UKRAINIAN CATHOLIC UNIVERSITY

BACHELOR THESIS

Myoelectric control of an elbow orthosis

Author:
Daria OMELKINA

Supervisor:
Dr. Anton POPOV

A thesis submitted in fulfillment of the requirements
for the degree of Bachelor of Science

in the

Department of Computer Sciences and Information Technologies
Faculty of Applied Sciences

Lviv 2023

Declaration of Authorship

I, Daria OMELKINA, declare that this thesis titled, "Myoelectric control of an elbow orthosis" and the work presented in it are my own. I confirm that:

- This work was done wholly or mainly while in candidature for a research degree at this University.
- Where any part of this thesis has previously been submitted for a degree or any other qualification at this University or any other institution, this has been clearly stated.
- Where I have consulted the published work of others, this is always clearly attributed.
- Where I have quoted from the work of others, the source is always given. With the exception of such quotations, this thesis is entirely my own work.
- I have acknowledged all main sources of help.
- Where the thesis is based on work done by myself jointly with others, I have made clear exactly what was done by others and what I have contributed myself.

Signed:

Date:

UKRAINIAN CATHOLIC UNIVERSITY

Faculty of Applied Sciences

Bachelor of Science

Myoelectric control of an elbow orthosis

by Daria OMELKINA

Abstract

In this thesis, we propose and develop an approach to a **myoelectric** (EMG-driven) **control of an upper limb orthosis**. This orthosis is intended for patients, who are unable to **flex their arm at the elbow joint** at will (i.e., due to traumatic injuries of the brachial plexus), but can extend it. The flexion of the orthosis is thus controlled indirectly — by rotating the patient's head to the right (or just tensing the left sternocleidomastoid muscle). In contrast, during extension, orthosis reacts to signals from the arm (more precisely, from the triceps brachii muscle); this way, it does not resist the extension of the patient's arm.

In the scope of the thesis, we focus on the development and testing of an approach to myoelectric control, including signal preparation, processing, and detecting target muscle activity in a noisy EMG signal from sensors placed on the Sternocleidomastoid muscle and Triceps brachii muscle and also designing experiments for data gathering and its analysis.

The injuries of patients for whom this orthosis is developed are considered irreversible and completely prevent forearm flexion and the restoration of that movement. Because of this, the orthosis is meant more for assistance than rehabilitation.

The idea, concept, and mechanical part of the orthosis were developed over the course of a few years by a team of researchers, mechanical and hardware engineers, and surgeons. The team also oversaw the development of myoelectric control, recorded experimental data, consulted on various issues, and assisted over the whole course of this thesis work.

Acknowledgements

I would like to express my gratefulness to my supervisor, Anton Popov, for guiding and helping me throughout the whole process of working on this thesis. I am thankful to the entire team working on the orthosis, including researchers, mechanical and hardware engineers, and medical professionals; especially to Professor Sergiy Yakovenko and Arsen Savchuk. I am also thankful to the people who volunteered to do signal recordings.

My gratitude also goes to my teachers, who tirelessly worked with us all these years, especially those who provided me a chance to enter further scientific work with their guidance.

And most importantly, I would like to say Thank You to my family and friends for their continuous and unconditional support and to the Armed Forces of Ukraine — for defending our lives and freedom and making work on this thesis possible.

Contents

List of Figures

List of Tables

List of Abbreviations

AAOS	**A**merican **A**cademy of **O**rthopaedic **S**urgeons
bpm	**b**eats-**p**er-**m**inute
CNS	**C**entral **N**ervous **S**ystem
CSP	**C**ommon **S**patial **P**attern
ECG	**E**lectro**c**ardio**g**raphy
EMG	**E**lectro**m**yo**g**raphy
FFT	**F**ast **F**ourier **T**ransform
FSM	**F**inite **S**tate **M**achine
HD-sEMG	**h**igh-**d**ensity **s**urface **E**lectro**m**yo**g**raphy
ICA	**I**ndependent **C**omponent **A**nalysis
iEMG	**i**ntramuscular **E**lectro**m**yo**g**raphy
MLO	**M**yoelectric **L**imb **O**rthosis
Movag	**Mov**ing **a**verag**e**
PCA	**P**rincipal **C**omponent **A**nalysis
PR	**P**attern **R**ecognition
RFFT	**F**ast **F**ourier **T**ransform (for **r**eal input)
RMS	**R**oot **M**ean **S**quare
RNI	**R**omodanov **N**eurosurgery **I**nstitute (Kyiv, Ukraine)
SD	**S**tandard **D**eviation
sEMG	**s**urface **E**lectro**m**yo**g**raphy
TKEO	**T**eager **K**aiser **E**nergy **O**perator
VA	U.S. Department of **V**eteran **A**ffairs
VAR	**Var**iance

Dedicated to my family and to the Armed Forces of Ukraine.
Grandpa, You would have loved to listen about this.

Chapter 1

Introduction

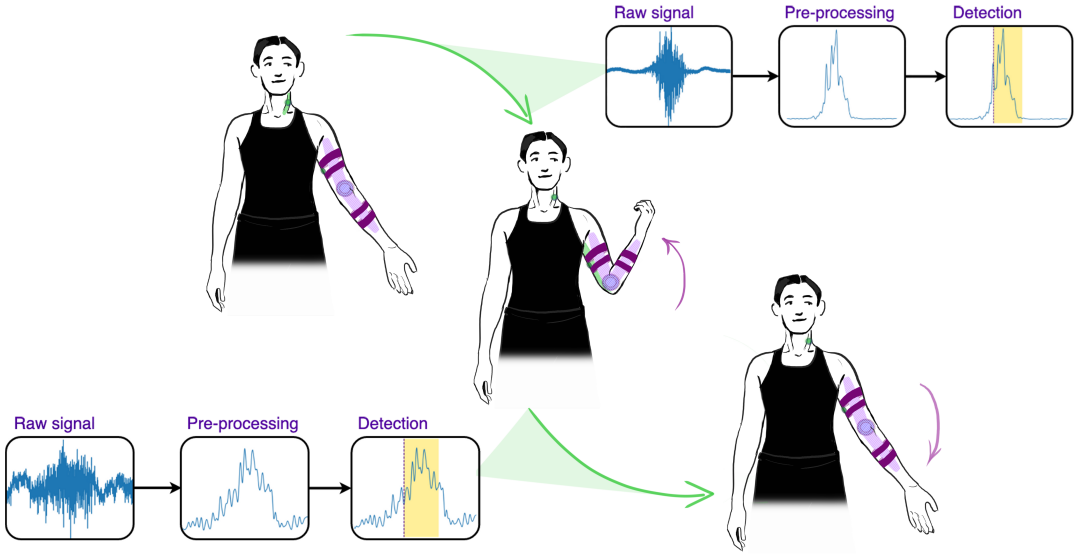

FIGURE 1.1: Overview of the approach to the orthotic control. Includes a sketch of the orthosis prototype. The orthosis is mostly located at the posterior side of the arm, so the sketch is partly semi-transparent/striped.

1.1 Motivation

Various courses of action exist for patients whose musculoskeletal system functionality is limited: surgical interventions, different treatments, rehabilitation, etc. When there is no foreseeable possibility of returning the patient's ability to move, another option exists – external movement assistance. This includes, for example, using an orthotic device. In our case, patients of the Romodanov Neurosurgery Institute (The State Institution of National Academy of Medical Sciences of Ukraine), for whom the orthosis is developed, are unable to flex their arms at elbow joints as a result of traumatic injuries of their brachial plexus. A team of various professionals (including surgeons, engineers, and researchers) has been working on this orthosis for the last couple of years. In this thesis work, we will focus on the part of research and development responsible for the myoelectric control of the orthosis.

1.2 Goals

- Research options for the control of the orthosis: including which muscles to monitor, which movements to choose for control, and other details
- Develop and test an algorithm of real-time pre-processing and onset detection in EMG signals for our task
- Provide customization capabilities so that the algorithm can be adjusted for different patients
- Final aim: prepare our myoelectric control approach for use in the orthosis

1.3 Structure

Chapter 2: Background Information
This chapter introduces the reader to the biological and medical aspects of the task and provides general overviews of prosthetic and orthotic devices and myoelectric signals.

Chapter 3: Related works
In this chapter, we will discuss literature related to the processing of myoelectric signals, motion detection in them, and usage of such signals for prosthetic and orthotic control.

Chapter 4: Datasets
This chapter describes the datasets we used during the algorithm development and some observations from the obtained data.

Chapter 5: Proposed approach
In this chapter, we introduce and describe our approach[1] to myoelectric control of an elbow orthosis, including the choice of muscles for control, sensors setup, and EMG processing pipeline with motion detection.

Chapter 6: Experiments
In this chapter, we will describe the most significant experiments conducted during algorithm development and testing. We will also compare our approach of onset detection to others found in various libraries.

Chapter 7: Summary
Last but not least, in this chapter, we will summarise the results of the work and achieved goals, and discuss improvement needs and future plans in general.

Without further ado, let's begin.

[1] The repository with implementation is currently not public. Access can be granted after a request followed by an agreement of non-disclosure of the data from the repository because, at the time of writing this thesis, the work on the orthosis is in progress. For the same reasons and the privacy of the volunteers, EMG datasets are not disclosed or present in the repository.

Chapter 2

Background information

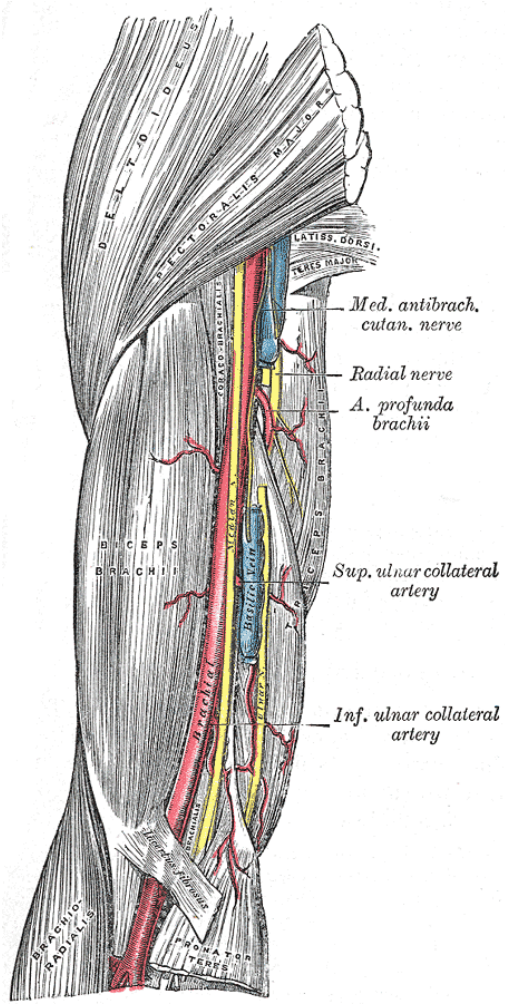

FIGURE 2.1: Anatomical illustration with biceps and triceps brachii, and radial nerve (Carter, 1858a). By Henry Vandyke Carter, Public domain, via Wikimedia Commons.

Before diving deeper into this thesis's primary task, let's discuss its biological and medical aspects. This includes the injury which leads to the need for orthotic assistance of the upper limb, the muscles we will use for orthotic control, a general overview of the development of orthotics and prosthetics, and myoelectric signals.

2.1 Biomedical background: arm flexion, brachial plexus injuries, and muscles involved in the orthotic control

As mentioned before, the orthotic device, for which we are developing an EMG-driven control, is intended to assist people with traumatic injuries of the brachial plexus. In our case, these injuries affect the musculocutaneous nerve, which originates in the brachial plexus, and prevent patients from controlling their elbow flexion. Moreover, such damages in our case do not allow us to directly predict the patient's intention of arm flexion via EMG because there is no signal passing through the musculocutaneous nerve to muscles, which we could record and process.

Let's briefly discuss the work of the musculoskeletal system and the upper limb in particular. Arm flexion, like most other movements of the human body, happens through muscle contraction. When muscles contract, movements only happen in cases when the muscle connects different bones at a

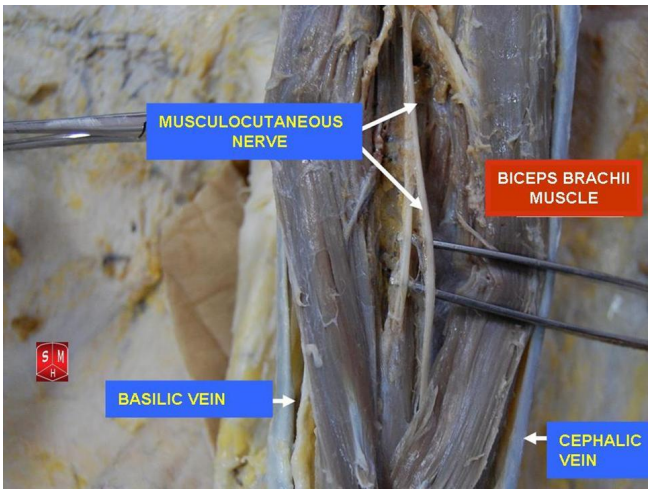

FIGURE 2.2: Cadaver dissection, which shows biceps brachii and musculocutaneous nerve (Halga, 2011). By Adrian Halga, ("CC BY-SA 3.0", n.d.), via Wikimedia Commons.

joint. In our case, for the arm flexion, movement happens at the elbow joint through **Biceps brachii muscle** contraction. The contraction is prompted by a signal from somatic motor neurons (the cells which carry myoelectrical signals from the CNS to muscles) of the musculocutaneous nerve, which innervates that muscle and is responsible for bending and flexing the elbow. (Achudhan Karunaharamoorthy, 2023; Houten et al., n.d.)

Thus, movements can be affected by different injuries to the bones, connecting muscles, supplying vessels (i.e., blood vessels — the triceps brachii is supplied by the deep brachial artery and superior ulnar collateral artery), and the nervous system (in our case — the brachial plexus and musculocutaneous nerve).

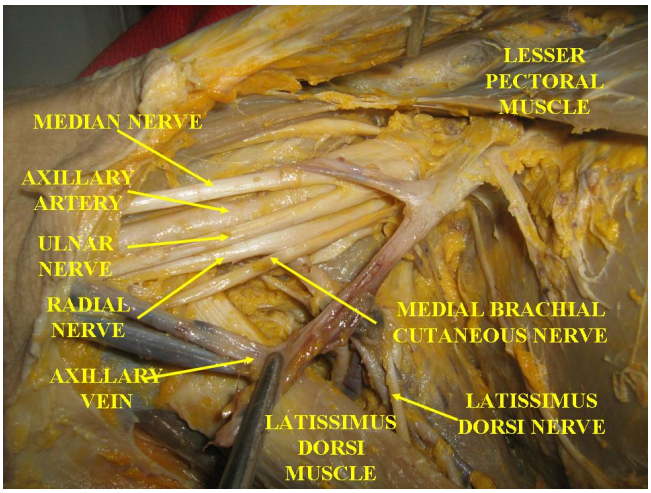

FIGURE 2.3: Cadaver dissection, which shows the distal part of the brachial plexus, including the radial nerve (Anatomist90a, 2011). By Anatomist90, ("CC BY-SA 3.0", n.d.), via Wikimedia Commons.

The brachial plexus consists of different nerves which supply the shoulders, upper limbs, and chest. They are formed from root nerves, which, for example, include: C5, C6, and C7 (lateral cord), that form a terminal branch called the musculocutaneous nerve (K. L. Moore & Agur, 2007), that innervates muscles responsible for

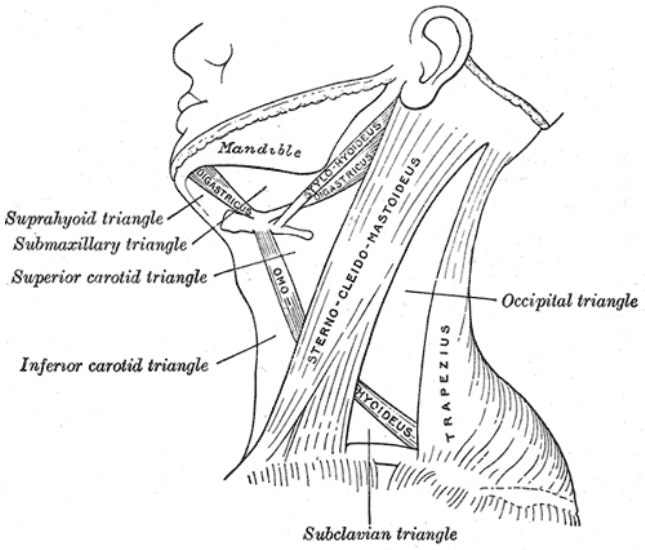

FIGURE 2.4: Anatomical illustration of neck muscles, including Sternocleidomastoid (Carter, 1858b). By Henry Vandyke Carter, Public domain, via Wikimedia Commons.

the flexion motion and anterolateral forearm skin. These, and other root nerves, in different combinations, form different branches that innervate a lot of muscles and other anatomical structures. So, any injury that somehow damaged any of the roots or branches themselves will affect the motion capacity of the shoulders, upper limbs, or chest. In some cases, the injury can heal without additional help over time, while in others, it can lead to paralysis and might need surgical intervention and rehabilitation ("Brachial plexus injuries - orthoinfo - AAOS", n.d.). If an injury severely affects the musculocutaneous nerve, the nervous system is unable to pass a myoelectric signal to muscles, which would have caused their contraction. That, in turn, prevents patients from flexing their arms, thus creating a need for a supporting or rehabilitation device such as an orthosis. This way, our orthosis assists in the movement for which the biceps brachii muscle is responsible. At the same time, our patients can extend their arms. The extension is performed through contraction of the **Triceps brachii muscle**, which is in turn innervated by the radial nerve (Sendić, 2022). While patients can control this movement, we need to make sure that the orthosis does not resist because it would require more force not only to extend the arm but also to extend the orthosis, which is holding it in the flexed position. To achieve this, we monitor the myoelectric activity of the Triceps brachii and detect its activation through EMG recordings. After we detect such activations, we order orthosis to extend.

Regarding flexion, we would like to control our orthotic device by a head rotation motion or, more precisely, tension of the muscles which take part in that motion. For this, we will assess neck muscles, which contract during head motions and neck tensing in general. We use only signals produced by this tension, sifting out other motions, such as forward and backward bends of the neck.

To detect neck movement, we will use EMG (discussed in the following subsections) sensors, which will record the activity of the **Sternocleidomastoid muscle**. The Sternocleidomastoid is a large visible muscle on two sides of the neck. The Sternocleidomastoid contracts during such neck movements as the head-turning to left

and right (one opposite side contracts), head turning up and down (both sides contract), and neck tensing (contraction depends on which side is tensed). Considering that we are interested in head rotation to one side to control elbow flexion by the orthosis, we need to detect exactly that motion from the recorded signal. That muscle is situated relatively close to the heart muscle, which causes the appearance of ECG artifacts in the recorded signal.

2.2 Orthotics and prosthetics: overview

As mentioned above, to assist patients with traumatic injuries of the brachial plexus, we decided to use an orthotic device. To give a general understanding of how such devices work, we will discuss them and prosthetics, considering that they are closely related.

The history of prosthetic devices goes back to ancient times. It was depicted in ancient pottery (i.e., dating back to 300 B.C.) and described in historical works (i.e., "History" by Herodotus from 484 B.C. tells about a Persian with a wooden leg replacement). There is a preserved mechanical hand from the fifteenth century, now displayed in a museum in Florence. An artificial foot from the 1800s served as a base for the "American leg," which later was improved and continues to be a basis for prosthetics development even now. Both prosthetics and orthotics development came to a turning point and started quickly progressing after the American Civil war and First and Second World wars, as a result of injuries suffered by soldiers and numerous amputation cases (Craelius, 2022).

FIGURE 2.5: Prosthetic toe from Ancient Egypt (Bodsworth, 2007). By Jon Bodsworth, Copyrighted free use, via Wikimedia Commons.

Prosthetic and orthotic devices are mostly meant for the musculoskeletal system, and even though they have other application areas (i.e., cochlear implants and bionic eyes), in our study, we focus more on support for the limbs. While prosthetics serve as replacements for missing body parts such as limbs or their sections, orthotics are external devices, which do not replace body parts but support them, enhance their functionality, provide various types of rehabilitation, etc (*Prosthetics and orthotics — Vocabulary — Part 3: Terms relating to orthoses*, 2020). That is why in our case, we will use an orthosis — because our target patients can move their arms, it is just that the movement is limited due to injury and require external assistance.

There are various benefits to using prosthetic and orthotic devices. They include but are not limited to gaining independence in daily life in general for people with

FIGURE 2.6: Prosthetic Arm by Open Bionics (StarWarsRey, 2015). By StarWarsRey, ("CC BY-SA 4.0", n.d.), via Wikimedia Commons.

limb losses, soothing phantom pains (usage of prosthetics devices, especially the ones which provided sensory feedback, for limbs was shown to decrease phantom pains of patients (Dietrich et al., 2012)), acquiring freedom of movement and mobility back, achieve a positive impact on users mental health and well-being in general, etc.

Nowadays, there are various cases in which patients might need orthotic or prosthetic devices. For example, these might include amputations due to diabetes, frostbite, various injuries, or, sometimes, people are born without some or all of the limbs. There are cases that I would like to highlight — limb losses during wars. Since the russo-Ukrainian war started in 2014, a lot of Ukrainians suffered limb losses either in battles or during various attacks and tortures by russians. Currently, there exist a lot of initiatives that help to provide them with the most advanced prosthetics devices. This serves as one of the main motives why prosthetics and orthotics should be developed, made low-cost or completely free, and as comfortable and useful as possible — for these people to be able to continue living without limits to their mobility.

Prosthetic and orthotic devices can be purely mechanical; that approach is one of the oldest and most commonly used. Currently, it is especially well-developed for lower limb prosthetics. Then, there are other options, like neuroprosthetics (i.e., robotic arms), which use information from biosensors (i.e., myoelectric signal recordings — EMG). In the following subsections, we will shortly discuss EMG for the control of orthotics, which is one of the primary themes of this thesis.

Moving on to modern prosthetics and orthotics development, let's discuss a couple of examples.

OpenBionics is a widely known bionics company, with one of their most famous prosthetics being the Hero Arm meant for below-elbow amputees. Recently they started creating these devices for Ukrainian veterans (T. Moore, 2023). Hero Arm is a bionic prosthetic arm that uses myoelectric signals. This custom prosthetic allows multi-grip functionality and proportional control of movements. In most cases, it uses two EMG sensors for control purposes. This prosthetic reacts to tension in muscles, which are responsible for the hand opening and closing movements, and, depending on the selected grip mode, it performs appropriate motion (i.e., various pinches, fist, hook, and wrist rotation). It also has a feedback system, for example, vibrations (Bionics, 2021; "The Hero Arm is a prosthetic arm made by Open Bionics", 2023).

There are also many open-source prosthetics, for example, the one described in (Liarokapis et al., 2014) for partial hand amputations. The authors of the paper discuss various aspects of the design of robotic fingers, for example, control strategies, such as myoelectric interfaces which use signals from the user's forearm, predictions based on flexion of the intact fingers, etc. Here the emphasis is on the affordability and personalization of such prosthetics because amputations, especially such partial ones, are unique and require a custom approach. By designing separate fingers, they allow the required extent of personalization. As the research shows, different control strategies might suit better for different amputation cases, which also indicates the importance of personalization for such types of devices.

Moving on to orthotics, here is, for example, a paper about exo gloves (Gerez et al., 2019), controlled by myoelectrical signals. These orthotics are meant to enhance the grasping capabilities of the user, either a healthy one or one whose grasping capabilities are lowered due to paralysis or stroke. The authors describe two versions of such tendon-driven devices: body-powered and motorized. In both cases, the part which assists in grasping resembles a glove and is an exoskeleton-like solution for the task, and the only difference is in the power source.

In (Rzyman et al., 2020), authors provide an overview of bionic orthoses for upper limbs. They state that EMG should be used as a solution for orthotic control because it can be used for intuitive and simple interfaces and can be accompanied by machine learning techniques. It is also emphasized that bionic orthotics usage is beneficial for rehabilitation purposes and treatment of the limbs. It also stated that the personalization of orthotics is important, but the optimal solution should be between personalized and universal, which would be more affordable.

According to (Gopura & Kiguchi, 2009), another important aspect of orthotic development is safety because orthotics closely interact with the (in our case, human) body. They also state that this development is a complicated task due to various requirements that should be considered and investigated (i.e., regarding biomechanics).

The field of prosthetics and orthotics is rapidly growing and developing. For example, researchers from VA (U.S. Department of Veteran Affairs) currently work on high-functional artificial limbs, Ukrainian startup Esper Bionics is developing a bionic self-learning hand prosthesis, and so on.

Although we mentioned different aspects of orthotics and prosthetics development, we should note that this thesis work is focused mainly on the EMG-driven control of an already created hardware device by a team of specialists who worked on it before the start of this thesis writing. The team also closely participated in the development of EMG-driven control and mentored the whole process.

2.3 Myoelectric signals and EMG: overview

As already mentioned, to control the flexion of the orthotic device, we decided to use the motion of the neck (rotation, if more precisely). For extension, we detect the elbow extension itself. To detect these motions, we used the myoelectric signal from one of the neck's most noticeable muscles – the Sternocleidomastoid, and the Triceps brachii, accordingly. In this section, we will go over myoelectric signals and the electromyography technique.

Electromyography is a technique for recording myoelectrical signals (electromyogram, abbreviated EMG) (Whittlesey et al., 2014). In short, these are electrical signals produced by the muscle cells in response to the control from the central

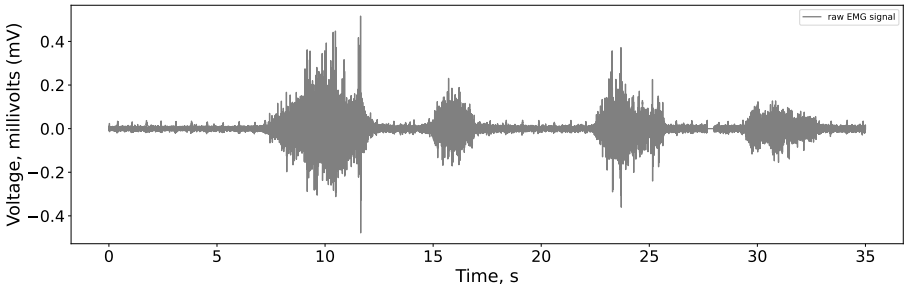

FIGURE 2.7: Raw EMG recording from the Sternocleidomastoid muscle.

nervous system, which passed through the peripheral nervous system to skeletal muscles. This causes muscles to contract, thus producing motion, essentially controlling the body's movement. Hence, decoding the myoelectric signal allows extracting information about muscles' contraction and, by doing so, it allows tracking or predicting movement, depending on the task (Konrad, 2005).

EMG, which essentially records action potentials at the membranes of muscle fibers, is typically performed using a couple of electrodes (one being the referential one and the other recording from the muscle of interest). Usually, the EMG signal is processed (i.e., rectified, filtered, etc) before being involved in any further applications because the shape of myoelectric spikes is of random nature and can be less informative in the raw form. Another reason for processing is noise, which can be produced by muscles cross-talk (i.e., in our case, we had ECG spikes in EMG recording of the neck due to its proximity to the heart), skin-related factors (i.e., temperature and thickness), external noises from electrical devices, etc (Konrad, 2005).

Another important notion that can be addressed in the context of this work is a motor unit. This is the smallest structure responsible for myoelectric control of the movement. The motor unit includes the motor neuron and the muscle fibers, which are innervated by it through its axon branches (Konrad, 2005).

There are various types of EMG sensors. For example, there are invasive — for iEMG (intramuscular EMG) and non-invasive — for sEMG (surface EMG) ones. As their names suggest, for iEMG, a needle (fine wire electrode) is inserted into the muscle body, and thus it allows to precisely record the myoelectric signal passing through it; sEMG, on the other hand, is recorded from the skin surface, which is a less invasive technique but leads to a more noisy signal. In our case, we chose sEMG due to its non-invasive nature.

Another type of EMG recording is an HD-sEMG (high-density surface EMG). HD-sEMG usually records a relatively high number of muscles simultaneously, while regular EMG focuses on a single muscle. HD-sEMG does not give information about each muscle from the recorded group separately, so if this information is needed, it must be extracted from the whole recording using methods such as wavelet analysis, ICA, PCA, etc (Drost et al., 2006).

Chapter 3

Related works

In this thesis, the main focus is on the processing of the myoelectric signals, detecting control movements in them, and using them to control an arm orthosis, so in related works, we will review approaches to these tasks.

3.1 EMG processing techniques

To detect neck motion, we will not just use raw EMG recording because the shapes of its spikes have random nature, and the signal is subject to noise and artifacts — so we will first process it. Considering that EMG is widely used in both scientific research and development, there exist a lot of studies on its preparation and processing. We will discuss some of them.

As one of the main sources on EMG, its processing techniques, and applications, we used (Konrad, 2005). According to it for quantitative amplitude analysis (which we partially use for motion detection in our algorithm), there are specific processing steps, which include: full wave rectification, smoothing, digital filtering, amplitude normalization, and ECG reduction.

Rectification can be performed by taking absolute values of the signal.

For smoothing, the authors offer two algorithms: moving average and root mean square. The smoothing is required due to randomness of inference — the same movements do not produce the same spikes, but the smoothing allows to asses of an overall shape produced by some window used in these algorithms.

Alternatively, instead of Movag and RMS, a digital filter can be used. For example, authors of (Konrad, 2005) recommend a low pass filter at 6 Hz for creating envelope (in general) and high pass filters at 20-25 Hz to reduce artifacts (in case of using fine ware electrodes for iEMG). At the same time, it is not recommended to use notch filers, for example, on 50-60 Hz, because these will remove much of the EMG signal itself.

Amplitude normalization is applied to reduce variance in different conditions of signal recording or even just from subject to subject, but it is said to be time-consuming and demanding. In our approach, we do not apply that step since we aim for customization for different patients.

Another crucial step is ECG artifact removal because they can affect amplitude assessment. This can be achieved, for example, through filtering.

The authors of (Chowdhury et al., 2013) reviewed EMG preprocessing and processing techniques, stating that overcoming noise in such signals is an important step to achieving a better quality of EMG and its further applications. They conclude that the optimal solutions would be the wavelet transform and using higher order spectra to both reduce noise and extract valuable information from EMG signals.

In (Parajuli et al., 2019), authors discuss real-time pattern recognition in EMG for prosthetics control. There, as a preprocessing step, they use ICA and CSP on the

signal. Later, after feature extraction, they also use dimensionality reduction. They state that preprocessing step is needed due to noises that can appear in the EMG as a result of electromagnetic disturbances, the motion of cables and electrodes, signal instability, etc.

3.2 Motion detection in myoelectric signals

For the task of motion detection itself, we again refer to the (Konrad, 2005). There, in the scope of EMG processing and analysis discussion, authors provide information on onset and offset detection in EMG and muscle activity analysis in general. In our case, we are interested in the onset the most.

Among the approaches offered for this task, there is, for example, using standard deviation, which is firstly calculated on a baseline (where there is no muscle activity) and then scaled (i.e., by a factor of 2 or 3) and compared with further muscle activity. The moment the SD of activity exceeds the scaled SD of the baseline, it is considered to be the onset. It is also important to remember that there can appear random spikes of artifacts, which will affect the onset detection. Thus the muscle activity should stay over the threshold for some period of time. Another method is assessing the percentage of peak activation and choosing a threshold appropriately. We can also just use a certain amplitude threshold, exceeding which will signify the onset.

The authors of (Vannozzi et al., 2010) describe another approach for detecting muscle activations in the sEMG. This method is based on finding discontinuities in the wavelet domain and is said to be beneficial, for example, in case of usage by an unskilled operator, because, unlike the single threshold method, it does not require choosing that threshold by the operator.

In the (Allison, 2003), authors discuss the detection of trunk muscle onset in the EMG signal, which is highly affected by ECG artifacts. There were two algorithms present in the study: Shewhart and integrated protocol. The results have shown that muscle fatigue highly affects the baseline variance for such muscles and that the integrated protocol method was shown to be more robust in such conditions. It was also stated that threshold methods should consider such variances in the baseline and ECG artifacts to detect activation effectively and without delays.

The authors of (Drapała et al., 2012) propose a two-stage activation detection method. This way, at first, the region of interest is approximated globally on the whole signal, and afterward, the algorithm searches for the activation only in that approximated region.

Three preprocessing algorithms for online movement prediction are discussed in (Tabie & Kirchner, 2013). Methods include Teager Kaiser Energy Operator (TKEO), using variance and using standard deviation. They are compared in terms of prediction time, which was stated to be highly affected by the speed of movement itself. Authors conclude that VAR and SD methods are more optimal for online predictions in embedded systems because they are 1.5 faster than TKEO. For all preprocessing methods, authors use an adaptive threshold method for onset detection.

3.3 EMG-driven control of orthotics and prosthetics

Now that we have processed EMG and are ready to detect control movements, we need to learn how to use that information for the control of orthotics. In this section, we will discuss different ways which can be used for that.

In (Geethanjali, 2016), authors provide descriptions of the state-of-art strategies of myoelectric control for assistive devices such as orthotics and prosthetics. These strategies include and are not limited to: on/off, proportional, direct, FSM, PR, regression, and posture.

The on/off control is also called a binary control, and it provides two degrees of freedom. As the name suggests, it can involve the detection of onset/offset and use this information for control at some constant speed.

In proportional control, on the other hand, the speed or the degree of the movement of the device is proportional to, for example, the intensity of the signal.

Direct control involves monitoring different EMG sites for controlling separate units of the device (i.e., separate fingers of a hand prosthetic).

Another type of control involves finite state machines, so every movement or position of the device is regarded as a predefined state, and the transition between them is also controlled in a predefined manner. For example, different inputs can be mapped to different grips of a prosthetic hand.

In pattern recognition, some features are extracted from the input EMG signal, and these features are used to, for example, predict the movement and, in this way, control an assistive device.

Posture control involves mapping input EMG signals to a PCA domain.

With regression, the control involves using simultaneous signals to obtain different positions of parts of the device.

The last mentioned control strategy in this work is closed-loop control. The loop is closed in the sense that not only do users provide signal input for the device, but they also get sensory feedback from it. It is also quite a promising area of study.

An example of using myoelectric control of a low-cost prosthetic device is described in this (Nguyen, 2018) thesis work. This work involves a whole development cycle of a prosthetic hand and thus involves a description of how EMG signals from the forearm were used for that. There, different sequences of the forearm movement were mapped to six hand prosthetic states. This involves EMG preprocessing and classification steps. Raw signal undergoes such processing steps: amplification, rectification, and integration (by MyoWare sensor), Movag filter, and Steady-State and Transient Savitzky-Golay filter (in software). Afterward, three EMG signals are put through a threshold, which determines the flexion or relaxation of muscles, and based on these three values, the classification determines which state the prosthetic will enter.

Authors of (Pulos et al., 2021) describe a myoelectric elbow orthosis, which is meant for patients with traumatic injuries of the brachial plexus (which resembles our task), and the benefits of using it. The study shows considerable improvement in strength and function and reduction of pain when using myoelectric orthosis for most of the patients who took part in it. The authors describe MyoPro — an orthotic device used during the study. This orthosis detects weak myoelectric signals in target muscles, such as the Biceps brachii, amplifies them, and accordingly augments the movement intended by the patient. MyoPro uses proportional control, so the flexion strength depends on the EMG signal, too.

Taking discussion of MLOs (myoelectric limb orthoses) for elbow function even further, authors of (Anderson et al., 2020) present case series in their work. They state that using MLOs for patients with traumatic injuries of the brachial plexus is a relatively novel approach. The special feature of such orthoses is the fact that patients can initiate and control the movement with their muscles. The patients, who took part in the study, reported positive results after using MLOs in therapy and

functional recovery, and it also gave them additional independence. In the conclusion of this study, it was shown that such orthoses could potentially improve the quality of life of patients of that category. Among the limitations to using MLOs for patients with brachial plexus injuries, there are the cost and heaviness of orthoses, so there is space for improvement in that field.

Chapter 4

Datasets

One of the difficulties with our task was the need to create custom datasets ourselves, which involved EMG recordings in the Romodanov Neurosurgery Institute and later using the AD8232 sensors (*Single-Lead, Heart Rate Monitor Front End*, 2020), which were chosen for the orthosis itself. There were multiple iterations of EMG recordings over the course of almost one year, which resulted in the creation of multiple datasets involved in this thesis. All the recordings were made using surface electrodes (non-invasive, also called sEMG).

4.1 Tentative dataset

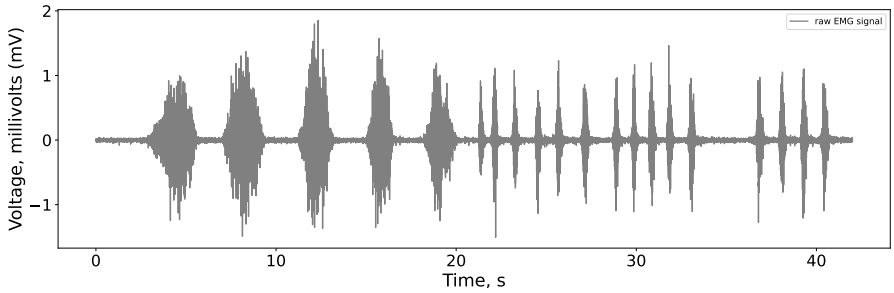

FIGURE 4.1: Sample from the tentative dataset: a recording from the Biceps brachii muscle.

The first dataset was recorded in the Romodanov Neurosurgery Institute under the supervision of medical professionals. In code, the tentative dataset is sometimes referred to as the "summer" dataset or "31_08_2022". It was used in the early stages of our algorithm development and during getting acquainted with EMG recordings of various muscles in general. There are various muscles in the dataset because, at that time, it was not completely decided which movement would be used for the control of the orthosis. Details about the data:

- Sampling frequency: 20000 Hz
- Number of subjects: 3 (healthy, not target patients)
- Muscles: Sternocleidomastoid, Biceps brachii, Trapezius, Orbicularis oculi
- Number of channels: 1
- Overall duration: 7.8 minutes

Here are some of the observations from the data:

- For the Sternocleidomastoid muscle: Periodic pulsations are present in the signal even during the rest period, when the neck is not moved, which we consider to be ECG artifacts (carotid pulsations). EMG recording from this site shows a very high activity rate during neck muscle tensing and rotation movements, which is expected. There are visible noises, for example, on the baseline. Lateral flexion and extension, which are not our control movements, still produce some activity but visibly less than rotation.

- For the Trapezius: Likewise, periodic pulsations are present in the signal. In a sitting position, shoulder lifting produces the most activity in these EMG recordings, slight lifting produces much less activity, and tension looks almost the same as the baseline noise. In a standing position, shoulder lifting produces abrupt high activity with high spikes. Another important observation in a standing position occurred during the recording procedure: sensors are prone to falling off during such movements, so it should also be considered during orthosis design (even though Trapezius is not among the muscles used for our orthosis).

- For the Biceps brachii: Flexion of the shoulder and forearm produced very high activity with high amplitude. During the rest period, a slight stable noise was present with a couple of spontaneous activations (possibly cable movement artifacts or other externally induced noises). As mentioned before, it is the movement produced by this muscle that we are trying to achieve with an orthosis.

- For the Orbicularis oculi: Closing the eyelids produces high activity with high amplitude. Rapid blinking also produces high amplitude but with shorter activity periods. Winking-like motions produced smaller activity with smaller amplitude.

One of the reasons why these EMG signals are so prone to noise is that the sensors could register the electric potential of a couple of microvolts, which is less than the noise.

4.2 Experimental dataset 1

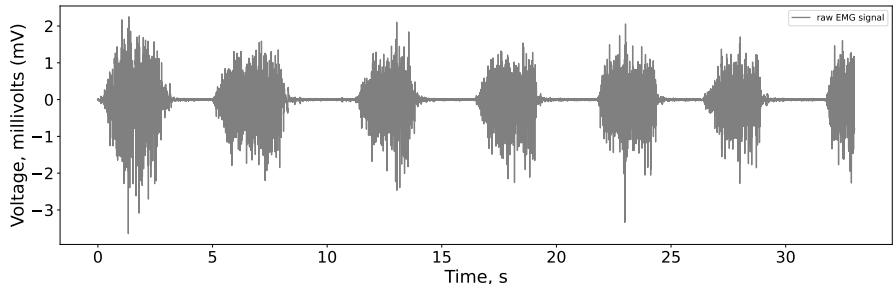

FIGURE 4.2: Sample from the Experimental dataset 1: a recording from the Triceps brachii muscle.

As well as the tentative dataset, the experimental dataset №1 was recorded at the Romodanov Neurosurgery Institute. This time it involved experiments design created beforehand: for the Sternocleidomastoid, there were recordings of rotating

head to the right (which is the control movement for orthosis and hence our target) at slower and faster speeds (i.e., 60 and 100 bpm of a metronome) and turning head to left/up/down (also at different speeds); for the Triceps brachii there were recordings of arm extension movement at slower/average/faster speeds (i.e., 12, 24, 60 bpm). The plan was created for further testing and improvement of the algorithm. Details:

- Sampling frequency: 20000 Hz
- Number of subjects: 2 (healthy, not target patients)
- Muscles: left Sternocleidomastoid, left Triceps brachii (approximately from the middle part of the muscle)
- Number of channels: 1
- Overall duration: 53.9 minutes

Here are some of the observations from this data, too:

- For the Sternocleidomastoid muscle: there are very prominent carotid pulsations this time, which are noticeable in the signal recording. Even though we expect very high activity from the left Sternocleidomastoid muscle during right rotation only, for one subject, there was a quite high activity for left rotation, too, making the task of control movement detection more difficult. During turning the heart up and down (extension and flexion of the neck), activity also was present, but on a smaller scale.
- For the Triceps brachii: There were no visible artifacts (for example, from the Biceps brachii). Another important observation is that t turns out that during regular extension movement, there might be no activity present in the signal, so the orthosis will be controlled more by the tension of the muscle (for flexion control, we expect more tension of the Sternocleidomastoid, too). Thus, during recordings, subjects tried to extend the elbow with a resistance (for example, another person's hand placed on the forearm).

4.3 Experimental dataset 2

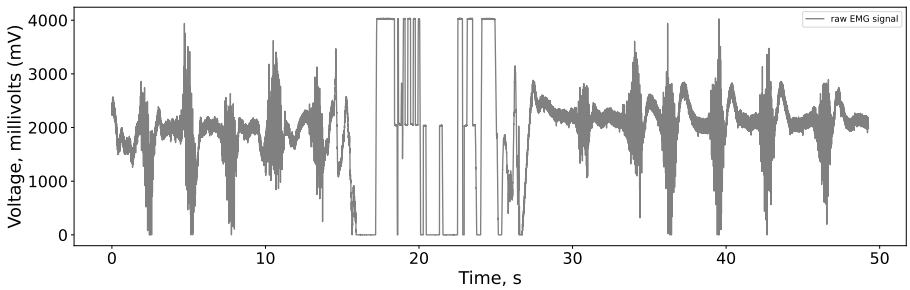

FIGURE 4.3: Sample from the Experimental dataset 2: a raw recording from the Triceps brachii muscle, which was interfered with by applying pressure on electrodes.

At this stage, data was recorded not in the RNI but using the AD8232 sensors (*Single-Lead, Heart Rate Monitor Front End*, 2020) and SkinTact F-261 ECG electrodes

("Skintact ECG electrodes", n.d.), intended for the orthosis. Initially, the recordings involved a lot of experiments regarding referential electrode placement, so there are present a lot of variations in the dataset. Afterward, experiments were more focused on preprocessing the signal to achieve standard spectra and to reduce noises and artifacts. Details:

- Sampling frequency: 500 and 1000
- Number of subjects: 1 (healthy, not target patient)
- Sensors: AD8232
- Electrodes: SkinTact F-261 ECG electrodes
- Muscles: Sternocleidomastoid, Triceps brachii
- Number of channels: 1
- Overall duration: 13.25 minutes

As we saw from this dataset, recordings can be hugely affected by a computer's power cable and other electronic devices. This dataset also showed that limiting the signal spectrum to the standard one for EMG significantly improves signal quality and filters out some of the noises and artifacts. More observations for this and other datasets will also be discussed in the Experiments section.

4.4 Experimental dataset 3

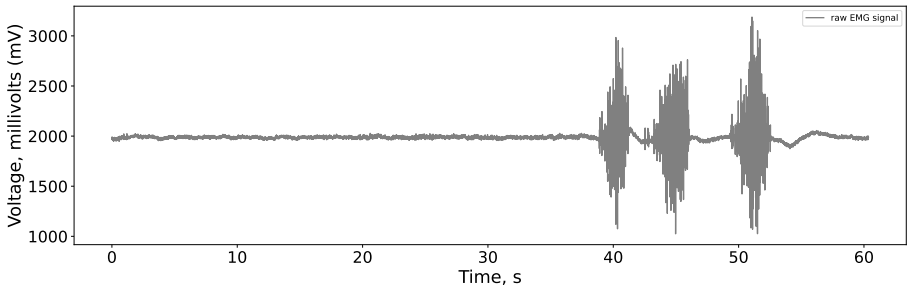

FIGURE 4.4: Sample from the Experimental dataset 3: a raw recording from the Triceps brachii muscle, before which electrodes were staying on skin for 34 hours.

For this dataset, data was again recorded using AD8232 and F-261 electrodes. These recordings were used for improvement of the onset detection algorithm, testing various methods for spectra limiting, checking whether the duration of electrode usage affects the detection results, comparing noisy incorrect data to correct EMG recordings, etc. Details:

- Sampling frequency: 1000 Hz
- Number of subjects: 1 (healthy, not target patient)
- Sensors: AD8232
- Electrodes: SkinTact F-261 ECG electrodes

- Muscles: Sternocleidomastoid, Triceps brachii
- Number of channels: 1
- Overall duration: 31.22 minutes (if counting muscles separately)

4.5 Experimental dataset 4

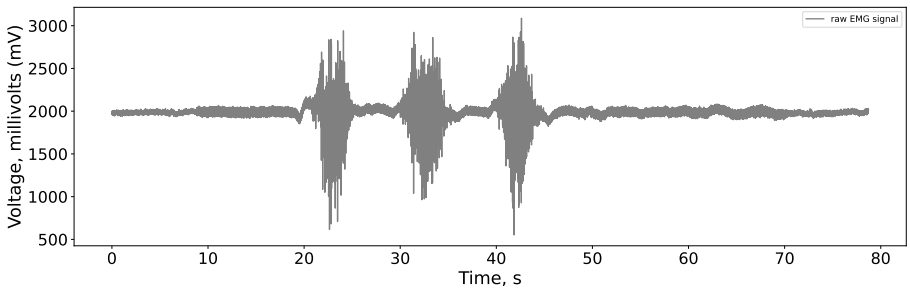

FIGURE 4.5: Sample from the Experimental dataset 4: a raw recording from the Sternocleidomastoid muscle.

This dataset was also recorded with sensors intended for the orthotic device itself. This time it involved new subjects, so it was used to test the customization of the algorithm and its robustness, and during the development of the automatic parameter tuning. Details:

- Sampling frequency: 1000 Hz
- Number of subjects: 8 (healthy, not target patients)
- Sensors: AD8232
- Electrodes: SkinTact F-261 ECG electrodes
- Muscles: Sternocleidomastoid, Triceps brachii
- Number of channels: 1
- Overall duration: 32.01 minutes (if counting muscles separately)

During development, we simulated real-time EMG recording flow in the software to make sure that the algorithms would be later successfully used in the orthotic device without additional modifications. As mentioned before, more observations from the datasets will be discussed in the Experiments section in greater detail.

Chapter 5

Proposed approach

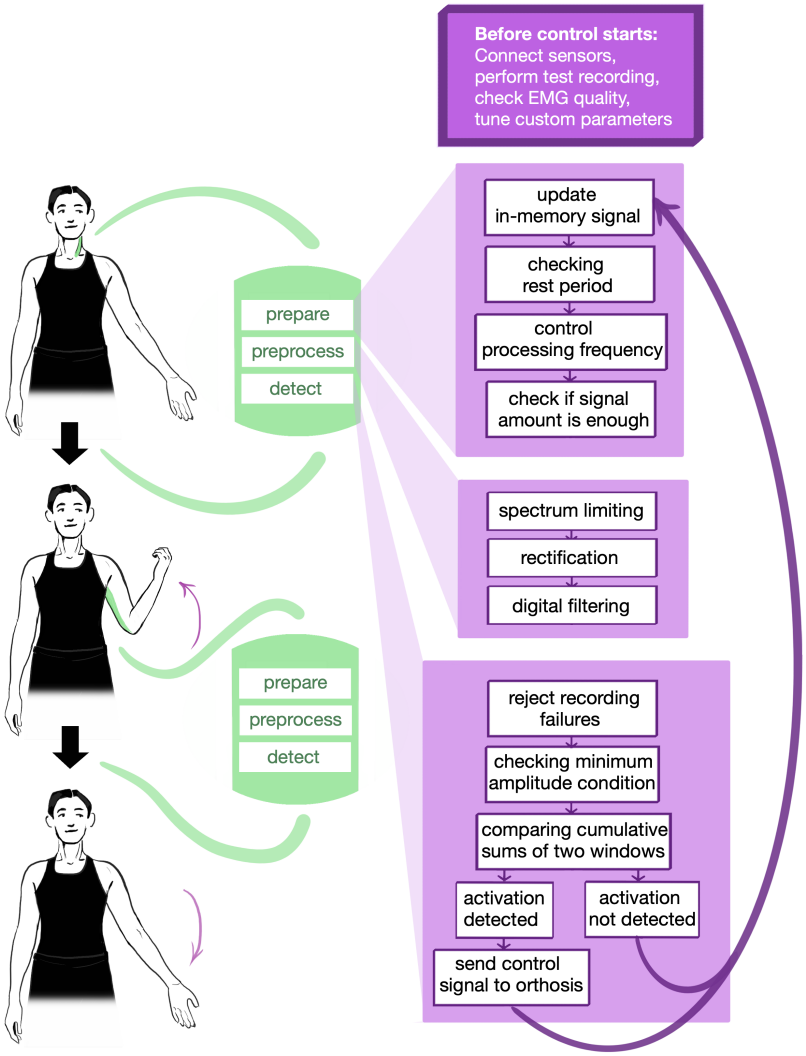

FIGURE 5.1: Overview of the pipeline of our approach.

In this chapter, we will discuss our approach to myoelectric control of orthosis. A brief overview of the approach is the following:

1. Sensors setup:
   (a) Connect sEMG sensors to the Sternocleidomastoid muscle and the Triceps brachii muscle
   (b) Start recording the myoelectric signal and its transmission to the processing unit

2. First test recordings
3. Checking if test signals were recorded correctly
4. Tuning the algorithm's custom parameters based on the test recordings
5. Orthotic control starts
6. Real-time EMG signal processing:
   (a) Preparation for processing
   (b) Limiting the spectrum of the signal to the standard EMG spectrum
   (c) Rectification and digital filtering of a portion of the signal
   (d) Detection of target muscles activations (onsets) using cumulative sum algorithm
7. Sending the orthotic device appropriate signal on detected muscle activation
   (a) Prompting orthosis flexion on Sternocleidomastoid muscle contraction
   (b) Prompting orthosis extension on Triceps brachii muscle contraction

Now let's discuss the steps in more detail.

5.1 Choice of muscles for orthosis control

In our case, the orthosis is controlled by myoelectric signals, which are involved in the contraction of the Sternocleidomastoid muscle and the Triceps brachii muscle. Thus, sensors are connected to them.

We chose the Sternocleidomastoid for flexion control because it is one of the most superficial and prominent muscles in the neck, and it will not be complicated to attach electrodes to it. It is also easily activated by neck tension and leads to high EMG activity during that tension; thus, the control would be rather easy to learn. We considered other options for flexion control, for example, Orbicularis oculi muscle activation. However, considering that it is involved in eyelids movement and can be accidentally activated with facial expression, we opted for the Sternocleidomastoid.

At the same time, for extension control, we chose the muscle directly responsible for the extension at the elbow joint — Triceps brachii. The reason is that patients can control it, so it would be more intuitive during orthosis usage. Moreover, the orthosis is not meant to completely reproduce and replace the patient's elbow extension, but rather to react to it and stop blocking it by reducing resistance to the patient's movement.

Just like for the last datasets, we used AD8232 sensors (*Single-Lead, Heart Rate Monitor Front End*, 2020) and SkinTact F-261 ECG electrodes ("Skintact ECG electrodes", n.d.) to record EMG signals for orthotic control. Electrodes are connected to the muscles, discussed above. At the time of writing this thesis, the processing pipeline was not yet integrated into the orthotic device, so there will be no further details on the hardware setup.

5.2 First test recordings

Before the orthotic control starts, we take the first test EMG recordings from the user. Test recording with target activations includes the following:

1. Approximately 10-second rest period when the user does not perform any target movement. This will allow us to see the baseline of the EMG signal.
2. Three consecutive tensions of the Sternocleidomastoid muscle. The user is required to tense the side of the neck, which was chosen for orthotic control. Rest between tensions does not need to be too long: approximately 5 to 15 seconds.
3. Three consecutive tensions of the Triceps brachii muscle. The user is required to tense the Triceps of the upper limb, to which orthosis is connected. Likewise, rest between tensions is not required to be very long.

Next, we need approximately 30 seconds of non-target movements to ensure that our algorithm will not produce spontaneous activations later. This includes slow head and upper limb movements, standing, sitting, or other daily activities that are not supposed to affect the orthosis.

5.3 Checking EMG signal quality

Before proceeding with orthotic control, we need to check if the EMG signal is being recorded correctly (i,e., if the electrodes are appropriately connected to the user's skin, if they work properly, and if there are not too many external noises, etc). We need to ensure that everything works correctly because we do not want to allow any False Positives or False Negatives during detection. This might lead to spontaneous activation of the orthosis, which can cause harm and discomfort to the user.

At the time of writing this thesis, the signal quality is checked visually. Hence, the process requires a person who would be able to look at the test signals and determine if the activations are present and if there is not too much noise interference. In future work, we plan to automate that process by finding and using features and/or correlations in data among well-recorded cases and those affected by noises or incorrect electrode placement. This must be done automatically so the user can start up and use the orthosis independently.

5.4 Tuning parameters of the algorithm

Various parameters affect the algorithm. Two of them are **custom** for each user of the orthosis ("words in quotation marks" are names of according variables in the code):

1. **Threshold of the minimum relative difference between cumulative sums for onset detection** ("onset_relative_threshold"). During the detection of the target muscle activity, we compare cumulative sums of two windows of the EMG signal: the current/most recent window and the window before that. By comparison, here we mean calculating the relative difference. Then we check if this difference is greater than the threshold. If it is, we consider that the activity increase in the current window is greater than in the previous window enough to assume that a muscle activation has happened.

   This parameter is individual for different patients because EMG activity highly depends on various aspects, such as muscle mass, strength, age, various health conditions, and just individual muscle features. The same movement may produce different activity levels for different people relative to their EMG baseline and spontaneous activations. Moreover, different conditions affect EMG sensors and electrodes, thus affecting the recording of the signal: body and environment temperature, sweating, the thickness of skin and other tissues below

it, etc. To ensure that the algorithm works properly, we need to adjust this parameter for different orthosis users. Usually, during experiments, this parameter ranges from 1.5 to 4 for Sternocleidomastoid and from 1.5 to 2 for Triceps brachii.

2. **Minimum amplitude of the target muscle tension** ("minimum_aplitude_of_target_muscle_tension"). Even if the algorithm detects a muscle activity, if its (preprocessed) amplitude is smaller than this parameter, we ignore it to skip non-control movements. The reason is that our target muscles are involved not only during their tension but also in many other movements. This creates muscle activity, but its amplitude is usually smaller. So, by setting a minimum amplitude, we can weed out muscle crosstalk, spontaneous activations, etc.

   For the same reason as the previous parameter, this one is individual for different patients. Usually, during experiments, this parameter falls in a range from 0.15 to 0.3 millivolts for Sternocleidomastoid and from 0.05 to 0.2 millivolts for Triceps brachii.

To **tune** them, we use the test recordings (if, during the previous step, it was decided that the recording was performed correctly and includes EMG signal), we perform the following steps:

1. We use a method based on a **bisection**.

2. The method takes as input an EMG recording with target muscle activations and another recording without them.

   We try to achieve such parameters, which will lead to the correct number of detected activations in the first recording (usually 3 activations) and will not lead to any activations in the second recording (it contains just daily activities, which should not affect the orthosis).

3. During bisection, on each step, the method checks if, with current parameters, we get the correct number of activations for recordings. If the number of activations is too high, we randomly choose one of two parameters and make it stricter (bigger in our case). If the number of activations is too small, we make the chosen parameter less strict (smaller) and recursively call the method again.

4. If the method is unable to achieve perfect parameters (i.e., there are not all activations detected in the "target" recording, and simultaneously there are detections in the non-target recording — an overlap of parameters), it tries to minimize the False Positives because the spontaneous activations of the orthosis can be more harmful.

   The method warns the user that it could not achieve parameters that would fully separate target activations from non-target ones and that the user might need to tense muscles with greater strength to activate the orthosis.

5. In the end, if the method succeeds, it does not just return the parameters it got; it checks what was the minimum amplitude among detected activations and what was the minimum cumulative sum and returns them, slightly scaled (0.99 scale). This way, it additionally tries to minimize the False Positives in later recordings.

6. To ensure that the process of tuning parameters doesn't take too much time, the function which is used for detections is, in this case, simplified and not real-time.

Other parameters, which affect the algorithm the most, but remain **constant** (or are derived from constant values) for all users, are:

1. Sampling frequency ("frequency"). This is just the sampling frequency of EMG recordings. In most cases, it is 1000 Hz because the sensor we use for orthosis records with this frequency.

2. Rest period after a detected activation ("No_detection_window"). After we detect a target muscle activation and send the orthosis an appropriate control signal to either start flexion or extension, for some period of time, we do not expect to detect additional activations. During testing, this rest period was usually from 1.5 to 2 seconds (the current constant is 1.8 seconds). Another reason why we need a rest period is that muscle activity might have different durations. If it is more prolonged, we might detect the same activation a couple of times, sending control signals to the orthosis when the user does not intend it. It also decreases the load on the processing unit and increases the speed by skipping signal processing for some time.

   In visualizations, the rest period is shown in **yellow color**.

3. Amount of recording units, which are left unit rest period finishes ("no_detection_recordings_left"). When an activation is detected, this variable is set to a value equal to the rest period. With every incoming recording unit, this variable is decreased. This is just a helper variable that controls the rest period.

4. Size of a signal batch that we keep in the memory ("Signal_recording_window"). We do not keep all the signals that are received because the orthosis is intended for hours of usage, and the devices we use have limited memory. For now, we opted for keeping only the last 10 minutes of the EMG recording. This also makes the processing faster yet still allows us to keep some usage history.

5. Size of cumulative sum window ("loop_latency_ms"). This is the size of the sliding windows, which we use to calculate the cumulative sum during target muscle activation detection. Through experimenting, we settled for a 0.8-second window. The bigger the window, the more prominent the difference between target movement and some spontaneous muscle activations is. At the same time, a bigger window means that target movements will be detected with a bigger delay. So, this constant requires to be balanced.

6. The minimum amount of signal for proper processing ("minimum_signal_window_length"). This constant is derived from the previous one and equals doubled cumulative sum window + 1. This is because we have two sliding windows during activation detection, so we need to have at least as much signal to perform it.

7. Frequency of processing the signal ("processing_and_checking_frequency_s"). To increase processing speed and decrease time delay, we do not perform signal processing with every received EMG recording unit. We do it, for example, every 0.1 seconds.

8. And other helper parameters, which have less effect on the main algorithm's functionality.

Some of these parameters will be additionally discussed and put into the appropriate context in the following sections.

5.5 Real-time EMG signal processing pipeline

Our approach to real-time EMG signal assessment can be divided into three main steps: preparation, signal preprocessing, and target muscle activation detection.

5.5.1 Preparation for processing

After the orthosis starts to work, it continuously and in real-time receives and assesses the EMG signals recorded by AD8232 sensors. Firstly, let's look at its characteristics:

- Number of channels: 1 for each muscle (Sternocleidomastoid and Triceps brachii)
- Sampling frequency: 1000

As mentioned above, we use 1 channel per muscle. In our system, we aim to process two muscles simultaneously to control both flexion and extension of the orthosis.

When the EMG signal is received by our algorithm, before starting its processing, we perform preparations, which involve some of the aforementioned parameters:

1. We update the in-memory signal batch by adding a new recording unit and removing the last if the size of the in-memory signal exceeds the "signal_recording_window" parameter.
2. We check if the orthosis is currently not in the "rest period" by checking the "no_detection_recordings_left" parameter and updating it accordingly. If the orthosis is indeed in the "rest period" after the previous activation, we skip signal processing and detection for that recording unit.
3. If the orthosis is not in the "rest period," we use the "processing_and_checking_window" parameter to control the frequency of processing. This way, we do not process the signal for every received recording unit but only with some predefined frequency.
4. Lastly, using the "minimum_signal_window_length" parameter, we check if we have enough signal for proper processing.

If the signal passes all these steps, we proceed to the signal preprocessing step.

5.5.2 EMG signal preprocessing

On the signal preprocessing step, the received EMG signal passes through the following pipeline:

1. **Spectrum limiting.** EMG signals lie on a spectrum between 20 and 300 Hz, so to extract them and filter out noises and artifacts, which may lie beyond this spectrum, we use bandpass filtering of the input signal. To be precise, we use a low pass 5th order Butterworth filter at 20 – 300 Hz.

2. **Rectification.** It is a standard EMG processing step. The original signal, if recorded correctly, has a mean value of 0; thus, such characteristics cannot be used. To make full use of an EMG recording, it is rectified — all negative values are turned positive. In short — we calculate the absolute value of the signal.

3. **Digital filtering.** Considering that EMG recordings are usually affected by the noise of various sources (muscle cross-talk, noise from the recording device, artifacts of cable movement, etc.), before further usage, we need to compute the envelope of the signal. There are various methods for that task, including but not limited to Movag, RMS, and digital filtering. In our work, we use the latter. To be precise, we use a low pass 4th order Butterworth filter at 6 Hz, a similar filter was recommended in (Konrad, 2005).

Some additional details on the aspects of the signal preprocessing step:

1. The processing happens in real-time. In other words, we continuously receive new signal recordings and must act accordingly. This includes keeping in mind the speed of processing because we cannot allow accumulation of delay in our system, for that would mean that orthosis will not be correctly activated when needed. Considering that signals are not prepared beforehand, we do not have any prepared labels which could be used to assess processing and detection quality on the go. We also must wait before starting signal processing when the orthosis is just turned on because, for the first couple of seconds, we do not have enough signal to perform processing properly (i.e., we have windows "sliding" on the signal, so we must consider their length). This delay of control start is not a serious problem because we do not expect orthosis activations the moment it starts to work.

2. The signal processing is meant to be performed in the assistive device itself, which creates additional memory limitations. To limit memory consumption, for now, we decided to keep only the last 10 minutes of the recording. So, the processing of the signal is performed only on this signal segment. At the same time, method parameters do not take up a lot of memory, so we just store them in various variables.

3. Speaking about parameters, the method includes many parameters which affect end results (most of them are constants, while some are meant for custom changes from patient to patient). A significant part of them is time-related.

4. One such important parameter that affects processing speed is the processing frequency. More precisely, we do not process the signal and try to detect activations with every incoming recording (single number) because then we would have an accumulating delay between receiving a recording with target muscle activation and detecting it and controlling the orthosis. Instead, we do it every 0.1 seconds, which becomes our processing frequency.

After the signal is preprocessed, we proceed to the target muscle activation detection step.

5.5.3 Target muscle activation detection

Right after preprocessing a signal batch, we check if there are target muscle activations by detecting the onset of the EMG activity. Here is the pipeline:

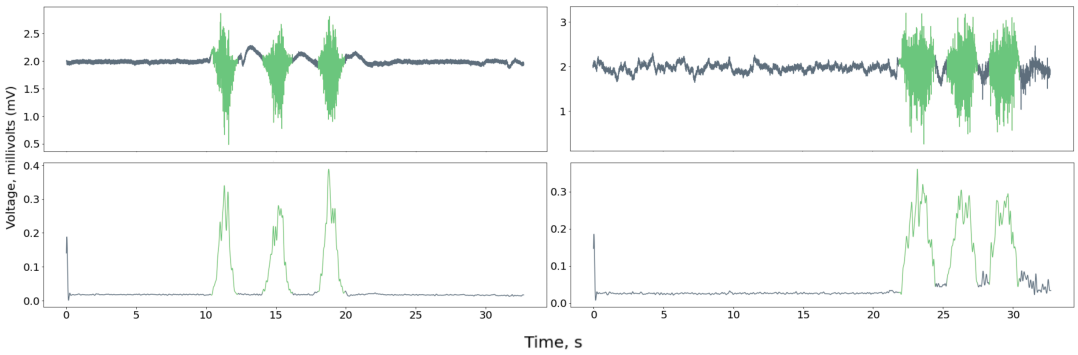

FIGURE 5.2: Examples of how an activation (in green color) of the target muscle, which the algorithm is meant to detect, looks for the Sternocleidomastoid muscle and for the Triceps brachii (unprocessed signal above, preprocessed signal below).

1. **Rejecting zero values.** Firstly, we discard from the signal any values from the $10e-4$ neighborhood around zero. These are most probably places where there were some recording failures because the baseline of the EMG signal is usually non-zero. Such zero recordings could generate False Positives during activation detection because the change between zero and baseline might be abrupt enough for detection.

2. **Checking if the amplitude meets the minimum threshold.** Next, we check if the current recording's amplitude is greater than a custom minimum threshold ("minimum_aplitude" parameter). We reject activation if it is smaller — this way, we can additionally weed out some of the other movements which might affect (i.e., crosstalk) or involve the muscle in question but are not meant to affect the orthosis.

3. **Calculating cumulative sums of two windows.** We take the current window of the signal (i.e., the last 0.8 of the recording in our case) and the same-sized window which came before that. Windows do not overlap. For each of them, we calculate the cumulative sum. From each cumulative sum, we subtract its minimum value — this way, during comparison, the amplitude would not matter as much as the speed with which the activity of the signal increases.

4. **Comparing these two cumulative sums.** It is a relative comparison, not an absolute one. We divide the last value of the cumulative sum of the current window by the last value of the cumulative sum of the window before that.

   (a) If the relative difference is greater than the custom threshold ("onset_relative_threshold" parameter), we consider that **an activation happened**. We send the orthotic device an appropriate message about detected activation, prompting its flexion/extension.

   (b) Otherwise, we consider that **an activation did not happen** and return to the start of the pipeline, waiting for incoming recordings.

Some additional details on the aspects of the target muscle activation detection step: As mentioned in the descriptions of the parameters, this detection is highly dependent on customization. There must be **an individual approach to different patients** because even people with seemingly similar healthy target muscles may

have very different EMG signal amplitudes or activity rates during muscle activations. Various circumstances affect both the EMG signal itself and the sensors that record it: level of physical fitness, speed of fatigue increase, body and environment temperature, sweating, skin thickness, the thickness of tissues under the skin, etc. The muscle activity itself is not reproducible. Due to the random nature of EMG spikes and the fact that it is impossible to repeat a movement with absolutely the same speed and power as before, we will still have a variety in muscle activations, even after the preprocessing step. This is why we were trying to achieve a rather robust algorithm with an as little amount of custom parameters as possible. There are also benefits of EMG signal variability: in future work, it can be used to create a more adaptive orthosis control (i.e., the intensity of activation might affect the degree of flexion, etc.).

For the proof-of-concept for our approach, we will have two algorithms (one with parameters for Sternocleidomastoid muscle and one for Triceps brachii muscle) running independently to detect activations. The orthosis itself just waits to receive a control signal from one of them to start flexion or extension of the elbow.

After activation is detected, the algorithm returns to the processing of new incoming EMG recordings after waiting for some "rest period." This completes the cycle of decoding the EMG signal into the orthosis control signal.

Chapter 6

Experiments

In this chapter, we will describe the most significant experiments conducted during algorithm development and testing.

6.1 Experiments on prerecorded signals

In this subsection, we will discuss experiments that were conducted on signals from the datasets described in previous sections (Tentative, Experimental 1, Experimental 2, etc). This way, the signals were prerecorded, so the experiments were conducted afterward, not during recording sessions.

The task, that these experiments were meant to solve, was development of an algorithm for processing EMG signals and detecting target muscle activations in them in real-time setting. To control an orthotic device we need to simultaneously monitor EMG signal which we receive from the Sternocleidomastoid muscle (to prompt flexion of the orthosis) and from the Triceps brachii muscle (to prompt extension of the orthosis). This way, in real-time we need to decode EMG signal into orthosis control signal by detecting onsets, which occur during tension of the muscles that were chosen beforehand. We aimed to detect such control onsets (examples of how they look are shown in figure 5.2 in the previous section) with the lowest possible sampling frequency of the signal, because it gives benefits in terms of the processing speed and memory, minimises delays and reduces the cost of required hardware.

The experiments are described **from the latest to the newest**, so You might notice gradual improvements of the algorithm as the descriptions progress toward the final date. The entries include: Date, Title, Hypothesis, Background, Results and Observations, and Summary.

6.1.1 Choosing an algorithm for onset detection (amplitude threshold vs. cumulative sum with static/dynamic comparison).

21 Sep – 19 Oct 2022

Hypothesis: as our first approach was based solely on amplitude threshold, we wanted to make the algorithm more robust by introducing cumulative sum to the target muscle activation detection step.

Background: the first approach we used could be considered a quantitative amplitude analysis. First, the EMG signal was preprocessed, and then the activations were detected by checking if the amplitude of the signal was greater than some predefined threshold. This can potentially lead to various mistakes in detection. For example, it can lead to False Positives in case some artifacts or spontaneous activation were not completely filtered out during the preprocessing step and have an amplitude that resembles the one of a target muscle activation. It might also lead to False Negatives in case the threshold was overestimated, and target movements

performed by the user of orthosis might produce EMG activity with less amplitude. Also, over time there can be some changes in a signal, which will change the amplitude but not the relative difference between the baseline and the muscle activation.

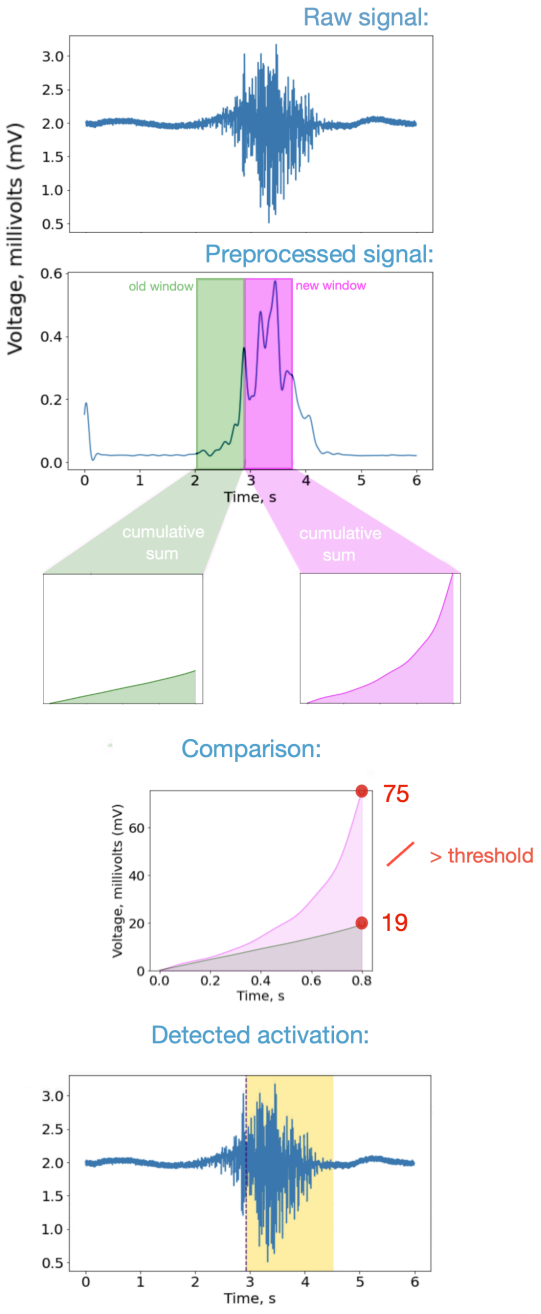

FIGURE 6.1: Example of the algorithm using cumulative sum. Shown on a sample (from Sternocleidomastoid muscle) from a recording from the Experimental dataset 4.

We decided to try an approach that uses the cumulative sum of a portion of the signal. Essentially, as we assess an EMG signal, we take the latest recordings from it (some window with a predefined size) and calculate its cumulative sum (afterward, we subtract the first smallest value to make sure that the result is not affected by the amplitude with which the window starts). Then we take the last (so the biggest) value of this cumulative sum and compare it:

1. with a predefined cumulative sum of a baseline noise. This is a static approach to comparison, because we have a static value with which we compare the cumulative sum of the current window.

2. with the cumulative sum of a window of the same size that came right before the last one (so we have two sliding windows, as shown in figure 6.1 at page 29)

As we compare two cumulative sums, we compare the speed with which EMG activity increases in these windows. Comparison is relative, and so is the threshold parameter for it (i.e., for one user, we expect that target muscle activity will increase twice as fast as, for example, just some baseline noises or muscle cross-talk; while for another user, it might be not two but three times faster, etc).

Results and Observations: as we tried cumulative sum algorithms, we could see that they worked well for recordings from the Tentative dataset, and considering that this comparison was relative and not absolute (like in the amplitude threshold approach), the algorithm became more robust in a sense that it was both easier to choose

a parameter for comparison (this parameter for cumulative sums has smaller deviations among different subjects than the parameter of threshold amplitude) and that speed of activity increase played a bigger role in detection than just amplitude.

Between the two approaches to using cumulative sum, we opted for the one with dynamic comparison. It made the algorithm more robust in the sense that we do not need to keep an additional parameter with the cumulative sum of an EMG recording's baseline (which is individual for different patients and would make parameter tuning more complicated). Also, this way, activations depend more on a local context, so if the baseline noise increases or decreases over time, it would not matter for the activation detection, as it would compare only the latest window of the signal with a window right before that.

Summary: we decided to use a cumulative sum algorithm with dynamic comparison (two sliding windows).

6.1.2 Limiting of the frequency spectrum and reducing sampling frequency of the signals from first datasets.

25 Oct 2022

Hypothesis: we expect that limiting the frequency spectrum to a 20-300 Hz range and reducing its sampling frequency to 1000 Hz will require parameter tuning for the algorithm, but at the same time, it might make processing much faster.

Background: Regarding the EMG spectrum, the standard spectrum of myoelectric signals is from 20 to 300 Hz, so in the first stages of the algorithm development, we needed to make sure that the algorithm would work for signals on such a spectrum. The same goes for the sampling frequency: usually, it is approximately 1000 Hz, but the first two datasets were recorded in the RNI with a 20000 Hz sampling frequency. This is quite a big difference and might affect the parameters or the algorithm development itself.

Results and Observations: both limiting the frequency spectrum and reducing sampling frequency did not affect the algorithm's quality. Both processing and target muscle activation detection went as expected. It indeed made the algorithm faster because the signal sample became 20 times shorter.

Additionally, we tried even smaller sampling frequencies. The algorithm works as intended starting from 700-750 Hz and higher. In general, such changes required some parameter tuning, but detection results continued to be reproducible.

Summary: the developed algorithm works well for the expected signal spectrum and sampling frequency.

6.1.3 Rejecting recording failures during EMG onset detection using cumulative sum.

10 Nov 2022

Hypothesis: if we do not include failed recordings in cumulative sum windows, the algorithm will not react to them and will not produce False Positives.

Background: during exploration and testing of the data from the Tentative dataset, we discovered that sometimes there were recording failures on the signal (small regions where amplitude was close to zero the whole time). The algorithm with cumulative sum reacted to abrupt change between such failure regions and the baseline noise and considered them as target muscle activations.

Results and Observations: before comparing two cumulative sum windows, we excluded all the recordings close to zero (we chose $10e{-}4$ neighborhood, smaller

ones were not enough). As shown in the figure 6.2 at page 31, this helped to get rid of a False Positive detection, and all target muscle activations were detected correctly.

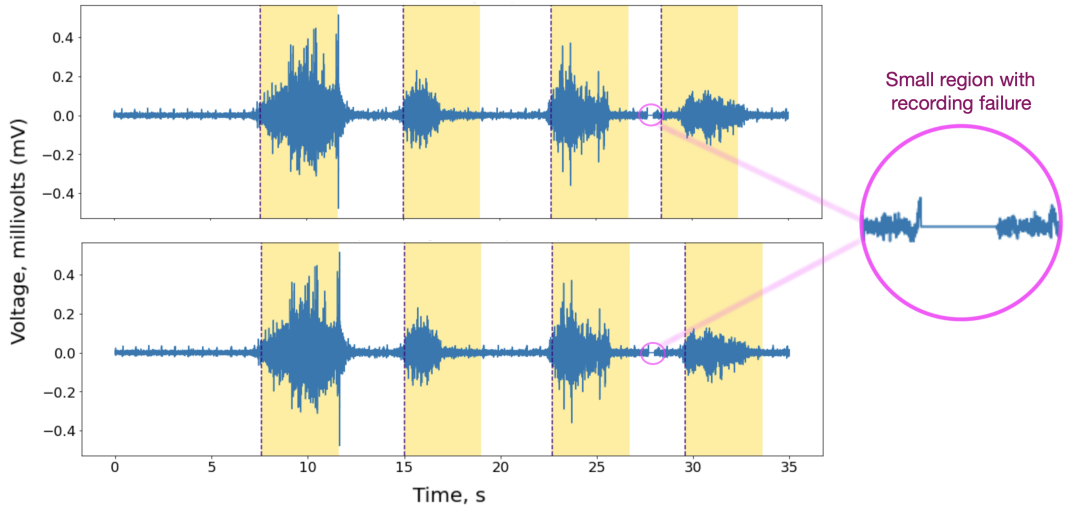

FIGURE 6.2: Comparison of target muscle activation detection before and after excluding signal recording failures.

Summary: excluding recording failures helps to get rid of False Positive detections.

6.1.4 Reducing ECG artifacts with EMG spectrum limiting.

3 Feb 2023

Hypothesis: considering that ECG artifacts are also produced by the electrical activity of muscles, but only of the cardiac ones, we do not expect that limiting signal spectrum to standard EMG spectrum will fully filter out such artifacts, but we hope that at least they might be reduced.

Background: on a data exploration step of the Experimental dataset 1, we noticed prominent pulsations of the carotid artery in the signal from the Sternocleidomastoid muscle. This was expected, as the artery and cardiac muscles are situated in proximity to the Sternocleidomastoid muscle. Pulsations did not seem to be prominent enough to affect the target muscle activation detection algorithm. Still, they might be bigger in other recordings and might make parameter tuning more complicated. In the worst-case scenario, they might lead to False Positive detections.

Results and Observations: we tried limiting the spectrum of the signal to the standard one for EMG (20 – 300 Hz) and, at the same time, changing the sampling frequency from 20000 to 1000 Hz (this sampling frequency is often used in sensors).

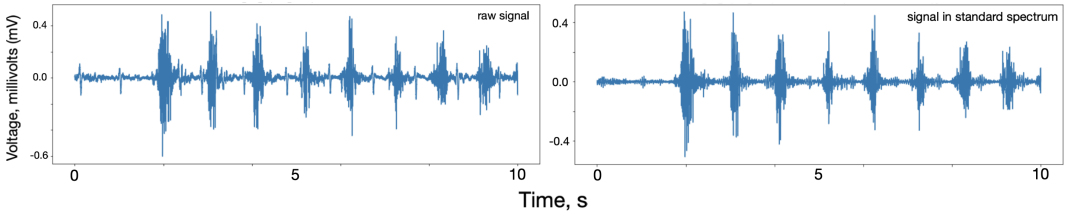

FIGURE 6.3: Reduction of ECG artifacts (pulsations of the carotid artery).

This noticeably reduced amplitude of pulsations of the carotid artery (figure 6.3 at page 31).

Summary: limiting signal spectrum to standard EMG spectrum indeed reduces ECG artifacts, even though not completely, yet this shows another benefit of including a spectrum limiting step to our preprocessing pipeline.

6.1.5 Testing how well the algorithm works for (very) fast target movement repetitions.

3 – 6 Feb 2023

Hypothesis: we do not expect this algorithm to work very well for too fast repetitions of target muscle activity.

Background: the algorithm incorporates a rest period, so the movements which repeat earlier than the rest period ends might not be properly detected. Additionally, very fast movements might cause EMG activities to merge, so it will be harder to differentiate between different movements. Also, the overall amplitude of EMG might decrease because it will be harder to produce powerful movement in very short periods of time.

Results and Observations: to express the speed of movement, we use the "beats-per-minute" (bpm) of a metronome. Subjects performed target movement with every beat of the metronome. For this experiment, recordings from Experimental dataset 1 were used. Observations for Sternocleidomastoid:

- At 60 bpm, all the activations were detected correctly.
- At 100 and 150 bpm, there were a lot of False Negative detections.

Observations for Triceps brachii:

- At 12, 20, and 24 bpm, all the activations were detected correctly.
- At 60 bpm for one subject, all the activations were detected correctly, while the other had some False Negatives.

Summary: the algorithm works well for fast detections, but it fails on very fast repetitions, especially if the same custom parameters are used. We do not expect the orthosis to be flexed, extended, and flexed again in such short periods of time, so the speed that can be well detected with the current algorithm is completely acceptable.

6.1.6 Designing plans for experimental EMG recordings and the test recording before orthotic control.

3 Feb – 17 Mar 2023

Hypothesis: we expect that the experimental recording and the test recording will include target and non-target movements to ensure that our algorithm works.

Background: for general experiments and development of the pipeline and the algorithm, we need various recordings: target and non-target movements, movements of different durations and repetition speeds, different intensities, etc. We also expect that the test recording will be relatively short, so the users will be able to use the orthotic device very soon after it. This test recording should be performed after the user connects to the orthosis and before we check the quality of the EMG recording and tune custom parameters.

Results and Observations: one of the important observations, which is mentioned in the description of the Experimental dataset 1 and some other experiments,

is the need to tense target muscles more than for usual daily movements. As mentioned before, even though we use target muscles that produce some movements, such as head rotation for the Sternocleidomastoid, we do not need the movement itself to happen for the orthotic control — we need only the tension of the muscle. Users can train to do this by trying to rotate head against some resistance (i.e., by holding the palm of the hand against the head in the direction of the rotation). Still, this tension should be enough to differentiate between target and non-target activations. For example, even though the left Sternocleidomastoid muscle is responsible for head rotation in the right direction, for one subject from the Experimental dataset 1, it produced high EMG activity even for the rotations to the left. This way, an intersection of parameters happened, and we either had to sacrifice some target activations (leading to False Negative detections), or we had to allow non-target activations (leading to False Positives). This way, we found that target tension should be at least slightly more intense than an average movement of the user.

Experimental datasets included such recordings:

1. Target muscle activations with different intensities. We checked how our algorithm works for stronger and weaker movements.

2. Target muscle activations at different speeds. The first objective was to test how well the algorithm performs when there are a lot of muscle activations in a row, and the second was to see if the intensity of activations will decrease due to fatigue or other factors. To control the speed of movements, subjects performed them with metronome assistance. Results for assessing the recordings with fast movements are described in another experiment.

3. Daily movements that are not supposed to affect the orthosis. For example, sitting, standing, walking, slow head rotations, turning the head up and down, resting mostly without any movements, etc. We used these recordings to make sure that the algorithm does not detect anything in them and does not produce False Positives.

4. Additionally, recordings with different electrode placements, different prior duration of electrodes staying on the skin, unsticking and falling off electrodes, recordings affected by electrical appliances near the sensors, etc. Such recordings were used to find out how different problems might affect EMG signals and to check how we can differentiate between correct and incorrect recordings.

The test recording, performed before the orthotic control, should include at least the following:

1. Small period of rest. This way, we can assess the baseline noise of the EMG recording and ensure that there are not too many artifacts (i.e., from ECG) and/or that they are successfully filtered out during the signal preprocessing step.

2. Sternocleidomastoid tensions (i.e., at least three). To make sure that recording is performed correctly and to tune parameters, we need the user to perform a predefined amount of the Sternocleidomastoid muscle tension repetitions. That muscle tension should resemble the one that the user is gonna perform when activating flexion of the orthosis. So it should be intense enough to differentiate between it and daily activities, and, at the same time, it should not

be too intense to make sure that it will be easy to perform and will not tire out the user.

3. Triceps brachii tensions (i.e., at least three). Same details as for the Sternocleidomastoid muscle, but for a situation when the user would like to perform orthosis extension.

Summary: we tried to include different scenarios to ensure diverse testing of the algorithm and, at the same time to make test recording relatively short but informative (for the algorithm).

6.1.7 Adding minimum amplitude of the target movement to weed out more unwanted movements.

8 Feb 2023

Hypothesis: setting a minimum amplitude of the target movement might help our algorithm to ignore muscle activity caused by non-target movement (i.e., during crosstalk).

Background: in some cases, during cumulative sum comparisons, we might detect some artifacts, unfiltered noises, or non-target movement (which still affect the muscle of interest), and usually, they have smaller amplitudes than target muscle activity. To weed them out, we decided to add a custom parameter, which sets the minimum amplitude of a processed signal during detection. It is custom because, in our datasets, we observed that in some cases, non-target movements have significantly smaller amplitudes than target ones, while in other cases, their amplitudes can get close. Examples of such signals were found in Experimental dataset 1, where for one of the subjects, the activity of the left Sternocleidomastoid muscle was almost the same during both rotations to the left and the right (while theoretically, the left Sternocleidomastoid is mostly responsible for rotations to the right). Another example is shown in figure 6.4 at page 34.

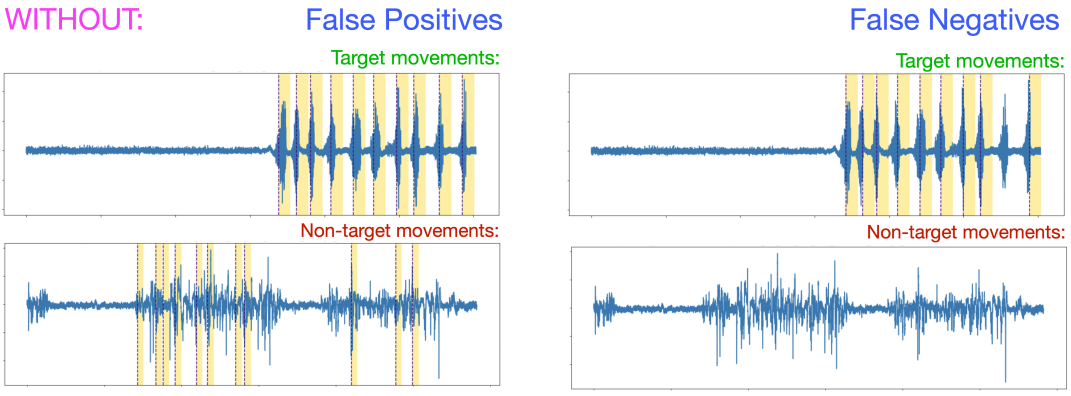

FIGURE 6.4: Example of detection without adding a minimum amplitude of the target movement parameter to the algorithm (a sample from Experimental dataset 3). We either allow False Positives or False Negatives, and even after tuning, we cannot get rid of both.

Results and Observations: during testing on recordings from the experimental datasets, an additional minimum amplitude parameter improved results and allowed us to decrease the parameter of the relative difference of cumulative sums, which previously led to False Positives. This way, we could mostly get rid of this

trade-off between False Negatives and False Positives because the minimum amplitude parameter filtered out the latter (figure 6.5 at page 35).

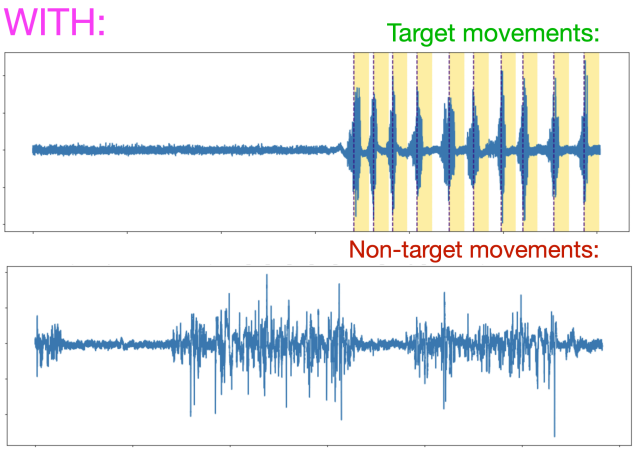

FIGURE 6.5: Example of detection with adding a minimum amplitude of the target movement parameter to the algorithm (a sample from Experimental dataset 3).

Summary: as this custom parameter was shown to improve the quality of the detection algorithm, we decided to use it.

6.1.8 Setting a minimum limit for the rest period.

8 – 20 Feb 2023

Hypothesis: to reduce repeated detections of the same movement, we need to set a rest period, and we expect that the rest period should be at least the size of one window of cumulative sum calculation.

Background: to make sure that we do not have multiple detections of the same target movement (i.e., detecting one Sternocleidomastoid tension two or three times), we have a rest period, during which we do not perform signal processing and target muscle activity detection. Sometimes this rest period is too small, and repeated detections still occur. This is why we need to set a minimum limit for it, and we will start testing from the size of one window of cumulative sum calculation. The rest period should depend on the window for cumulative sum because the detection happens through a comparison of two cumulative sums on such windows. When a target activation is detected, it means that activity in the latest window was significantly higher than in the previous window. If we wait for one window afterward, a comparison will happen between a newer period and the window which already had a high activity last time, so this might be used as a minimum limit for the rest period. However, it needs further testing on real signals.

Results and Observations: during this experiment, we first tested it with the algorithm that had a 0.4-second window for cumulative sum and later on the improved algorithm with a 0.8-second window (this is the one that You can see on the visualizations and which was used for results described in the experiment). We tried different rest periods (visualizations shown in figure 6.6 at page 36):

- 0.5*window. Just in case, we tested a rest period, smaller than one window. Predictably, there were numerous repeated detections.
- 1*window. There were still repeated detections for a rest period of one window size. It seems that there were still significant changes between windows.

- 2*window. Starting from the double-window size, there were no repeated recordings. This way, windows that took part in cumulative sum comparisons that resulted in the detection do not intersect with windows during the following detections.
- 2.5*window. Just in case, we checked an even bigger rest period. There were no repeated detections, just like for double-window size.

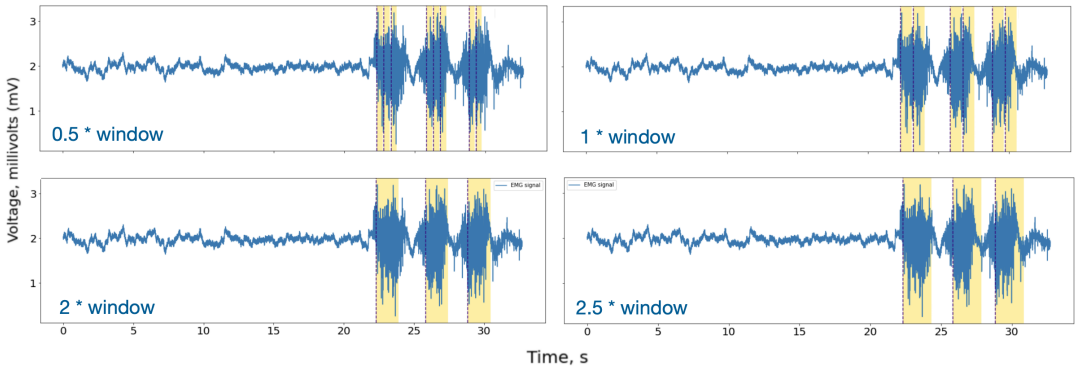

FIGURE 6.6: Comparison of different sizes of rest period relative to the window for cumulative sum calculation (on a signal sample from Sternocleidomastoid muscle from Experimental dataset 4).

Summary: as a minimum limit for the rest period, we chose a double size of the cumulative sum detection window.

6.1.9 Checking how different placements of the reference electrode, problems with electrodes, and computer power cable noise affect the EMG recording.

15 Feb – 20 Mar 2023

Hypothesis: we expect to be able to see the effects of incorrect reference electrode placement, problems with electrodes, and contamination with computer power cable noise visually and also on the signal spectrum, which might later be used to automatically detect such problems and warn the orthosis user about them.

Background: as we previously observed from recordings from Experimental datasets 2 and 3, incorrect placement of the reference electrode, unsticking and falling off electrodes, as well as noise from such appliances as a power cable, affect EMG recordings in different severity. Such problems with the EMG recording might cause False Positive and False Negative target muscle activation detection during the usage of the orthosis. We need to explore the characteristics of such signals and, for example, their frequency spectrums, so we can later use this information to develop some tools or functions which will automatically detect these problems and alert the user of an orthotic device about it (i.e., after the placement, one of the electrodes started unsticking from the Triceps brachii muscle area, but the user did not notice it, etc).

Results and Observations: here we will have a list of findings from the experiment:

1. One of the main observations during this experiment was that even when the signals seem to be contaminated by noise (not as severe as noise from the

power cable), extracting and using only recordings which fall into the standard EMG spectrum at the preprocessing step helps to get rid of most of the noise and leave EMG signal of good quality. So, at this point, we decided to keep this standard EMG spectrum extraction in the preprocessing step of the pipeline.

2. The best results were produced when the reference electrode was near the muscle, from which we needed to record activity, yet it was in a place that was not as much affected by target motions. The examples of how different reference electrode placements affect EMG signal recording can be seen in figure 6.7 at page 37.

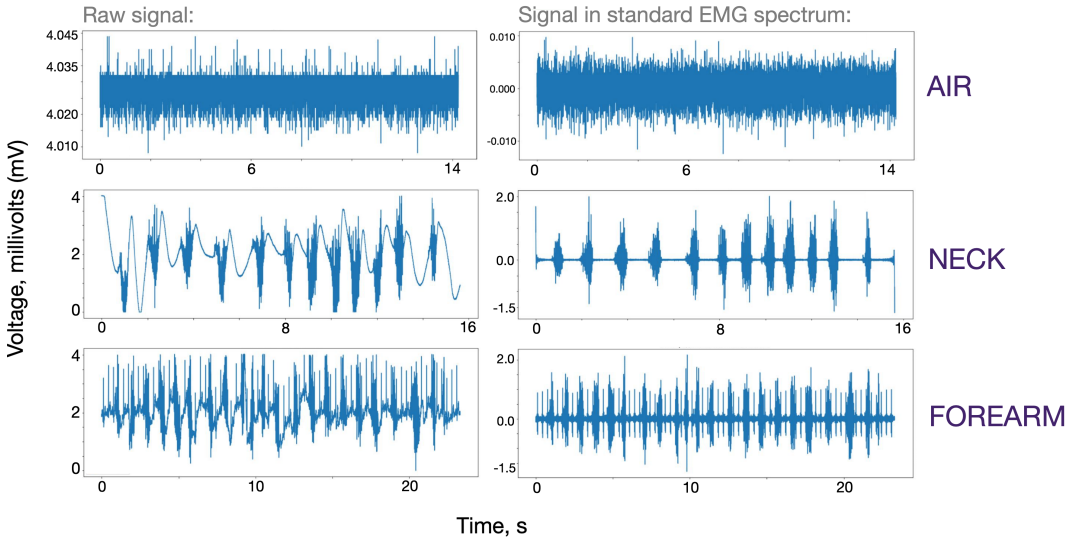

FIGURE 6.7: Comparison of effects of different reference electrode placements when recording signal from the Sternocleidomastoid muscle (raw signals above and signals in standard EMG spectrum below, samples from the Experimental dataset 2).

3. We noticed that ECG artifacts sometimes appeared on recordings from the Triceps brachii, too. They had very small amplitudes and did not intervene with the algorithm.

4. Noise from the computer power cable had very significant effects on EMG recording quality. Signals affected by that noise could not be used for target muscle activity detection even after extracting standard EMG spectrum and preprocessing in general (figure 6.8 at page 38). This noise appeared because, during recordings, the sensor was in proximity to the computer that was connected to the power cable. For proper EMG recordings, sensors should be isolated from devices connected to 220V.

5. Using EMG signals from the Experimental dataset 3, we compared their spectrums (figure 6.9 at page 38). Before comparison, we extracted standard EMG spectrums so that we could compare on a limited range of frequencies. As we observed, unsticking and falling off electrodes produced a spectrum very close to the correct one but with mostly slightly bigger amplitudes. At the same time, noise from the power cable led to a spectrum much different from the correct one and with much higher amplitudes. However, each recording,

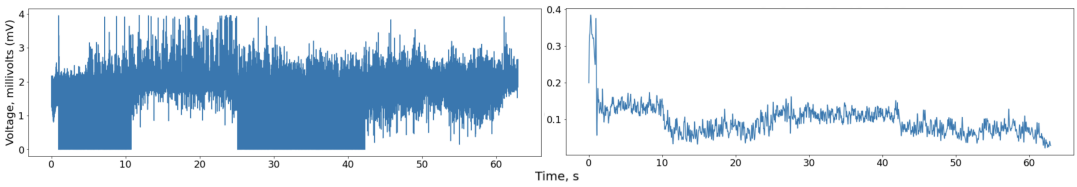

FIGURE 6.8: EMG recording that was affected by noise from the computer power cable (raw recording to the left, recording in the standard EMG spectrum to the right). This recording was supposed to have target muscle activity, but it is not present even after standard spectrum extraction.

even for the same subject, had very noticeable variations in the amplitude of spectra, which led to intersections between correct and incorrect recordings in that regard, so using only amplitude analysis might not be enough to detect problems with EMG recordings.

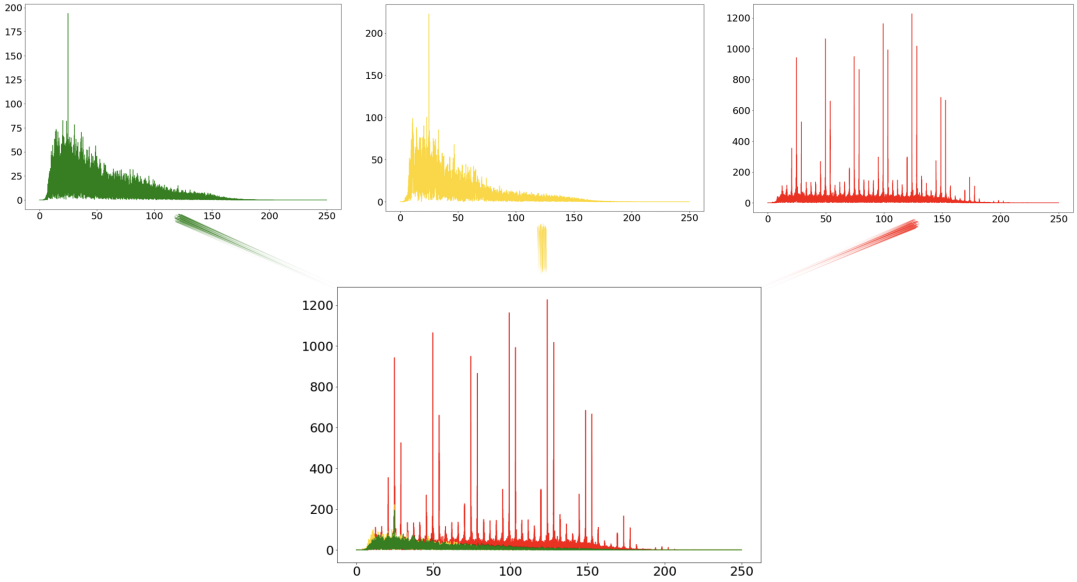

FIGURE 6.9: Comparison of frequency spectra of a couple of samples from Sternocleidomastoid of (1) properly recorded EMG, (2) signal recorded with unsticking electrodes, and (3) signal contaminated with noise from the power cable. All of them were limited to the range of the standard EMG spectrum before visualization.

6. Additionally, we extracted and compared various features of such signals using a correlations heatmap (figure 6.10 at page 39). We tried to find some features that correlated the most with EMG recording problems. List of features for consideration and partially code for computing them was taken from (Gambera, 2021).

   We compared different muscles separately. For Sternocleidomastoid, the most correlations were between noise from the power cable and maximum and peak (absolute maximum) values of the signal. For Triceps, the most correlations were also for noise from the power cable. It correlated the most with kurtosis and kurtosis in the frequency domain (after FFT).

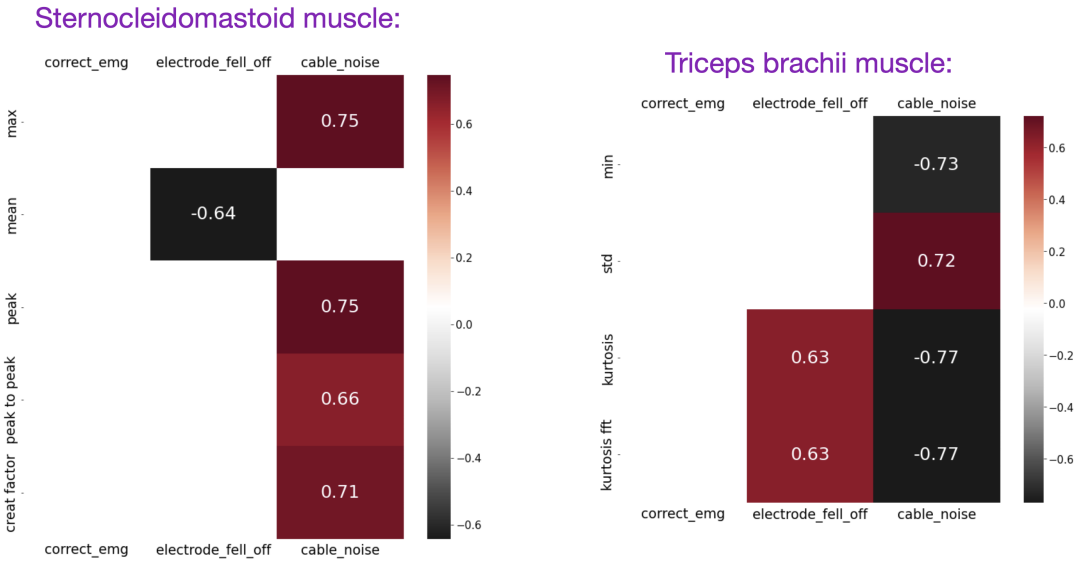

FIGURE 6.10: Correlations of features of the signals. Only shown correlations more than 0.6 in absolute values.

It should be noted that the Experimental dataset 3 is relatively small and includes only 15.6 minutes of recordings from the Sternocleidomastoid and 15.6 from the Triceps brachii, so the correlations might not be representative enough.

Summary: we observed that extracting the standard EMG spectrum is a significant part of the preprocessing step. We also chose the most advantageous reference electrode placement and compared correct and incorrect EMG recordings.

6.1.10 Checking whether the duration of electrodes contact with skin affects the results of processing and detection.

15 – 17 Mar 2023

Hypothesis: we expect that after staying on the skin for some long periods of time, electrodes will not produce proper EMG recordings.

Background: considering that the orthosis is continuously controlled by EMG signals and that users would want to use the orthosis in daily life and not only for small durations of time, we need to check how much the electrodes will be affected from staying on skin for long durations of time. They might start unsticking or falling off, and they might produce EMG with more noise or just of less quality if the gel starts to dry or if the body sweat affects them, etc.

Results and Observations: here are the observations from recordings, which were made with electrodes that stayed on the skin for different durations of time (in a row):

- Fresh, 1 and 12 hours (figure 6.11 at page 40). Electrodes, which were freshly attached to the skin, or stayed on it for 1 – 12 hours prior to the recording session, produced recordings of high quality, on which the processing and target muscle activation detection algorithms worked well.

- 24 hours. Recordings from the Sternocleidomastoid muscle were noticeably affected but still contained enough information for target muscle activation detection. Recordings from Triceps seemed to be unaffected.

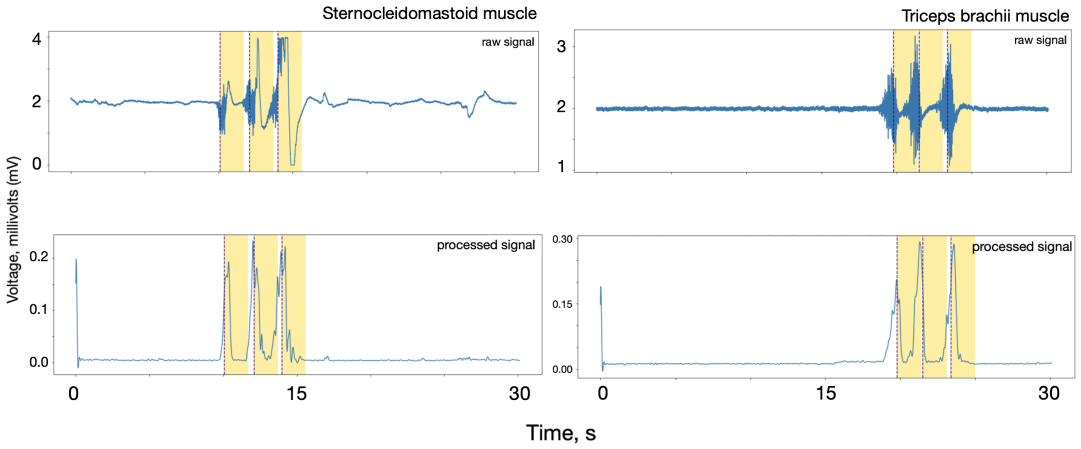

FIGURE 6.11: Samples of recordings with electrodes that stayed on the skin 24 hours prior to the recording session. Slightly affected recording from the Sternocleidomastoid to the left and proper recording from the Triceps brachii to the right. Upper visualizations are of raw recordings, while lower are preprocessed.

- 34 hours (figure 6.12 at page 40). After staying on the skin for 34 hours in a row, some electrodes started to unstick (this led to the appearance of False Positives when using the same parameters that worked well previously) from the Sternocleidomastoid muscle and eventually started falling off (which resulted in no detections at all and EMG activity stopped being noticeable in the signal). On the other hand, there were no such problems with Triceps. Recordings from it continued to be properly processed using the same parameters as before.

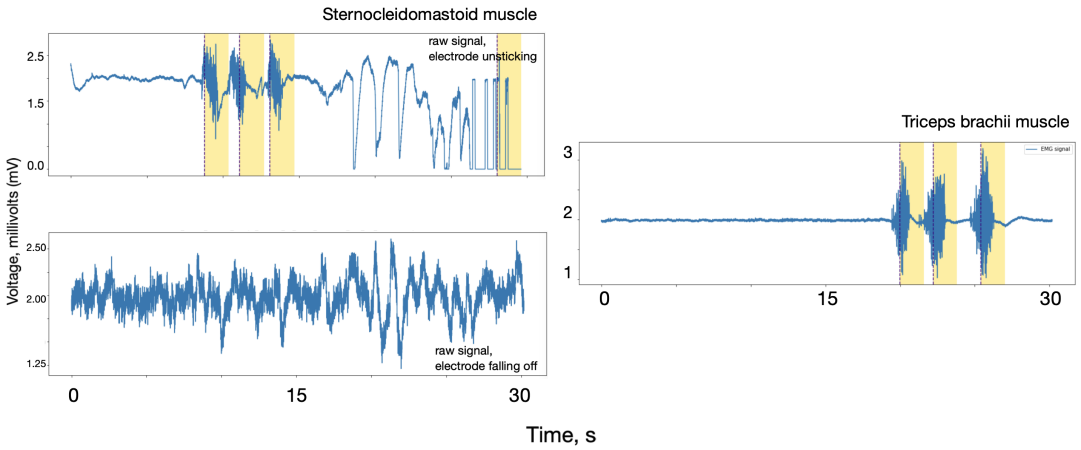

FIGURE 6.12: Samples of recordings with electrodes that stayed on the skin 34 hours prior to the recording session. Unsticking and falling of electrodes from the Sternocleidomastoid to the left, and again proper recording from the Triceps brachii to the right.

These signals are from the Experimental dataset 3.

Summary: in some cases, prolonged electrode usage might lead to such problems as them unsticking or even falling off, so they should be well-fixed on the users' skin and renewed after some periods of time.

6.1.11 Choosing methods of limiting signal spectrum (fixing false positives occurrences due to filtering artifacts)

17 Mar 23

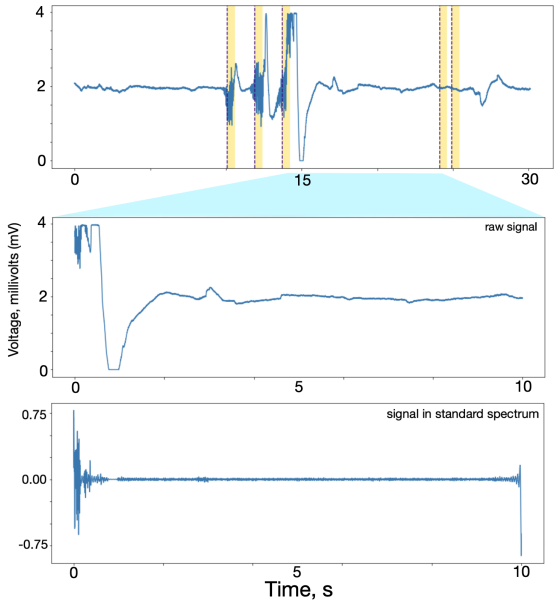

FIGURE 6.13: False positive occurrences in an EMG recording from Sternocleidomastoid. Below is the interval before the False Positive raw and after the spectrum limiting step using RFFT.

Hypothesis: replacing RFFT in the spectrum limiting function by FFT or a bandpass filter might help to get rid of False Positives in the signal, which were caused by filtering artifacts.

Background: during testing EMG signals from Sternocleidomastoid (Experimental dataset 3), which were recorded using electrodes that stayed on the skin 24 hours before the recording session, there occurred a couple of False Positive detections seemingly without causes in the signal. As we do not want spontaneous activations of the orthosis, we need to get rid of False Positives.

Results and Observations: when observing the signal on different stages of preprocessing on the interval right before False Positive detections showed that after the spectrum limiting step, there appeared peaks on the ends of the interval (figure 6.13 at page 41). It seems that these are filtering artifacts. They caused cumulative sum growth in these regions, so it was decided to either modify or replace the spectrum limiting function.

The method that we used there for spectrum limiting involved RFFT. We compute the RFFT of the signal and Discrete Fourier Transform sample frequencies and filter out recording units, which on the spectrum are beyond the standard EMG spectrum (from 20 to 300 Hz). Next, we use only the recordings which fall into the appropriate spectrum and perform inverse RFFT. This way, we get the signal on the standard EMG spectrum. As alternatives to this method, we tried using FFT, modifying the size of the interval, and finally using a bandpass filter instead. Replacing with FFT helped to get rid of False Positives for this subject. However, on further inspection, we noticed that it still left some processing artifacts, which may lead to False Positives in other recordings or for other subjects. Changing the whole window size (length of the in-memory signal) only shifted False Positive occurrences in time. Finally, the best effect was achieved with a bandpass filter (figure 6.14 at page 42). We chose a 5th-order Butterworth filter at 20 – 300 Hz.

Summary: bandpass filter worked the best for limiting the signal spectrum, so it will be used in the algorithms instead of FFT/RFFT.

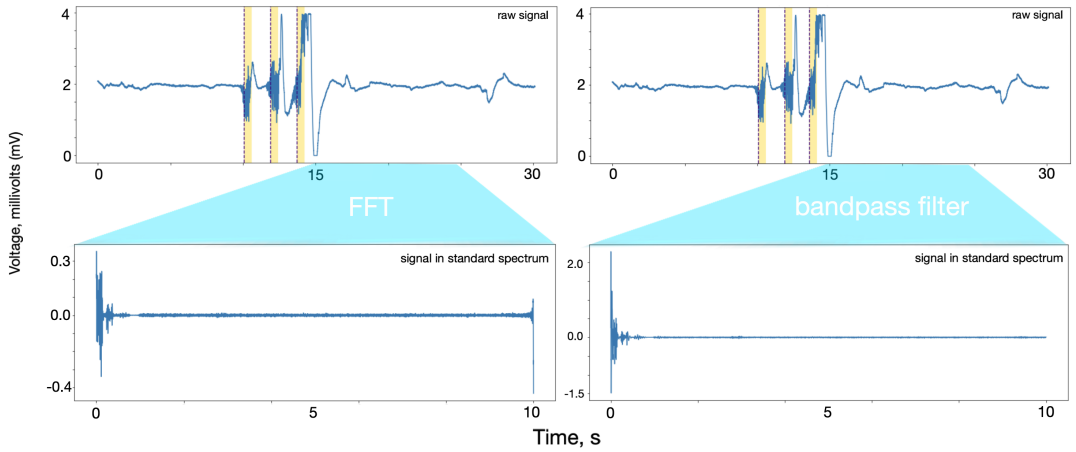

FIGURE 6.14: Comparison of using FFT and a bandpass Butterworth filter to get rid of False Positives.

6.1.12 Making the algorithm more robust by increasing the size of the window of cumulative sum calculation

20 Mar 2023

Hypothesis: 0.4-second window size is too small to make the algorithm more robust in terms of differentiating between the target muscle activity and non-target movement, crosstalk, and spontaneous activations; thus, a bigger window might help.

Background: during testing of signals from Experimental dataset 4 (subject 1), we noticed that it was impossible to choose such custom algorithm parameters which would ensure that all the target movements are detected while non-target are left undetected (in other words, we could not get rid of False Positives and False Negatives). For example, the minimum threshold for cumulative sum differences for a target movement was smaller than the maximum for a non-target movement, which creates a parameter-wise intersection between them.

This would mean that we would either have to opt for smaller parameter values, at the same time allowing False Positives (which is very undesirable for control of a medical device), or we would increase parameters, and this way allow False Negatives (which is undesirable, too).

Considering that for movement detection, we use relative comparison between cumulative sums of two "sliding" windows, we decided to try increasing this window, so this way, the difference between baseline and muscle activity would be more noticeable.

Results and Observations: After increasing the window size to 0.8 seconds and slightly tuning the custom parameters of the algorithm, we achieved improvement in the performance by reducing False Positives and False Negatives to zero (figure 6.15 at page 43). We retested the algorithm with this window on Experimental dataset 3 and observed that the modification did not lead to the appearance of False Positives and False Negatives. The only downside is that detection now might be slightly shifted in time, increasing the delay.

Summary: doubling the window size to 0.8 seconds helped to get rid of the parameter-wise intersection between target and non-target muscle activations, reducing number of False Positives and False Negatives on Experimental dataset 4 (subject 1) to zero.

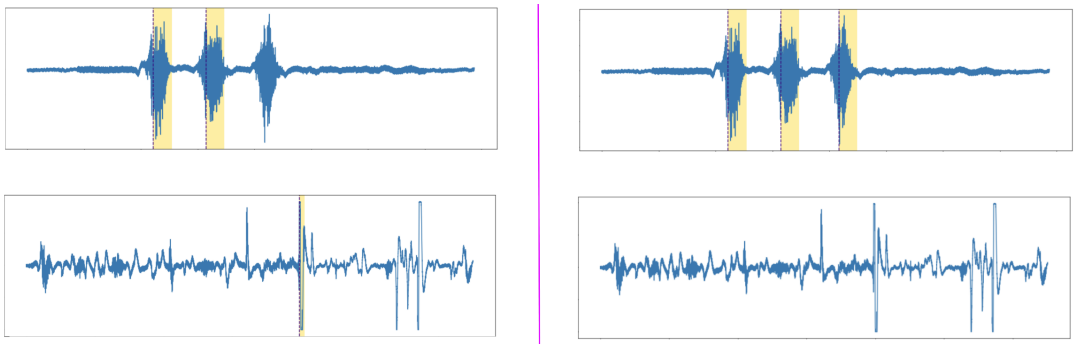

FIGURE 6.15: Detection of target muscle activation before and after increasing the size of the window for cumulative sum calculation (upper visualization contains the signal with target muscle activation, while the lower does not contain them).

6.2 Comparison with other methods of EMG onset detection

We compared our algorithm with non-real-time EMG onset detection implementations from various Python libraries. These libraries include **NeuroDSP** (Cole et al., 2019) (we used the function detect_bursts_dual_threshold for onset detection), **NeuroKit2** (Makowski et al., 2021) (we used their preprocessing functions and emg_activation function with different parameters and methods silva, biosppy, mixture and threshold), **BioSPPy** (Carreiras et al., 2015–) (for detection we used following functions: emg, find_onsets, hodges_bui_onset_detector, and silva_onset_detector).

For evaluation, we used signals from the Experimental dataset 4 and the Experimental dataset 3 (only the signals where the electrodes were not affected by noise from other electrical appliances). We used both subjects for which target and non-target activations are easily differentiable and subjects for which there occurred intersections (i.e., same amplitude and change of cumulative sums) between target and non-target activations — to test how well will our algorithm (it should opt to minimize False Positives in such situations) and other methods perform with such tricky cases. To easier assess such cases, we separated them into **two groups**.

Details on **all of the tested signals** (here by a recording, we mean an EMG recording from one muscle (i.e., only from Sternocleidomastoid or only from Triceps brachii), but it should be noted that signals from these two muscles were recorded simultaneously, so the actual number of files is precisely two times less than the number of separate recordings; same goes for their duration):

- Total number of subjects: 9
- Total number of recordings: 56
- Total duration of recordings: 44.93 minutes
- Included datasets: Experimental datasets 3 and 4

Details on two groups separately:

- **Group 1.** Easily **differentiable** cases (here again, we treat signals from different muscles as separate recordings, even though they were recorded simultaneously):
  - Number of subjects: 9

  - Number of recording pairs for Sternocleidomastoid (target + non-target signals): 12
  - Number of recording pairs for Triceps brachii (target + non-target signals): 15
  - Duration of unique recordings: 37.74 minutes

- **Group 2. Non-differentiable** (or unsatisfactorily differentiable) cases with intersections between target and non-target activations, for example, affected by electrodes falling off, etc (again, we treat signals from different muscles as separate recordings):

  - Number of subjects: 4
  - Number of recording pairs for Sternocleidomastoid (target + non-target signals): 6
  - Number of recording pairs for Triceps brachii (target + non-target signals): 3
  - Duration of unique recordings: 9.64 minutes

Regarding parameter tuning, we tuned parameters in such a way that they should both detect target activations in a recording with them and, while being the same, not produce any False Positives in a recording without target activations. This way, for each evaluation step, we actually used a **pair of signals** (target and non-target, sometimes concatenated into one signal), with target signals being unique, while non-target were sometimes repeated (this is why the duration of all unique recordings is smaller than the sum of durations of unique recordings inside each of the groups — some non-target signals are used more than once). The reason is that during the parameter tuning step, we need to ensure that there are no False Positives, which could potentially lead to spontaneous orthosis activations. For our method, we used automated parameter tuning. For other methods, we either tuned parameters manually, implemented additional tuning functions, or used the tools offered by their libraries. If we used parts of our pipeline with other methods, we specified that in the parentheses after the names of the libraries and methods in the table.

As evaluation metrics, we used **recall** (True Positive Rate), **precision**, and F_1-**score** (which combines two previous metrics). We do not use, for example, the accuracy metric because it requires the number of True Negatives, which we can not describe in a discrete manner. Considering that our data was recorded specifically for that project, it does not come with labels on EMG onsets or noises, so conditions for True/False Positives/Negatives are slightly more relaxed than for labeled datasets. We consider detection True Positive if it happened during the visible onset of the activity or close to it ($<\approx$1-second difference); in other cases, these are False Positives. If the detection did not happen in such a window, we consider it a False Negative; in other cases, these are True Negatives.

Our method showed competitive results in comparison to various Python libraries and methods. It should be noted that most methods from different libraries also required parameter tuning, so we might not have achieved the best results that they could offer with our automated or manual tunings. We should also keep in mind that our method is meant for real-time data processing, while the methods we compared with are not (they can be modified for real-time processing and incorporated into the pipeline if needed). In general, if a part of our method (detection of

	(1) Well-differentiable cases			**(2)** Non-differentiable cases		
	Recall	Precision	F_1-score	Recall	Precision	F_1-score
Our real-time method (automatic parameters tuning + pre-processing + onset detection)	0.938	0.968	0.952	0.333	0.5	0.4
NeuroDSP (+ our pre-processing, parameter tuning)	0.875	**1.0**	0.933	0.444	**1.0**	0.615
NeuroKit2* (*silva*)	0.156	0.938	0.268	0.111	**1.0**	0.2
NeuroKit2* (*biosppy*)	0.896	0.227	0.362	0.778	0.172	0.282
NeuroKit2* (*mixture*) (+ our parameter tuning)	0.823	0.859	0.84	0.481	0.433	0.456
NeuroKit2* (*threshold*) (+ our parameter tuning)	0.667	0.97	0.79	0.444	0.6	0.511
BioSPPy* (*emg*)	0.823	0.632	0.715	**0.852**	0.59	0.697
BioSPPy* (*find_onsets*) (+ our pre-processing, parameter tuning)	0.812	0.897	0.852	0.481	0.867	0.619
BioSPPy* (*hodges_bui_onset_detector*) (+ our parameter tuning)	**0.948**	**1.0**	**0.973**	0.667	**1.0**	0.8
BioSPPy* (*silva_onset_detector*) (+ our parameter tuning)	**0.948**	**1.0**	**0.973**	0.704	**1.0**	**0.826**

TABLE 6.1: Comparison of different methods of EMG onset detection.

onset using comparison of two cumulative sums) was to be replaced for the orthosis, it would be replaced by the method from **NeuroDSP** (example in the figure 6.16 at page 46), for it showed good performance and very good rate of False Positives and did not require as much additional result processing as methods, for example, from BioSPPy (example also in the figure 6.16 at page 46). Other parts of our pipeline would remain mostly the same, only with some modifications (i.e., a bisection-based method for tuning would be used on one parameter instead of two, etc).

We mostly tested our algorithm in terms of onset detection and its parameter tuning. We did not evaluate (in terms of comparisons) the preprocessing separately, because preprocessing is a highly specific task, and its results can be interpreted in different ways. We also did not evaluate (again, in terms of comparisons) our approach to making that pipeline real-time and also to our approach to the myoelectric control in general (choice of muscles, choice of the way the orthosis will be activated, using direct and indirect control, etc), because the task that we aim to use it for is quite specific and the setting is such, too.

*For these methods, for every onset occurred many detections (i.e., tens or even hundreds), which were closely situated to each other and mostly covered the region where detection occurred. In order to not count them as False Positives, for each such group of detections, we counted only one (we skipped every detection which was less than a second close to the previous detection — this way, we ensured that there was at least 1-second (1.5 for BioSPPy's *emg* and *find_onsets*) difference between onsets).

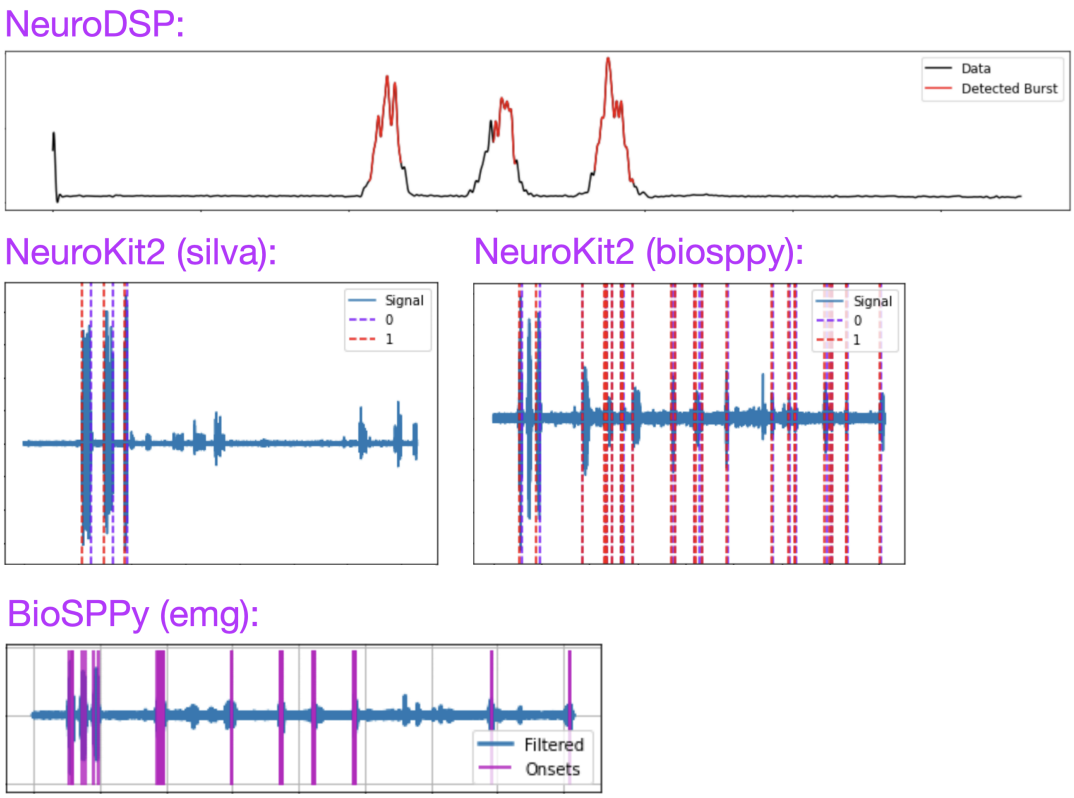

FIGURE 6.16: A couple of demonstrations of onsets detected by different libraries (visualized using tools from respective libraries).

Chapter 7

Summary

Conclusions: We proposed an approach to a myoelectric control of an orthosis device for people with traumatic injuries of the brachial plexus. We proposed, implemented, and tested the pipeline for EMG signal processing and evaluated the part responsible for the onset detection; we also designed plans for EMG recordings for the datasets, explored the received signal, and used them for the development and testing of the algorithm and described the most significant experiments and their outcomes.

Future work: The work on the thesis comes to an end, but the work on our method for myoelectric control for the orthosis continues. Here are some of our plans:

- Adding adaptive control so users can control speed and degree of flexion and extension, maybe using AI algorithms for this;
- Considering the reaction time, to make sure that there is not too much delay between muscle activation and orthosis flexion/extension;
- Considering the state of orthosis — is it currently extended or flexed;
- Automating the step for checking EMG quality;
- Replacing detection, that uses cumulative sums comparison, by the threshold-based detection from the NeuroDSP library, if further experiments will show such need;
- Integrating myoelectric control into the orthosis and providing it for testing by the patients from RNI;
- And so on.

Bibliography

Achudhan Karunaharamoorthy, A. (2023). Biceps brachii muscle. https://www.kenhub.com/en/library/anatomy/biceps-brachii-muscle

Allison, G. (2003). Trunk muscle onset detection technique for emg signals with ecg artefact. *Journal of Electromyography and Kinesiology*, *13*(3), 209–216. https://doi.org/10.1016/s1050-6411(03)00019-1

Anatomist90a. (2011). Brachial plexus [Online; accessed 21-February-2023]. https://commons.wikimedia.org/wiki/File:Axilla.jpg

Anderson, G. R., Beahrs, T. R., Kircher, M. F., & Shin, A. Y. (2020). Use of myoelectric limb orthoses for elbow flexion in patients with brachial plexus injury: A case series. *JPO Journal of Prosthetics and Orthotics*, *33*(1), 70–72. https://doi.org/10.1097/jpo.0000000000000284

Bionics, O. (2021). *Hero arm user manual version 6.0*. Open Bionics. Bristol, UK. https://openbionics.com/wp-content/uploads/2021/06/d100161_06-00-EXTERNAL-USE_Hero-Arm-User-Manual.pdf

Bodsworth, J. (2007). Cropped version of image of a prosthetic toe from ancient egypt, now in the egyptian museum in cairo. [Online; accessed 22-February-2023]. https://commons.wikimedia.org/wiki/File:Prosthetic_toe.jpg

Brachial plexus injuries - orthoinfo - aaos. (n.d.). https://orthoinfo.aaos.org/en/diseases--conditions/brachial-plexus-injuries

Carreiras, C., Alves, A. P., Lourenço, A., Canento, F., Silva, H., Fred, A., et al. (2015–). BioSPPy: Biosignal processing in Python [[Online; accessed April 21, 2023]]. https://github.com/PIA-Group/BioSPPy/

Carter, H. V. (1858a). Anatomy of the human body [Online; accessed 21-February-2023]. https://commons.wikimedia.org/wiki/File:Gray525.png

Carter, H. V. (1858b). Anatomy of the human body: Triangles of the neck [Online; accessed 21-February-2023]. https://commons.wikimedia.org/wiki/File:Gray512.png

Cc by-sa 3.0. (n.d.). *Creative Commons*. https://creativecommons.org/licenses/by-sa/3.0

Cc by-sa 4.0. (n.d.). *Creative Commons*. https://creativecommons.org/licenses/by-sa/4.0

Chowdhury, R., Reaz, M., Ali, M., Bakar, A., Chellappan, K., & Chang, T. (2013). Surface electromyography signal processing and classification techniques. *Sensors*, *13*(9), 12431–12466. https://doi.org/10.3390/s130912431

Cole, S., Donoghue, T., Gao, R., & Voytek, B. (2019). Neurodsp: A package for neural digital signal processing. *Journal of Open Source Software*, *4*(36). https://doi.org/10.21105/joss.01272

Craelius, W. (2022). *Prosthetic designs for restoring human limb function*. Springer.

Dietrich, C., Walter-Walsh, K., Preißler, S., Hofmann, G. O., Witte, O. W., Miltner, W. H., & Weiss, T. (2012). Sensory feedback prosthesis reduces phantom limb pain: Proof of a principle. *Neuroscience Letters*, *507*(2), 97–100. https://doi.org/10.1016/j.neulet.2011.10.068

Drapała, J., Brzostowski, K., Szpala, A., & Rutkowska-Kucharska, A. (2012). Two stage emg onset detection method. *Archives of Control Sciences*, *22*(4), 427–440. https://doi.org/10.2478/v10170-011-0033-z

Drost, G., Stegeman, D. F., van Engelen, B. G., & Zwarts, M. J. (2006). Clinical applications of high-density surface emg: A systematic review. *Journal of Electromyography and Kinesiology*, *16*(6), 586–602. https://doi.org/10.1016/j.jelekin.2006.09.005

Gambera, M. (2021). How to extract features from signals [Online; accessed 30-March-2023]. https://m-gambera.medium.com/how-to-extract-features-from-signals-15e7db225c15

Geethanjali, P. (2016). Myoelectric control of prosthetic hands: State-of-the-art review. *Medical Devices: Evidence and Research*, *Volume 9*, 247–255. https://doi.org/10.2147/mder.s91102

Gerez, L., Chen, J., & Liarokapis, M. (2019). On the development of adaptive, tendon-driven, wearable exo-gloves for grasping capabilities enhancement. *IEEE Robotics and Automation Letters*, *4*(2), 422–429. https://doi.org/10.1109/lra.2019.2890853

Gopura, R. A., & Kiguchi, K. (2009). Mechanical designs of active upper-limb exoskeleton robots: State-of-the-art and design difficulties. *2009 IEEE International Conference on Rehabilitation Robotics*. https://doi.org/10.1109/icorr.2009.5209630

Halga, A. (2011). Musculocutaneous nerve [Online; accessed 21-February-2023]. https://commons.wikimedia.org/wiki/File:Musculocutaneous_nerve_2.jpg

The hero arm is a prosthetic arm made by open bionics. (2023). https://openbionics.com/hero-arm/

Houten, T. V., Parker, M., & Bick, A. (n.d.). Harvardx: At1x human anatomy: Musculoskeletal cases [mooc]. https://www.edx.org/course/anatomyx-musculoskeletal-cases

Prosthetics and orthotics — Vocabulary — Part 3: Terms relating to orthoses (Standard). (2020). International Organization for Standardization. Geneva, CH.

Konrad, P. (2005). The abc of emg. *A practical introduction to kinesiological electromyography*, *1*.

Liarokapis, M. V., Zisimatos, A. G., Bousiou, M. N., & Kyriakopoulos, K. J. (2014). Open-source, low-cost, compliant, modular, underactuated fingers: Towards affordable prostheses for partial hand amputations. *2014 36th Annual International Conference of the IEEE Engineering in Medicine and Biology Society*. https://doi.org/10.1109/embc.2014.6944140

Makowski, D., Pham, T., Lau, Z. J., Brammer, J. C., Lespinasse, F., Pham, H., Schölzel, C., & Chen, S. H. A. (2021). NeuroKit2: A python toolbox for neurophysiological signal processing. *Behavior Research Methods*, *53*(4), 1689–1696. https://doi.org/10.3758/s13428-020-01516-y

Moore, K. L., & Agur, A. M. (2007). *Essential clinical anatomy (3rd ed.)* Lippincott Williams & Wilkins.

Moore, T. (2023). State-of-the-art bionic arms given to ukrainian soldiers who were badly wounded by landmines. https://news.sky.com/story/state-of-the-art-bionic-arms-given-to-ukrainian-soldiers-who-were-badly-wounded-by-landmines-12789154

Nguyen, N. T. N. (2018). *Developing a low-cost myoelectric prosthetic hand* (Bachelor's Thesis). Metropolia University of Applied Sciences.

Parajuli, N., Sreenivasan, N., Bifulco, P., Cesarelli, M., Savino, S., Niola, V., Esposito, D., Hamilton, T. J., Naik, G. R., Gunawardana, U., & et al. (2019). Real-time emg based pattern recognition control for hand prostheses: A review on existing methods, challenges and future implementation. *Sensors*, *19*(20), 4596. https://doi.org/10.3390/s19204596

Pulos, N., van den Berg, C., Kaufman, K. R., & Shin, A. Y. (2021). Application of myoelectric elbow flexion assist orthosis in adult traumatic brachial plexus injury: A retrospective clinical study. *Prosthetics & Orthotics International*, *45*(6), 521–525. https://doi.org/10.1097/pxr.0000000000000046

Rzyman, G., Szkopek, J., Redlarski, G., & Palkowski, A. (2020). Upper limb bionic orthoses: General overview and forecasting changes. *Applied Sciences*, *10*(15), 5323. https://doi.org/10.3390/app10155323

Sendić, G. (2022). Triceps brachii muscle. https://www.kenhub.com/en/library/anatomy/triceps-brachii-muscle

Single-lead, heart rate monitor front end [Rev. D]. (2020). Analog Devices Inc. https://www.analog.com/media/en/technical-documentation/data-sheets/ad8232.pdf

Skintact ecg electrodes. (n.d.). https://en.leonhardlang.at/skintact/ekg-elektroden

StarWarsRey. (2015). 3d printed prosthetic hand made by open bionics in collaboration with ilm xlab [Online; accessed 22-February-2023]. https://commons.wikimedia.org/wiki/File:Star_Wars_Bionic_hand.jpg

Tabie, M., & Kirchner, E. A. (2013). Emg onset detection - comparison of different methods for a movement prediction task based on emg. *Proceedings of the International Conference on Bio-inspired Systems and Signal Processing*. https://doi.org/10.5220/0004250102420247

Vannozzi, G., Conforto, S., & D'Alessio, T. (2010). Automatic detection of surface emg activation timing using a wavelet transform based method. *Journal of Electromyography and Kinesiology*, *20*(4), 767–772. https://doi.org/10.1016/j.jelekin.2010.02.007

Whittlesey, S. N., Hamill, J., Caldwell, G. E., & E., R. D. G. (2014). *Research methods in biomechanics*. Human Kinetics.