavelet had to be coded from scratch, defining both the CWT method and the mathematical equation for the mother wavelet (also including the Fast Fourier Transform for the CWT). As no significant differences can be observed between the reference work and the current research, the CWT methodology can be considered valid, and accurate. That makes the proposed methodology in this research a powerful, reliable and validated tool for the analysis of EMG signals, although there is plenty of room yet to improve. In the future, the codes should be improved to perform the analysis as efficiently as possible, trying to reduce the computational cost to a minimum. Another suggestion for further improvement could be to present an instance to the team of PyWavelets proposing to add this new function to the open-source code.

Other aspects to be commented concerning the CWT validation involved the analysis of the raw original data. Even though that approach would not be so desirable (EMG signals are always preferred to be, at least pre-processed), it is fine for the scope of this study as results were used to only validate the proposed methodology and no physiological explanation was intended to be given. In the original paper it can be found the results for the cleaned data too. Unfortunately, the divided and cleaned data were considerably big, overpassing the capacities of the computer on which the validation was performed. Maybe, the use of raw data allowed us to analyse the data with less error, as less manipulations were done to the signals beside the own CWT methodology. A note for further research on the topic could be to do the additional step of performing the CWT analysis on the big dataset generated by the step-dividing process and cleaning of the signals and verify if any differences can be found between the raw and filtered signals.

Also, during the statistical validation of both methodologies, the normality assumption for both populations (experimental, and the one obtained from the original paper), may carry also some error, as such normality can be assessed in our experimental data (it was already proven for DWT experimental results), but not in the original paper. That could lead to huge error during the statistical validation.

Lastly, it must be noticed that both methodologies – DWT and CWT – analyse the same aspects, so some comments on the reasons to choose one or another should be made. Even though DWT is computationally very efficient, it has some inconvenience, as it can only factorize by powers of 2 the sEMG signal given [54]. That can be problematic when analysing very slight changes in muscle activation patterns, since the resolution of the DWT may not be sufficient.

On the other hand, CWT has shown to be very precise, as it can reach much more resolution by performing a continuous transformation of the signal. The main disadvantage is that its computational cost is quite high. However, it is worth it because CWT enables the observation of subtle changes in muscle activation/deactivation, while also yielding valuable insights into the physiological and biological processes underlying motor tasks, thereby facilitating a functional interpretation of the results. As stated before, this capability is crucial for the integration of this technique into clinical practice [55].

5.2. Future lines of research

It must be taken into account that both methodologies – DWT and CWT – analyse the same aspects and should give similar results. Said so, it could be interesting for future research to make a comparison of both methodologies for the same sEMG signal to assess the similarity of both results.

Another possible future line of research could study the data characteristics that have not been studied during this investigation. For instance, regarding the normality assumption that has been done. It would be valuable to run additional tests to verify the distributional properties of our populations and explore more complex approaches, such as non-parametric tests, that could be better adapted if groups were found to deviate from a normal distribution.

As both methodologies have been validated, plenty other lines of research arise. It has been enabled the possibility of analysing the sEMG signals of different nature and with different purposes. For instance, the use of this methodology could be helpful for characterising healthy human gait, stablishing lateral asymmetries among individuals and characterising pathological gait concerning different neuromotor disorders.

Also, combined with the use of sEMG, these methodologies could be very helpful in a clinical context, as they are not usually used during rehabilitation process. As an example, these methodologies could provide a way of tracking the progress of patients following rehabilitation.

6. Conclusions

In conclusion, the four remaining challenges for the application of EMG in clinical settings have been addressed in this research.

Firstly, the standardization of EMG data format is a significant step towards fostering collaboration and interoperability among research groups. In this context, the Eurobench format for EMG signals has proven to be an effective approach to universalize the data. It not only ensures consistency in data representation, but also facilitates seamless data exchange, thereby promoting collaborative efforts in the research community and the reusage of pre-existing data.

Secondly, it has been evidenced that there is a lack of large-scale, diverse nature and openly accessible public databases in the literature, based on the few that we have found, highlighting the necessity for these resources for the validation of the results obtained over the years by the scientific community. Moreover, the acceptance of a universal data format would have a positive impact on the creation of these datasets.

Thirdly, we have managed to develop accessible and validated methodologies to ensure reliable and reproducible analyses across different research settings. Both the DWT and the CWT have demonstrated high accuracy and performance. Despite the complexity of EMG data, these methodologies have effectively handled the intricacies involved in the signal analysis, even though CWT is preferred to study EMG signals due to better resolution. In this work, both DWT and CWT methodologies were validated, which will be crucial for future studies that will apply these techniques on diverse EMG experimental settings, including pathological gait, asymmetry characterization and normative gait pattern on irregular terrains. The definition of these two methodologies will have a positive impact on the community, as they could be shared or used to upgrade the packages currently used in signal processing, such as PyWavelets Python package.

Lastly, when applied to EMG signals, these methodologies will provide a comprehensive explanation of the underlying neuromuscular mechanisms in various motor activities, such as human gait, addressing the challenge of the ongoing need for functional explanation in clinical contexts. For instance, they may offer deeper insights into MUs recruitment in motor disorders like stroke, spinal cord injury, or Parkinson's disease, linking them to visible motor symptoms such as asymmetry, foot drop, or reduced neuromuscular complexity.

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