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Project report
Robotics 30.0 credits

ASSISTED FUNCTION EXOSKELETON (AFES)

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2024-01-28

Abstract

Research has demonstrated that physically demanding occupations significantly reduce the expected work life, leading to increased average sick leave and unemployment. In response to this, we propose the Assisted Function Exoskeleton (AFES) as a solution. This exoskeleton utilizes electrical motors and EMG sensors to detect the wearer's upper body movements, providing support and enhancement.

The target demographic for this project comprises healthy workers in industries such as healthcare, construction, and agriculture. The primary focus is not rehabilitation but rather enhancing the capabilities of individuals engaged in physically demanding roles.

Due to time and budget constraints, the scope of this project was limited to the development of a single arm. The group's efforts resulted in a prototype featuring the mechanical structure of the arm, including motors and gearboxes, signal processing and filtering software, and a motor control unit. Despite production constraints that necessitated 3D printing of the hardware, the prototype proved robust enough for testing and demonstration. The software team concentrated on measuring biceps contractions and achieved a 93% accuracy level while streaming data online, utilizing a pretrained Support Vector Machine (SVM) model even across different users.

Acknowledgments

The project group wishes to express its profound appreciation to several key contributors and entities who played pivotal roles in the successful execution of this endeavor. Mikael Ekström and Pontus Sundkvist of MDU served as invaluable supervisors, their guidance being instrumental in making this project achievable. Bengt Gustafsson, also from MDU, provided crucial assistance in machining the axles, a contribution essential to the project's functionality. Henrik Falk, also affiliated with MDU, played a crucial role in procuring all the necessary materials, significantly facilitating the project's progress. Additionally, Daniel Morberg's expertise and guidance in implementing code functionality, specifically concerning the Shimmer sensor, were invaluable to the project's success. Finally, the unwavering support and financial backing from Mälardalen University were indispensable in bringing this project to fruition. The group is immensely grateful for the collective efforts and contributions that made this project possible.

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List of Abbreviations

AFES Assisted Function Exoskeleton

AI Artificial Intelligence

CAD Computer Aided Design

DOF degrees-of-freedom

ECoG Electrocorticogram

EEG Electroencephalogram

EMG Electromyography

EOG Electrooculogram

FD Frequency Domain

LR Linear Regression

MAV Mean Absolute Value

MDU Mälardalens University

MEG Magnetoencephalography

RMS Root Mean Square

SD Secure Digital

sEMG Surface Electromyography

SNR Signal-to-Noise Ratio

SVM Support Vector Machine

TD Time Domain

TFD Time-Frequency Domain

WL Wavelength

ZC Zero Crossing

DT Decision Tree

PR Polynomial Regression

RF Random Forest

IMU Inertial Measurement Unit

MUAPs Motor Unit Action Potentials

MPF Mean Power Frequency

PSD Power Spectral Density

FFT Fast Fourier Transform

ECG Electrocardiogram

K Kernel

MC Muscle Contraction

MR Muscle Relaxation

CCW counterclockwise

CW clockwise

1. Introduction

Physically demanding jobs can be found around the world in wide variety of sectors. As researched by Pedersen et al. [1] working in a physically demanding job significantly shorten the expected work life and increase the average sick leave and unemployment. Based on this it must be in societies interest to support and assist those people in jobs that require above average amount of physical work. An approach to solving this problem is the development of an Assisted Function Exoskeleton (AFES). An exoskeleton, while also found in nature, also describes a wearable mechanical structure that supports its user by augmenting and enhancing its physical capabilities.

1.1 Motivation and Goal

The AFES project aims to assist healthy individuals with high workloads for example in construction, agriculture and healthcare, by supporting them through increased stamina and stability. In addition, demonstrating the feasibility of such a project can serve as a foundation for future research at Mälardalens University (MDU). By investigating its potential, we hope to inspire future students and researchers to further develop this concept and maximize its impact.

1.2 Problem Formulation

Due to the constraints placed upon this project, the goal is limited to design a single-arm AFES prototype in order to lay the foundation for the future development of a complete upper-body AFES.

The Research Goals (RGs) of this project are:

- **RG1**: To design and build a prototype single arm exoskeleton that fulfills the given medical and industrial requirements.
- **RG2**: To acquire, analyse and process online and offline Electromyography (EMG) signals to control the exoskeleton.
- **RG3**: To integrate a motor controller that controls the exoskeleton based on the EMG signals.

1.3 Tasks & Responsibilities of Team Members

In an effort to enhance project completion and organization, specific roles and responsibilities have been assigned to individuals. The Exoskeleton project team includes Albin Gustafsson as the Hardware Team Leader, with Sebastian Ahlström and Moritz Schmidt serving as Hardware Developers. Furthermore, Irini Provatidis has taken on the role of Software Team Leader and together with Jalal Taleb serving as the Software Developer they are responsible for software implementation of the project. During this time, a collaboration with students from the Technological University of Panama is held, to gain additional ideas.

The hardware team is responsible for integrating electronics and mechanical components into the Exoskeleton. They are tasked with designing the Exoskeleton, selecting suitable materials and components to ensure its robustness and safety, ensuring compliance with the project manager's requirements and developing the motor controller including the communication between the different parts of the system.

The software team handles data processing, analysis, and the development of the Exoskeleton's control system. Their responsibilities include accurately acquiring sensor data, filtering and detecting motion patterns using Artificial Intelligence and Machine Learning. They focus on designing a stable control system that not only collects critical feedback but also effectively estimates system errors to provide precise force commands to the Exoskeleton's motors.

2. Background

The forthcoming section will delve into fundamental background concepts essential for understanding this project. To enhance comprehension, the section will be divided into two parts: a hardware-focused segment and a software-oriented segment, ensuring clarity in the exploration of these crucial concepts.

2.1 Hardware

As already mentioned in the *Introduction*, section 1. the word "exoskeleton" originates in nature. In the field of robotics however, "exoskeleton" refers to a wearable, mechanical device that improves the wearers physical capabilities [2]. They can be separated into passive and active exoskeletons with the separating criteria being if it is or is not powered. So while passive exoskeletons employ springs and straps to support the wearer, active ones use for example electrical motors or hydraulics [3]. Furthermore, exoskeletons can be separated by their area of use (rehabilitative, supportive) or by which parts of the human body they support (upper-body, lower-body, full-body). With the different kinds of exoskeleton come different challenges.

2.2 Software Related Background Concepts

This section aims to equip the reader with essential insights into EMG signals. This foundational understanding precedes an exploration of the software system's functionality outlined in the *Method*, section 4. By delving into the basics of EMG signals, the goal is to enhance comprehension of the project's software implementation.

2.2.1 Electromyography (EMG)

The initiation of movement within the human body sets off a fascinating chain reaction—a symphony of neural communication [4][5]. When the decision to move is made, the brain dispatches signals, termed action potentials or neural impulses, down the pathways of motor neurons. These electrical transmissions rapidly navigate the spinal cord, traveling along the axons of motor neurons until they reach their destination: the motor unit. This crucial component comprises the muscle fibers activated by a single motor neuron, collectively forming what we call a 'motor unit'.

Consider the act of lifting a hand weight: among the multitude of muscles engaged in this action, the biceps brachii takes center stage. During this motion, the sarcomeres positioned within the skeletal muscle fibers undergo a remarkable transformation—they shorten, generating the force necessary for movement. This process, known as muscle contraction or tension, is accompanied by a surge of electrical activity as signals propagate through the axons of motor neurons. This amalgamation of electrical impulses is captured by EMG , revealing Motor Unit Action Potentials (MUAPs). The primary source of this EMG signal lies in the depolarizing and repolarizing zones within the muscle fibers, offering insight into the intricate relationship between neural commands and muscular responses.

Expanding our perspective, let's delve into the diverse spectrum of motor units—a spectrum mirroring the versatility of human movement [6]. A large motor unit is characterized by a single motor neuron overseeing a substantial number of muscle fibers within a muscle. These robust units primarily facilitate broader, less intricate movements, prominently involving muscles like those in the thigh or back. They possess a significant network, with the motor neuron extending into numerous terminals, supplying thousands of muscle fibers.

In contrast, smaller motor units present a different narrative—a testament to precision and finesse in motor control. Evident notably in the extraocular eye muscles responsible for the complex task of shifting eyeball direction, these units are defined by their selectivity. They consist of a single motor neuron connecting to a relatively modest number of muscle fibers, sometimes fewer than ten.

EMG signals serve as valuable indicators that reflect both the anatomical and physiological properties of muscles [7]. They offer insight into intentional and reactive motor behaviors. Additionally, EMG provides information about the intensity of muscle contractions, the recruitment of motor units, and the myoelectric manifestation of muscle fatigue. This data helps in understanding how muscles adapt their intensity and velocity of contraction, offering perspective into the body's control and regulation of forces exerted by muscles on the joints.

The detection of EMG signals can be achieved through invasive methods involving electrode insertion into muscle tissue or non-invasive means by placing surface electrodes on the skin, directly above the target muscle. This dual approach enables researchers and clinicians to access a wealth of information, offering insights into the intricacies of neuromuscular interactions across various applications and contexts.

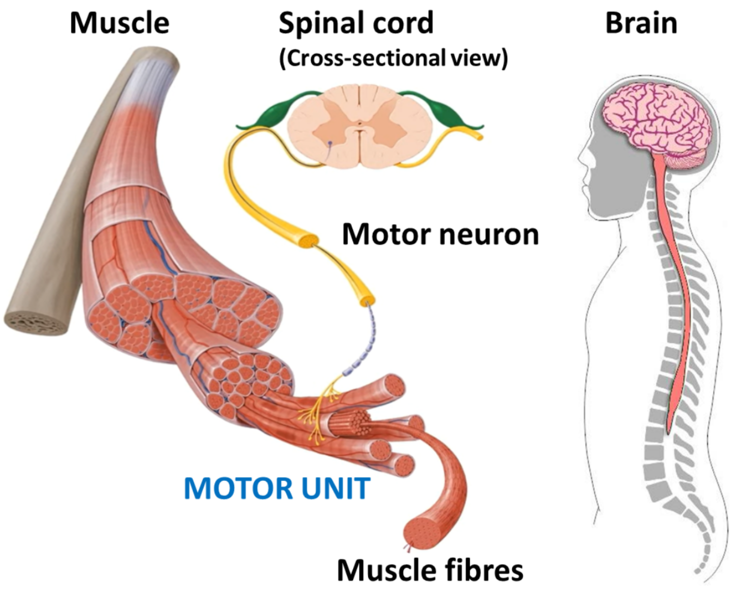

Figure 1: The illustration depicts the primary organs involved in executing movement. Action potentials originating from the brain travel through the spinal cord before reaching the muscles. When the axon of a motor neuron is activated, it generates an electrical potential, which is subsequently detected and captured by EMG.

2.2.2 Surface EMG

Surface electrodes are commonly crafted from silver/silver chloride (Ag/AgCl) or gold (Au) [7]. Ag/AgCl electrodes are nearly non-polarized, meaning the impedance between the electrode and the skin is primarily resistive rather than capacitive. This characteristic reduces the sensitivity of the recorded electrical potentials to movements between the electrode and the skin, establishing a more stable interface when an electrolyte solution, such as gel, is applied between the skin and electrode. Consequently, this diminishes noise interference during EMG signal acquisition, resulting in more dependable and accurate signal outcomes.

After acquisition, these biological signals demand proper treatments to unveil pertinent information. De Luca [8] astutely stated that *"EMG is too easy to use and consequently too easy to abuse"*. These signals typically exhibit a low Signal-to-Noise Ratio (SNR), necessitating careful consideration of filtering methods. Surface Electromyography (sEMG) signals boast high temporal resolution, signifying their capability to capture and discern rapid changes in muscle activity over time. In simpler terms, temporal resolution pertains to "when" changes in the signal of interest are detected. Conversely, sEMG presents limited spatial resolution. Spatial resolution refers to the precision or level of detail in measurements concerning space or location. This is reflects the information of "where" the signal of interest is shown. As EMG records the amalgamation of action potentials from numerous muscle fibers beneath the electrodes, it lacks precision in pinpointing activity from small muscle groups.

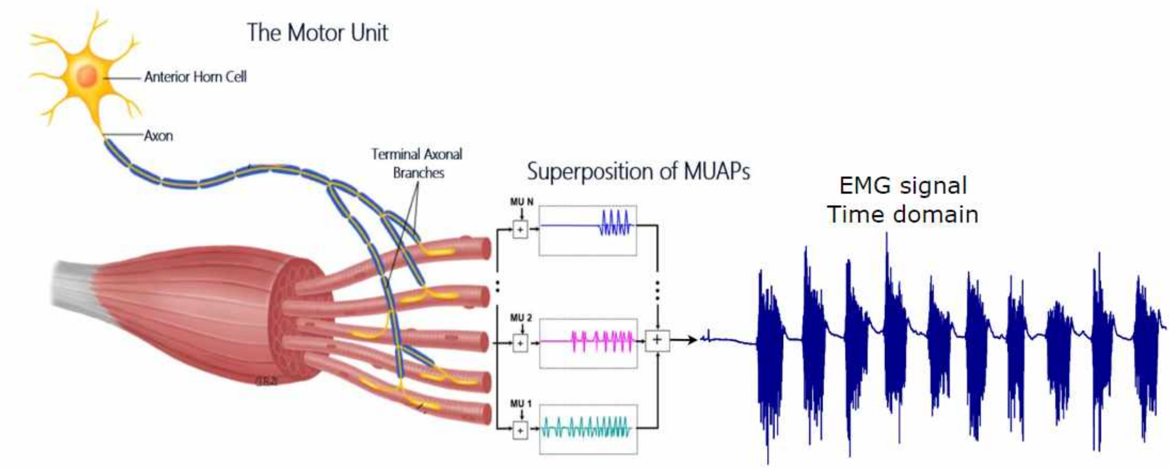

Figure 2: This figure illustrates the foundational process of acquiring EMG signals. The displayed signal represents the composite of MUAPs plotted in the time domain, providing a depiction of muscle activity.

2.2.3 Skin preparation

Ensuring low-noise EMG recordings begins with adequate skin preparation. This involves removing body hair and oils to decrease impedance in the electrode-gel-skin interface [9]. Essential steps include shaving, moistening, and cleaning the skin with alcohol before placing the electrodes. Proper electrode placement depends on the targeted muscle group, and a valuable resource for accurate positioning is the SENIAM website. SENIAM, part of the European Union's Biomedical Health and Research Program, focuses onsEMG techniques. It offers detailed instructions for electrode placement, skin preparation, suggested signal processing techniques and more.

2.2.4 Sampling frequency

Furthermore, the Nyquist-Shannon sampling theorem is a crucial parameter regulating the sample frequency of a signal [10]. Within the realm of signal processing, this theorem acts as a pivotal link between continuous-time signals and discrete-time signals. It asserts that for accurate representation and to prevent aliasing distortion, the sample rate should be a minimum of twice the bandwidth of the signal.

2.2.5 EMG common artifacts & noise

The EMG signal's characteristics are influenced by various factors along its path from the muscle membrane to the electrodes [11]. Initially, the tissue characteristics of the subject play a pivotal role. Factors such as the muscle's location on the body, tissue type and thickness, and physiological changes, including temperature variations, contribute to the variability of the raw EMG signal output.

Neighboring muscles also affect EMG signal acquisition. While targeting a specific muscle, the recorded EMG signal may capture activity from nearby muscles, a phenomenon known as 'Cross Talk.' Typically, this interference accounts for no more than 10%-15% of the overall signal content. Moreover, baseline noise, manifesting as minor fluctuations around the signal's baseline when the muscle is at rest, is another factor. This noise may arise due to electrode movement, skin impedance fluctuations, or electrical interference. Additionally, Powerline Interference at 50-60 Hz is caused by nearby electrical sources close to the EMG electrodes.

Body movement artifacts pose challenges in distinguishing genuine muscle contractions from noise. Commonly, artifacts from signals like ECG, particularly when extracting muscle activity near the heart's location, can obscure accurate readings. The sensitive nature of EMG signals makes them susceptible to external noise and various artifacts. This sensitivity necessitates comprehensive signal processing and filtering techniques to ensure accurate interpretation and analysis.

2.2.6 EMG Time & Frequency characteristics

The amplitude and frequency characteristics of an EMG signal play a crucial role in understanding the nature and behavior of muscle electrical activity [11]. Typically, the amplitude range of an EMG signal falls within 0 to 10 millivolts (-5 to +5 mV) before amplification, reflecting the electrical potential generated by muscle contractions. In terms of frequency, EMG signals exhibit a spectrum ranging from 6 to 500 Hz. Within this spectrum, the dominant frequencies tend to concentrate between 20 and 250 Hz. These dominant frequencies represent the primary components of muscle activity and are pivotal for capturing and interpreting the essence of muscle contractions.

3. State of the Art

This section aims to present an overview of previous work related to exoskeletons. It will delve into various research methodologies used by others in implementing, designing, and developing exoskeleton systems for diverse applications. This exploration will contribute to gaining valuable insights into potential solutions that align with the approach adopted in this project.

3.1 Design and Implementation of Exoskeleton Systems

Human-robot collaboration systems have a wide range of applications, and currently they are entering the daily lives of humans [12]. The development of sensor technology is establishing an interaction between humans and robots, which makes it possible to communicate, predict, and understand the current state of each partner of the system in a shared environment. Human-robot research is applied in diverse areas such as entertainment and education, robot-assisted surgery, intelligent vehicles and aircraft, assisted and rehabilitation technology, etc. Some of their basic aims are to enhance the quality of tasks, improve productivity, reduce the workload of humans, and help with the rehabilitation process after trauma.

To facilitate communication between humans and robots, predict intentions, categorize data, and develop control systems using sensor data input, researchers have used various signals that are non-biological and/or biological over the years. Biological signals are electrical signals that travel between our brain, skin, organs, glands, and muscles and are generated by the nervous system. The human body generates various biological signals: Electrooculogram (EOG), Electrocorticogram (ECoG), Electroencephalogram (EEG), Magnetoencephalography (MEG) and EMG. On the other hand, examples of non-biological signals are kinematic parameters such as force/torque sensor data, velocity, or signals generated from temperature sensors, etc.

Exoskeleton control systems are applications reflecting assistive robotic technologies. The research and state of the art of this project are limited to the assistive technology of exoskeletons. In general, exoskeletons are categorized as upper-limb exoskeletons, lower-limb exoskeletons, or full-body exoskeletons. The majority of designed and developed exoskeletons are still in the experimental stage of clinical testing, and more research and effort are essential to bring them out of the laboratory.

Controlling any exoskeleton requires sophisticated technologies and methods [13]. The main requirements of accuracy, long-term reliability, and safety are vital for the control system of exoskeletons. EMG is frequently used in the controlling methods of exoskeletons and prosthetics since it reflects the motion intention or muscle activity of the user. Furthermore, sensory data from temperature and force/torque sensors is also utilized as feedback control information in EMG-based control systems for exoskeleton applications. Even though EMG is one of the most efficient signals to utilize in the control method of an exoskeleton, muscle fatigue introduces variations in the EMG amplitude and frequency, which influence the input data to the control system.

Senarath et al. researched hybrid EMG-EEG-based control approaches aimed at exoskeleton applications. Their paper includes a review of EMG-based methods proposed for assistive robot control. One of the aspects they aim to explore is related to muscle fatigue in EMG-based control systems. Their proposed method included training multiple fuzzy-neuro modifiers to adapt to the muscle fatigue conditions to compensate for the effects of muscle fatigue on EMG-based control, and the effectiveness of the results was experimentally validated. The results of their experiments indicated that an EMG amplitude feature such as EMG Root Mean Square (RMS) alone is not adequate as an input signal for an effective EMG-based control during muscle fatigue conditions. It is essential to use frequency domain EMG features as additional input features to identify muscle fatigue conditions and use them in EMG-based control systems.

The broad range and diversity of approaches available for the development and control of robots using sEMG poses a significant challenge for researchers, prompting them to explore the optimal ways to design such systems. Song et al. [14] present and provide a comprehensive overview of techniques and methods for controlling robots using sEMG. The article provide an overview of sEMG-based robot control concluding two important aspects:

1. sEMG signal processing and classification methods.
2. Robot control strategies and methods based on sEMG.

Raw sEMG signals cannot be directly utilized for limb movement detection or controlling an exoskeleton due to the need for achieving a higher SNR. To achieve this, the signals must undergo proper data acquisition, pre-processing, feature extraction, potential dimensionality reduction, and subsequent pattern recognition. The selection of feature sets extracted by the processed signal is an important factor for the accuracy of the classifiers, which is the core of pattern recognition. They present a variety of sources related to sEMG and data processing methods as well as a statistical analysis to know the level of success of each attempt depending on the purpose and goal of the project. Numerous approaches have been explored and developed over the years. The filtering of raw EMG signals remains relatively consistent across many applications. However, when it comes to extracting features from EMG signals and implementing Artificial Intelligence (AI) algorithms, a wide array of approaches has emerged, each offering distinct solutions. Extracted features can be represented in the Time Domain (TD),Frequency Domain (FD), and Time-Frequency Domain (TFD) of the EMG signal. The choice of features is heavily dependent on the specific application's objectives, and the same holds true for selecting the appropriate AI algorithm. Researchers have explored and used diverse approaches to classify data and achieve accurate predictions.

Most research on exoskeletons primarily focuses on rehabilitation purposes, aiming to support individuals with conditions such as spinal cord injuries, strokes, or other neurological issues [15]. The control system of an exoskeleton application is one of the most important aspects of its development since it must be designed with respect to the needs of the patient. Delgado et al. have achieved a significant milestone by developing a simulated model that demonstrates effective human-exoskeleton synergy, particularly for individuals with weakened muscle activation. Their proposed strategy centers around an adaptive Fuzzy Sliding Mode Control, designed to manage the inverse dynamics of a nonlinear 4-degrees-of-freedom (DOF) exoskeleton, allowing for the estimation of muscle activation and effort. The system utilizes signals from the biceps brachii muscle, and the error in exoskeleton position serves as input for a fuzzy inference system. This system generates an output to adjust the sliding mode control law parameters, thus providing the correct assistive motor force to the actuators. The simulation model has successfully equipped users with the necessary support they require.

Triwiyanto et al. [16] designed an upper limb exoskeleton tailored for post-stroke patients, with control facilitated by a single-lead EMG signal employing embedded machine learning on a Raspberry Pi. The EMG signal is obtained from the biceps at a sampling frequency of 200Hz, while the 3D-designed exoskeleton arm incorporates a high-torque servo motor. The entire process, encompassing data acquisition, feature extraction, and the control system, is orchestrated through a Raspberry Pi 3B+. EMG features are derived using time-domain TD features such as Mean Absolute Value (MAV), RMS, and variance. Subsequently, various AI methods, Decision Tree (DT), Linear Regression (LR), Polynomial Regression (PR), and Random Forest (RF), are applied to these features for testing. The outcomes of these assessments reveal that the decision tree and random forest models exhibit impressive accuracy, achieving $96.36 \pm 0.54\%$ and $95.67 \pm 0.76\%$, respectively.

Treussart et al. [17] devised an intuitive control law for managing an upper limb exoskeleton through an EMG signal to aid in carrying an unknown load. The estimation of movement and direction in one degree of freedom is achieved using a wireless EMG armband, capturing signals from seven muscles. The intended control law aims to simulate gravitational effects without accounting for the mass of the unknown load. To assess the effectiveness of this approach, ten subjects participated in tests involving a one-degree-of-freedom exoskeleton. They performed under three distinct conditions: without assistance, with precise gravity compensation, and with the proposed method utilizing the EMG armband (Myo Armband). Upon analyzing the test results, a notable reduction in muscle activity was observed for the biceps (20%±14), erector spinae (18%±12), and deltoid (25%±16) when compared to the condition with no assistance. Similar outcomes were noted in the other two test conditions.

Senarath et al. [13] performed a study into the control of an upper limb exoskeleton using both EMG and EEG signals. This paper is divided into two distinct studies, with the first part dedicated to EMG utilization and the latter half focusing on EEG signals. The primary emphasis of this project is on the first part of this study the EMG part, where the authors delved into the challenges associated with using EMG for exoskeleton control, particularly addressing issues related to muscle fatigue. An experiment was designed to explore muscle fatigue across different subjects, aiming to develop an effective EMG control strategy capable of mitigating muscle fatigue. The paper introduces a method employing multiple fuzzy-neuro modifiers, utilizing EMG Mean Power Frequency (MPF) in conjunction with EMG RMS as inputs. Three subjects were tasked with flexing and relaxing to control the exoskeleton arm using EMG signals and the proposed method. The study yielded noteworthy results, demonstrating that the proposed method effectively reduces overshooting of the exoskeleton arm compared to EMG RMS during conditions of muscle fatigue. This contribution provides valuable insights into advancing the control mechanisms of upper limb exoskeletons, particularly in addressing and minimizing the impact of muscle fatigue.

Zhou et al. [18] conducted a Model-Based comparison of active and passive assistance in upper limb exoskeletons for overhead lifting. Their study employed simulations integrating a musculoskeletal model with five degree-of-freedom exoskeleton to assess biomechanical effects on musculoskeletal loadings. The results highlighted the effectiveness of both spring-based passive and EMG-based active assistance methods. Notably, EMG-based active assistance showed superior reductions by up to 46 % in shoulder joint forces and broader assistance throughout the lifting range. While the best spring-assist case only managed to reduce the force by 9.3 %. The study indicates potential applications and outlines plans for further optimization through parametric simulations and human-subject experiments across diverse lifting conditions.

Kim et al. [19] present the all-encompassing design, modeling, control, and performance evaluation of Harmony, an exoskeleton designed for upper-body rehabilitation. Harmony is crafted to deliver smooth, natural shoulder movements with a broad range and customizable force and impedance. Highlighting an anatomical shoulder mechanism with five active DOF, along with one DOF elbow and wrist mechanisms powered by series elastic actuators. The dynamic model is created through a recursive Newton–Euler algorithm and the inclusion of a baseline control algorithm, that ensures dynamic transparency and supports scapulohumeral rhythm. Experimental assessments affirm the exoskeleton's outstanding kinematic alignment with the human body, showcasing a wide range of motion and consistent task-space force and impedance control behaviors.

In the realm of exoskeleton design, it is important to explore the area of creating a cost-effective solution, a characteristic our system aims to embody [20]. A noteworthy article in this domain is the work conducted by Atia et al., where they undertook the design and analysis of a low-cost upper limb exoskeleton. The main focus of their system was creating a 2 DOF arm, allowing movement at the shoulder and elbow. They used multiple Inertial Measurement Unit (IMU) components to measure arm joint angles, helping the system activate motors with the right power at the right times. They compared simulation data with real system data and achieved good performance with a maximum error of 0,0696 rad in the first joint and 0,0729 rad in the second.

Intisar et al. [21] explored the design of a low-cost exoskeleton system featuring a 1 DOF elbow joint for rehabilitation and mobility. The system incorporated three input controls: EMG signal control, joystick control, and phone control to dictate servo motor movement. Testing involved achieving angular positions (90, 120, 150 degrees) with a maximum 5-degree error for each input control over multiple iterations, resulting in a successful protocol with no failures. Despite its construction cost of around 70 dollars, limitations include a singular DOF and the reliance on a threshold EMG control, making it unsuitable for specific individuals.

Otsuka et al. [22] developed the Hybrid Assistive Limbs (HAL) robot suit, featuring a 3 DOF shoulder joint and a single DOF elbow joint, specifically designed for assisting reaching movements during meal assistance. The system employed a trajectory calculation approach, utilizing a weighted pseudo-inverse matrix and a minimum jerk model to calculate precise trajectories. The adoption of a weighted pseudo-inverse aids the angle trajectory calculation based on the human joint range of motion. Their testing protocol involved sequential tasks, including reaching for a bottle, graphing, reaching to the mouth, and returning to the initial position. The system managed to achieve the fundamental capabilities by successfully completing the testing protocol. However, a notable limitation of the system is the need for manual setup of target nodes for each item, impacting the overall automation of the process.

Vitiello et al. [23] presents NEUROExos, a powered elbow exoskeleton designed for physical rehabilitation. The system implements three key solutions to enhance its effectiveness in rehabilitation: an ergonomic design allowing human-robot interface, a mechanically designed four DOF passive system, and an impedance antagonistic actuation system offering two controllable modes (patient in charge or robot in charge). The exoskeleton allows passive rotation on the frontal and horizontal planes (30° and 40°, respectively) and horizontal translation (30 mm). Notably, results from testing on five healthy subjects demonstrate the system's capability to accurately track the elbow axis throughout its entire range of movement.

The study by Christensen et al. [24] presents a full-body exoskeleton (FB-AXO) designed to aid elderly individuals. Comprising of 27 DOF, with 10 active and 17 passive, the 25 kg system integrates lower and upper body subsystems. It effectively supports activities like walking, standing, bending, lifting, and carrying. Sensors, including force and position sensors, along with EMG data, enhance user to machine interaction. Given tests indicate positive outcomes in usability and functionality, displaying good user to exoskeleton compatibility. However, challenges such as the exoskeleton's weight and misalignment due to different user sizes were noted.

Building upon the insights shared earlier, a large amount of methods has been employed in the creation of exoskeletons. These methods have diverse aspects ranging from signal acquisition, determining the system's DOF, as well as decisions regarding which components to develop and considerations of financial constraints. With these considerations, our choice was to design a system with a targeted 2 DOF, specifically for the shoulder and elbow joints. Inspired by the cost-effective approaches outlined in the works of [20] and [21], which successfully implemented low-cost systems, we have adopted a similar approach due to the constraints of our limited budget. What sets our project apart from the given works is our approach on employing custom gearing mechanisms to generate the necessary strength for assisting in carrying objects. This approach not only aligns with our financial considerations but also contributes to maintaining a more compact and lightweight system.

Furthermore, the software implementation of this project will utilize the widely adopted approach for processing EMG signals, primarily focusing on signal classification. The classification task will involve testing various advanced artificial intelligence methods, including Logistic Regression, Support Vector Machines, Artificial Neural Networks, K-Nearest Neighbors, among others. The objective is to achieve and maintain a high level of accuracy in signal classification.

To accomplish this, the software implementation will explore methodologies outlined in prominent literature sources such as [16], [14], [15], among others. These references provide comprehensive insights into EMG signal processing techniques and AI methods, serving as valuable resources for this project.

4. Method

This section outlines the methodology employed in the development of the AFES, the proposed framework and implementation. Initially, it details the construction of the exoskeleton, encompassing drawings, CAD designs, and the materials utilized (Section 4.1). Subsequently, the section delves into comprehensive insights into software implementation. It explicates the utilization of EMG data to govern the exoskeleton, encompassing signal processing procedures, the application of artificial intelligence for data classification and the elucidation of the exoskeleton's control system (Section 4.2).

4.1 Hardware

This section details the methodology concerning the hardware implementation tasks of the exoskeleton. It commences by listing the hardware components employed in the project.

4.1.1 Electronic components

- Solo Uno V2 (Motordriver) [25]
- KDE4014XF-380 (Brushless motor) [26]
- Shimmer3 EMG Unit [27]
- EMG/ECG Electrodes [28]
- Generic pc

4.1.2 Mechanical components

- Generic PLA plastic filament for 3D-printing
- SWG2-R1J14 Ground worm [29]
- AG2-30R1J14 Worm wheel [29]
- UFL001 (Flanged bearing unit) [30]
- STWN12 (Retaining ring) [31]
- KES5-30 (Parallel key) [32]

4.1.3 3D designing software

- SolidWorks 3D CAD

4.1.4 Design

The product was designed from the ground up by the team to be in accordance with the requirements provided by the project supervisors. The arm consists of 4 major parts; The Shoulder joint connecting the arm to a mounting mechanism on a test stand, the upper-arm linkage providing the main structure and acting as a mounting plate for the mechanics and electronics, the elbow joint containing a gearbox and transfers the torque from the motors to the forearm and lastly the forearm connector attaching to and transferring the force to the user.

The 3D-models and technical drawings of the arm and its subsequent components were designed using the CADComputer Aided Design (CAD) software SolidWorks, the software can be found at their website www.solidworks.com. The arm was designed using common manufacturing processes such as milling and lathing in mind making the parts simple to manufacture. Several of the components are sourced from known manufacturers and as such did not need to be designed or manufactured by the project team but influenced the design process greatly.

The forearm connector from fig 3 is the sub-assembly responsible for transferring the force to the user, the design of the forearm is very important as it needs to handle the forces of the motor and the weight of both the users arm and the weight the user is currently lifting. It needs to be strong while at the same time be very lightweight as to not add any more stress on the system than is necessary. To achieve this the parts were designed to be as strong as possible while using as little material as possible, the curved arm holder part was designed for aluminium sheet metal to be easy and cheap to manufacture while having enough stiffness to provide the user with assistive force.

The main linkage connecting the arm-holder and the axle was designed for 3D-printing or injection molding, it was designed using topology optimization to keep the strength high while at the same time lowering material usage. The linkage was designed to handle a force of 20 Kilograms without permanently deforming, this was validated using SolidWorks deformation simulations. The axle is the part connecting the linkage to the rest of the arm through the elbow joint, it has to be very resistant to torsion forces since it carries force from the arm, the user and the load. Steel provides more than enough strength and stiffness and an axle made of steel could be produced using a lathe, a common manufacturing process, to secure the joint to the axle and transfer the force of the motor a slot has to be milled to fit a 5x30mm parallel key that then fits into a gear in the joint assembly.

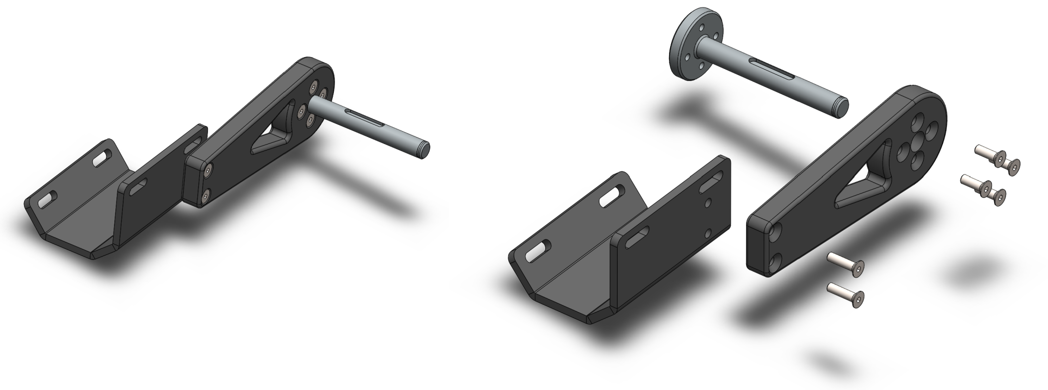

Figure 3: The forearm connector in its assembled and exploded state. This sub-assembly consists of a curved forearm holder and linkage both made of plastic, an axle made of steel connecting the sub-assembly to the rest of the skeleton and 6 countersunk M5 screws holds everything together.

The elbow joint from fig 4 is the sub-assembly containing the motor and gearbox, it provides the force to the forearm connector and in turn the user. The joint consists of 4 major parts; The brushless dc motor providing force to the system, the axle connecting the motor to the gears, the ground worm and the worm wheel acting as a gearbox and transferring the force to the forearm connector.

The joint is connected to the forearm connector through the axle that runs trough the worm wheel and is part of the forearm sub-assembly. The gearbox has a gear ratio of 30:1 meaning it magnifies the force of the motor 30 times while at the same time decreasing the speed to a 1/30th of its rated speed. The sub-assembly also contains some fasteners and additional hardware to connect everything together, 4 M3x10 screws holds the axle to the motor and 2 5x30mm parallel keys transfer the force between the axles and the gears as both the axles and the gears have slots milled into them to accept the keys.

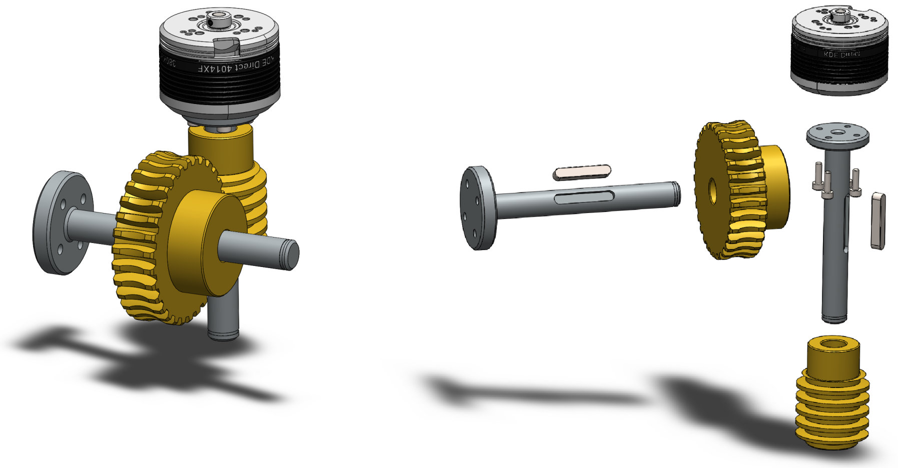

Figure 4: The Elbow joint in its assembled and exploded state. This sub-assembly consists of a brushless dc motor, an axle made of steel connecting the motor to the gearbox consisting of a worm gear assembly and the leftmost axle connecting the joint to the forearm sub-assembly.

The different parts were chosen based upon the requirements that were provided in the beginning of the project, one of the requirements was that the skeleton should provide up to 20kg of assistive force, therefore it was reasonable to expect that one arm by itself should provide up to 10 kg of force and all calculations and decisions for the gearbox was in some way based upon this requirement. The motor was chosen as it would be easy to control with the motor controller that was chosen and it did not require a very large gear ratio to provide the force that was needed. The person that the arm was modelled to fit had a 25cm long forearm and considering that it had to provide 10kg of force at the hand the gearbox had to be designed to provide enough torque to achieve this. The torque was calculated using the following formula where "T" is the torque, d is the forearm length in meters, m is the mass that the arm would need to lift and "a" is the acceleration of gravity.

$$T = d * m * a \tag{1}$$

Calculating this using d = 0.25 meters, m = 10 kg and a = 9.82 m/s^2 gives a required torque of T = 25 Newton meters. The motor can provide 0.8032 Nm of torque continuously at the motor controllers current rating of 32 Amperes[26, 25] Calculating the gear ratio (R) needed is then a question of dividing the required torque (Tr) by the provided torque (Tp) in the following formula.

$$R = Tr/Tp \tag{2}$$

Calculating this gives a required gear ratio of 31:1 considering that getting the exact gear ratio could be difficult any gear ratio close to 30:1 would be acceptable. To achieve this gear ratio a worm drive was chosen as it was the simplest and most compact way to get the required ratio in a single gear stage, this simplifies the design process in a major way as there is fewer pieces that needs to fit in the assembly in contrast to a planetary gearbox that would need several pieces and stages to achieve the required gear ratio.

The shoulder joint shares the same design as the elbow joint although it is mirrored compared to the elbow joint, this is beneficial as it reduces the amount of unique components in the arm making it easier to assemble and reduces the amount of needed spare parts as the parts could be used in several places. The shoulder joint consists of the same parts as the elbow joint however the axle that would connect to the forearm instead is available for attaching to a mount for the arm.

The last of the major components is the upper-arm linkage in fig 5, this is the main structural sub-assembly of the arm on which every other sub-assembly is attached to. It consists of a main plate running along the upper-arm, two sheet metal brackets that hold the joints and 6 flange-bearings holding the axles of the gearboxes straight to reduce the strain on the gears and motors.

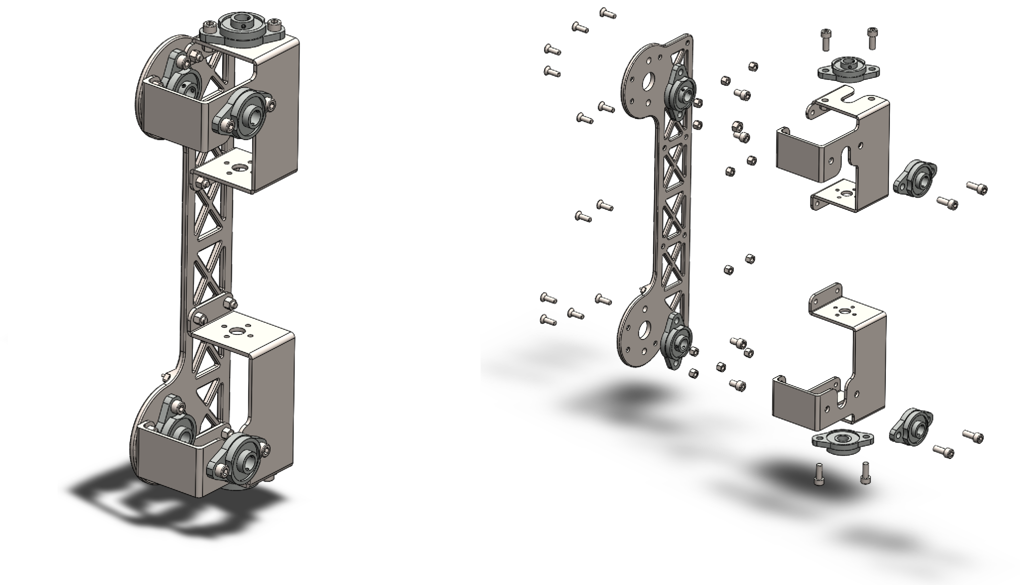

Figure 5: The upper-arm linkage in its assembled and exploded state. This sub-assembly consists of several sheet-metal parts, 6 flange bearings for mounting the axles of the joints and several pieces of mounting hardware such as screws and nuts.

The sub-assemblies all come together to form the finished arm which can be seen in fig 6.

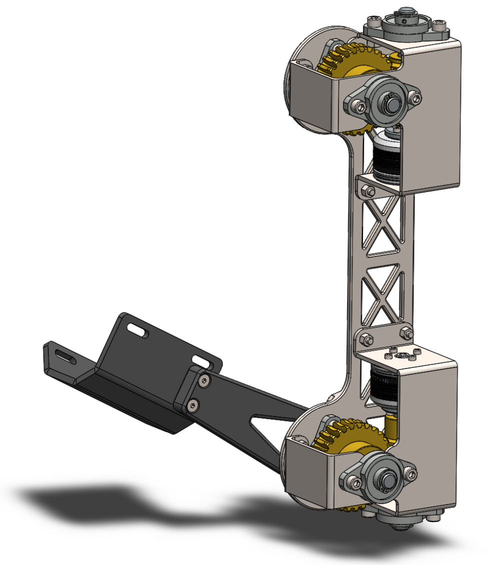

Figure 6: The exoskeleton arm in its assembled state.

4.2 Software

Let's explore the intricacies of the software implementation aspect within this project. Our objective is to effectively manage the exoskeleton through the utilization of muscle activity data captured by EMG. To accomplish this goal, a series of defined tasks need to be executed in a precise and sequential manner. This section will include the following subsections:

- **4.2.1 System Overview:** Explained using a flow diagram, this subsection delineates the system into three fundamental components: Sense, Plan, and Act. The implementation of each component is analyzed in the following subsections.
- **4.2.2 Sense:** This subsection elaborates on the first component, "Sense."
- **4.2.3 Plan:** Further analysis is provided for the second component, "Plan."
- **4.2.4 Act:** Descriptive details are offered for the third component, "Act."

This section is meticulously organized to facilitate a comprehensive understanding of the exoskeleton, representing a robotic system that encompasses the crucial elements of *Sense, Plan, Act.* Sensing constitutes a pivotal task in the development of the exoskeleton, as the recorded muscle activity through EMG serves as fundamental data for analysis, supplying accurate commands to the control system. This underscores the imperative need for acquiring high-quality data suitable for both online and offline applications. Moreover, the subsequent stage involves elucidating the signal processing methodology, shaping the planning phase of the project. This phase is of utmost importance as it governs the input and output of the EMG data processing. Finally, the acting phase in a robotic system is where tangible actions manifest. In the context of the exoskeleton project, this pertains to the activation of motors based on EMG signals. This section details the intricacies of sending precise commands to the motor controller, ensuring seamless implementation within the system. The *System Overview* strives to articulate the operational essence of the system, portraying it as an amalgamation of interconnected subsystems working cohesively to assist a subject in lifting objects. This autonomous process engages the exoskeleton's motors to apply precise rotational force upon detecting muscle activity.

4.2.1 System Overview

Research in exoskeleton technologies has led to the development of a so-called myoelectric control system. This system operates based on the classification of EMG data and follows fundamental steps akin to those in a robotic system: Sensing, Planning, and Acting.

The system overview diagram illustrated on Figure 7 provides a visual representation of the fundamental framework within the myoelectric system. It consists of three main rectangles, each outlining distinct stages of action: sensing, planning, and execution. Additionally, smaller boxes in various shades of grey, blue, and red complement these rectangles. In this representation, red boxes signify processes conducted offline, blue denotes those performed online, and grey indicates processes integrating both online and offline functionalities. The system is designed for online applications to promptly aid users during object lifting, enhance endurance, and reduce muscle fatigue. However, to achieve these objectives, certain procedures necessitate offline handling as well.

The myoelectric control system operates through a sequence of steps: Initially, the EMG sensor captures the unprocessed muscle activity signal. This raw data undergoes an offline procedure where it is saved and subjected to signal processing techniques, resulting in a refined and filtered signal. Following this, features are extracted from this processed signal in both the time and frequency domains, and subsequently normalized. Each feature sample is meticulously labeled, contributing to the creation of a customized dataset crucial for training the classification model. This model, utilizing supervised learning algorithms, becomes adept at classifying various patterns within the EMG data. Once trained, the model and its corresponding parameters are stored for future use.

Moving towards the online phase, the sensor captures the continuously streamed EMG data. This data undergoes real-time filtering and feature extraction processes. The extracted features serve as inputs for the pre-trained classification model. This model then predicts an output value indicative of muscle contraction or relaxation. These predicted values act as commands for the motors integrated within the exoskeleton, enabling seamless control within the myoelectric control system.ess. The sensor captures the online streamed EMG data, followed by online filtering and feature extraction. Then, these features are used as input for the pre-trained classification model. The model is then predicting an output value that signifies muscle contraction or relaxation. Those values serves as commands for the exoskeleton's motors within the myoelectric control system.

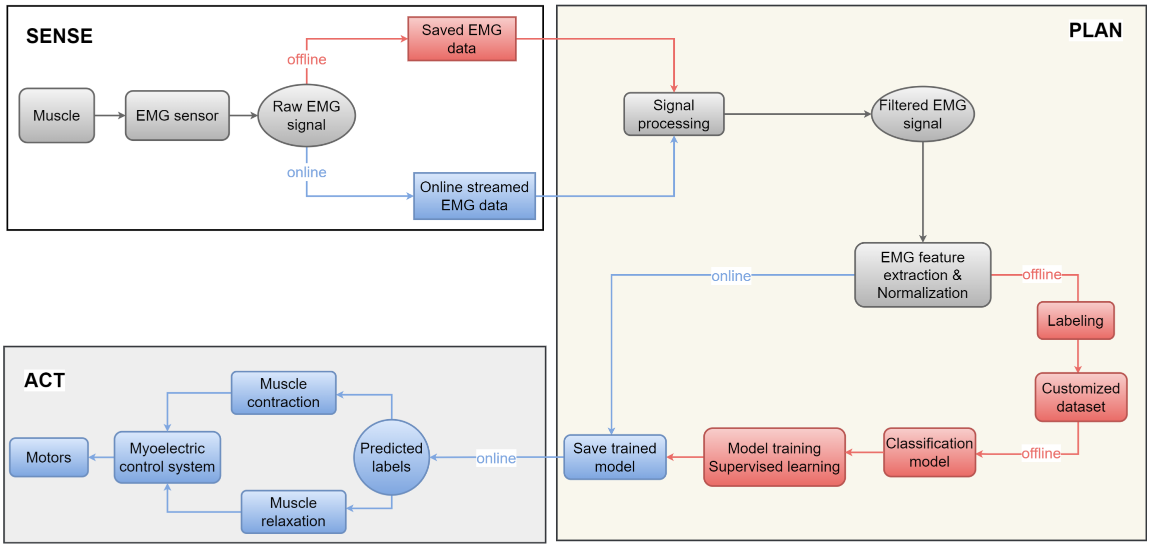

Figure 7: The diagram provides an overview of the myoelectric control system incorporated into the AFES setup, segmented into three fundamental actions: Sensing, Planning, and Acting.

4.2.2 Sense

For data acquisition, the Shimmer3 Electrocardiogram (ECG) Unit is employed in its EMG configuration. This sensor system utilizes cable electrodes connected to gel pads positioned on the subject's muscles. Specifically, to capture muscle activity from the bicep brachii, two electrodes are strategically placed linearly along that muscle, while a reference electrode is positioned on the elbow bone, as depicted in Figure 8. The selection of appropriately conditioned electrodes and suitable cable lengths is imperative to optimize signal quality. Additionally, precise electrode placement significantly impacts signal efficiency. Maintaining an electrode-to-electrode distance not exceeding 2 cm is recommended for optimal results. Moreover, following the preparatory skin cleaning procedures detailed in Section 2., the EMG signals are then collected.

To facilitate the live representation of EMG data, configure the necessary settings, choose the suitable sampling frequency, save and export data, and oversee sensor devices, we employ the software Consensys. The sample frequency is set to 1024 Hz with respect to the Nyquist Shannon sampling theorem. Consensys is a comprehensive software compatible with all Shimmer sensors, specifically designed to streamline these tasks seamlessly.

Figure 8: The electrode setup to capture online and offline muscle activity from the biceps brachii.

Utilizing Consensys provided the capability to store data onto the Shimmer sensor's Secure Digital (SD) card and subsequently export it as a .csv file. This methodology allows for the collection of data crucial for training purposes. Each acquisition trial involves a specified time duration for recording, during which the subject performs tasks involving muscle contraction and relaxation.

The acquisition trials were conducted with a duration of approximately 2 minutes each. During these trials, the subject followed a specific pattern: contracting the bicep muscle for 5 seconds followed by a rest period of 10 seconds, repeated until the 2-minute duration elapsed. Additionally, variations in the trials involved the use of different weights, ranging from 0.5 to 10 kg, held by the user to serve as varying loads.

The application relies on Python as the programming language of choice. To enable online functionality, data streaming to a Python script is essential, achieved through Bluetooth Classic 2.0. Consequently, a dedicated script was developed to facilitate streaming EMG data from the Shimmer sensor to Python. To ensure accurate data capture within Python, a continuous updating plot illustrating the signal in the time domain has been integrated.

Bluetooth protocols include automatic mechanisms to retransmit lost packets, ensuring successful packet delivery. However, this retransmission process can unintentionally introduce latency into the online application. To overcome this, an interpolation method has been implemented within the script that handles the streamed data from the sensor, aiming to minimize latency as much as possible. The software team has devised a method to seamlessly stream data from the Shimmer sensor to Python. Consequently, raw EMG data is collected online in Python and is readily available for further processing. The basic steps undergoing in the Python script that interacts with the Shimmer sensor to stream the data online are the following:

1. Establish a Bluetooth connection between the Shimmer sensor and the computer.
2. Import required libraries and variable initialization.
3. Serial communication set up.
4. Read incoming data from serial port.
5. Convert raw sensor values to mV and append them to respective lists for plotting.
6. Initialize a live plot figure updating every 500 data points.

4.2.3 Plan

- **Signal pre-processing:** The removal of the mean from the EMG signal is an initial step aimed at centering the signal around zero. This pre-processing technique not only mitigates bias but also facilitates future signal processing methods, allowing a clearer focus on the signal's variations, patterns, and specific frequency components. Additionally, eliminating the mean enhances the signal-to-noise ratio (SNR), contributing to a more accurate analysis of the EMG signal. In formula 3, $x'(n)$ represents the processed EMG signal from which the mean has been subtracted. In Figure 9, an example of a plotted EMG signal showcases two distinct representations: one exhibiting the mean offset and the other with the mean removed. The initial plot to the left exhibits a baseline centered between -12 to -16 mV when the signal's mean is retained. However, upon removing the mean, the signal realigns around zero, as portrayed in the plot to the right.

$$x'(n) = x(n) - \text{mean}(x(n)) \tag{3}$$

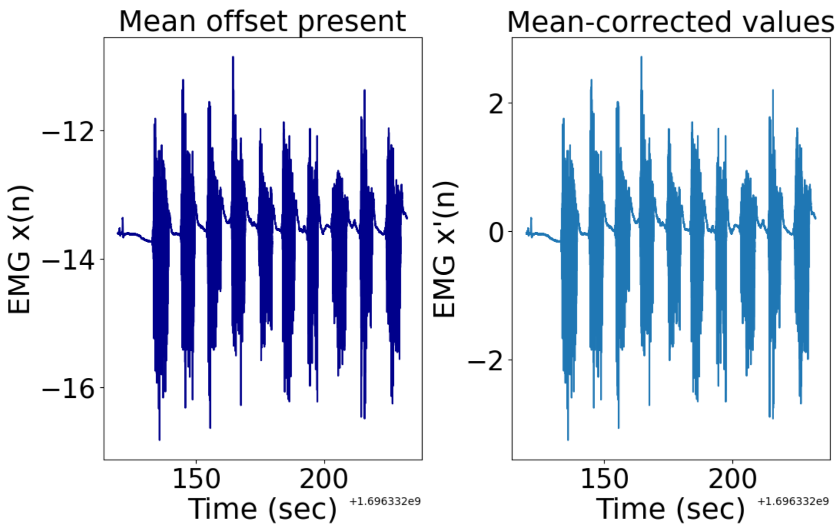

Figure 9: The signal depicted on the left side (colored in dark blue) illustrates the bicep muscle activity without mean removal. Conversely, on the right side, after removing the mean from the same signal, it becomes evident that the signal is centered around zero.

- **Signal filtering & processing:** The EMG signal, typically dominant in the frequency range of 20-250 Hz, requires signal enhancement within this specific range. Employing a fourth-order Butterworth bandpass filter with cutoff frequencies set at 20 Hz (lower limit) and 250 Hz (upper limit) aligns with the signal's characteristics. Butterworth filters are favored due to their ability to maintain a flat frequency response, providing a consistent amplification within the designated passband. They exhibit a sharp roll-off, effectively diminishing frequencies beyond the intended range, making them well-suited for applications that demand seamless, predictable filtering without oscillations or variations within the passband. Figure 10 presents the frequency response of the designed Butterworth filter. The plot demonstrates the successful attenuation of frequencies outside the range of 20 to 250 Hz, indicating the filter's effectiveness in isolating and emphasizing this specific frequency band.

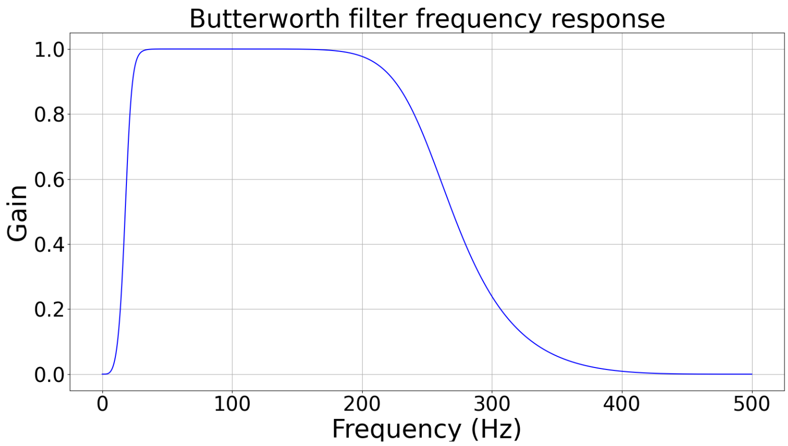

Figure 10: Frequency response of designed Butterworth filter.

The designed bandpass filter is implemented on the unfiltered EMG signal, followed by full rectification achieved by computing the absolute value of the signal. Subsequently, the signal's envelope is computed, reflecting the smoothed amplitude variations derived from the rectified signal. When the signal is presented in this manner, distinguishing between muscle contraction and relaxation becomes visually apparent by plotting the EMG envelope in the time domain.

Figure 11 emphasizes the contrast between a raw EMG signal and its visually enhanced representation after undergoing filtering. On the left side, the dark blue signal illustrates the unfiltered EMG signal recorded during the subject's contraction and relaxation of the bicep muscle. The presence of noise, especially noticeable at the signal's baseline, is apparent. Conversely, the signal on the right side, depicted in light blue, has been processed using the Butterworth filter. This transformed signal facilitates the extraction and utilization of crucial information embedded within the EMG signal.

Figure 12 displays the subsequent stage of the EMG signal processing. The filtered EMG signal is represented in the left signal plot, now fully rectified. On the right, the light blue signal plot showcases the calculated envelope of the rectified EMG signal. The envelope of the signal is derived by employing a low-pass filter of sixth order, aimed at smoothening the rectified EMG. This provides a clearer representation of the amplitude variations in the EMG signal over time, aiding in the analysis of muscle activity and pattern recognition.

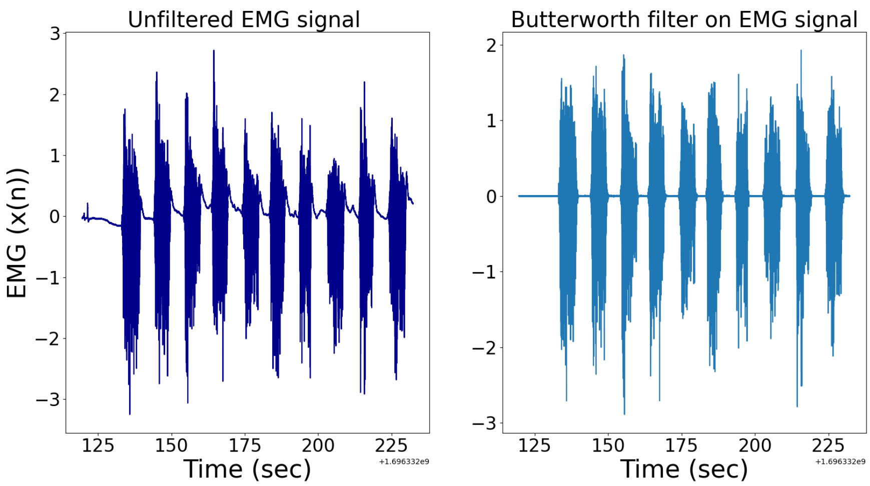

Figure 11: The signal displayed on the left is the unfiltered EMG signal, whereas the signal on the right depicts the same signal after undergoing the initial filtering.

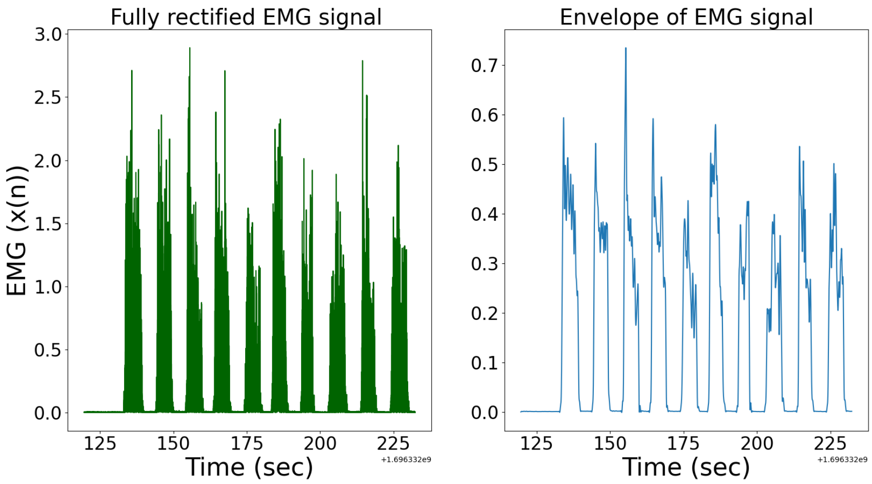

Figure 12: The signal on the left represents the fully rectified signal, while the plot on the right showcases the signal's envelope.

- **Threshold & Labeling Process:** The process of establishing a threshold to identify muscle contraction or relaxation is pivotal, as it serves as the basis for labeling the training dataset utilized in the supervised classification model. In the context of muscle activity analysis, percentiles help determine thresholds that delineate between muscle contraction and relaxation based on the amplitude or characteristics of the EMG signal. Percentiles are useful for various applications, especially in understanding the distribution of data, identifying outliers, and establishing thresholds for specific categories or behaviors within a dataset[33].

  In this stage, the processed EMG signal undergoes detailed analysis by segmenting it into smaller windows, each set at a size of 50 samples with a 10-sample overlap. Utilizing the percentile method within these windows, distinct labels indicating muscle contraction and relaxation are assigned. Specifically, the range from the 40th to the 60th percentile is employed, tailored to the characteristics of the recorded EMG dataset. If the sample value of the EMG signal exceeds the percentile value, the assigned label is 1, indicating muscle contraction. Conversely, if the signal values fall below the percentile value, the assigned label is 0, indicating muscle relaxation.

  The labels assigned to all windows across the entire signal are stored in a flexible dynamic list or array. This adaptability allows the list to dynamically modify its size during runtime, adjusting as elements are added or removed.

  In Python, the `percentile(data, percentile_value)` function is utilized to compute percentiles from a dataset. Here, the data parameter typically denotes the filtered EMG signal. The percentile_value parameter characterizes the data distribution statistically, representing the percentage of values that are smaller than or equal to that specific percentile

- **TD and FD Feature Extraction & Normalization:** Each window captures vital aspects of the signal, enabling a more detailed examination of its characteristics and facilitating the extraction of significant temporal and frequency features within these defined segments. These windows, delineated by a predetermined size and adaptable overlap, ensure thorough coverage of the entire signal by forming consecutive segments. TD and FD features are commonly employed when working with EMG signals due to their ability to simplify the complexity of the signal. Utilizing features aids in enhancing the comprehensibility and analysis of the signal.

- **Features computed in the TD [16] [34]:**
  - MAV is computed using the formula:

$$\text{MAV} = \frac{1}{N}\sum_{i=1}^{N}|x_i| \tag{4}$$

    - N represents the number of samples in the window.
    - x_i denotes each individual sample within the window.
  - RMS reflecting the mean power of the EMG signal.

$$RMS = \sqrt{\frac{1}{N}\sum_{i=1}^{N}x_i^2} \tag{5}$$

    - N is the number of samples in the window.
    - x_i represents each individual sample in the window.
  - Wavelength (WL) is determined by summing the numerical derivative of the EMG signal.

$$WL = \sum_{i=1}^{N-1}|x_{i+1} - x_i| \tag{6}$$

    - N is the number of samples in the window.
    - x_i represents each individual sample in the window.
  - Zero Crossing (ZC) is determined by counting the changes in the amplitude sign of the EMG signal.

$$ZC = \sum_{i=1}^{N-1}|\text{sign}(x_i) - \text{sign}(x_{i+1})| \tag{7}$$

    - N is the number of samples in the window.
    - x_i represents each individual sample in the window.
    - sign$(\cdot)$ denotes the sign function.

- **Features calculated in FD [10]:**
  - Fast Fourier Transform (FFT) is an algorithm that transforms a signal from its time-domain representation to the frequency domain, revealing the frequency components present within the signal and providing a more comprehensive understanding of the signal's spectrum.

$$X(k) = \sum_{n=0}^{N-1}x(n)\cdot e^{-i2\pi\frac{kn}{N}} \tag{8}$$

    - $X(k)$ represents the transformed value at frequency index $k = 0, 1, 2, ..., N-1$.
    - $x(n)$ denotes the signal value at discrete time index n.
    - N is the total number of samples in the signal.
    - i stands for the imaginary unit.
  - Power Spectral Density (PSD): offers critical insights into a signal's power distribution across frequencies, identifying dominant frequencies and distinguishing signal components from noise. It aids in characterizing signal properties, guiding filtering operations, and is crucial in spectrum management and communications for efficient frequency allocation and interference avoidance.

$$S_{xx}(f) = \lim_{T\to\infty}\frac{1}{T}\cdot|X(f)|^2 \tag{9}$$

  * $S_{xx}(f)$ represents the PSD of the signal.
  * $X(f)$ denotes the Fourier transform of the signal.
  * f is the frequency.
  * T the duration of the signal (as $T \to \infty$, representing an infinitely long signal).

  Lastly, normalizing the extracted features from each window holds crucial significance in numerous machine learning algorithms. This normalization process is vital as it standardizes the features, ensuring they operate on a similar scale. It effectively prevents specific features from exerting undue influence solely due to their larger magnitudes. Achieved by centering the data around its mean and scaling it to exhibit unit variance, this normalization process enhances the robustness and fairness of the feature set, facilitating more effective and balanced model training. The function `StandardScaler()` in Python is used for that purpose. The Python function *dump()* is employed to save the calculated normalized values as an object, storing them in a file to be accessed and utilized at a later time for the online application.

- **Customized training dataset:** At this stage, features from each segment of the filtered and fully rectified EMG signal are extracted in both the TD and FD. These features are labeled to represent muscle contraction or relaxation, contributing to the creation of a customized dataset. This dataset serves as input to the classification model.

  The classification model undergoes offline training using the customized dataset, as illustrated in the labeled dataset representation clarified in Table (1). The table delineates the structure of the customized dataset employed in training the supervised classification model. The 'windows' $(w_1, ..., w_n)$ columns, the 'features' $(f_1, ..., f_n)$ columns, and the 'label' column are structured to compose the dataset. For the offline procedure, 80% of the customized dataset is dedicated to training the classification model, while the remaining 20% is reserved for assessing the model's accuracy in classification.

  In the context of the online application (outlined in the subsection labeled *Act*), the classification model, trained on a customized dataset, is stored as an object in a file using Python's `dump()` function. This approach enables the preservation of trained models or objects for future utilization, eliminating the need to retrain or reconstruct them when needed later.

Table 1: Training dataset provided offline as input to the classification model.

Customized Train Data					
	f_1	f_2	f_n	Label	Indication
w_1	x_1	y_1	z_1	1	Muscle Contraction (MC)
w_2	x_2	y_2	z_2	1	MC
w_3	x_3	y_3	z_3	0	Muscle Relaxation (MR)
w_n	x_n	y_n	z_n	0	MR

- **Classification algorithm:** Upon completing the extraction of signal features and defining labels for muscle contraction and relaxation, the subsequent pivotal step involves selecting an apt classification algorithm aligning with the project's prerequisites and desired outcomes. The chosen classification model must be well-suited for online applications, ensuring minimal computational load to avert system response delays. Following comprehensive research and experimentation with diverse methods, the most viable AI approach identified for this project is the Support Vector Machine (SVM) method.

  SVM stands out as a supervised learning algorithm widely acclaimed for its efficacy in addressing classification problems. Within this project, distinct classes are denoted as MC and MR. The SVM algorithm functions by discerning a hyperplane that accurately segregates the data into these two classes. The algorithm operates by utilizing the data to create a hyperplane that maximizes the margin, representing the distance between the hyperplane and the closest data points from each class, known as support vectors. This optimized hyperplane effectively partitions the data into distinct classes, enabling new data points to be classified based on their position relative to this hyperplane [35]

  Figure 13 provides an overview of the key principles underlying the Support Vector Machine (SVM). In this illustration, a linearly separable dataset is depicted for simplicity and comprehension. The green dots symbolize class A positioned on the negative side of the hyperplane, while the blue squares signify class B located on the positive side of the hyperplane. It is important to note that this representation of the algorithm's functionality is idealized and does not mirror real-world scenarios accurately. In practice, datasets often necessitate non-linear methodologies to construct a hyperplane capable of effective classification.

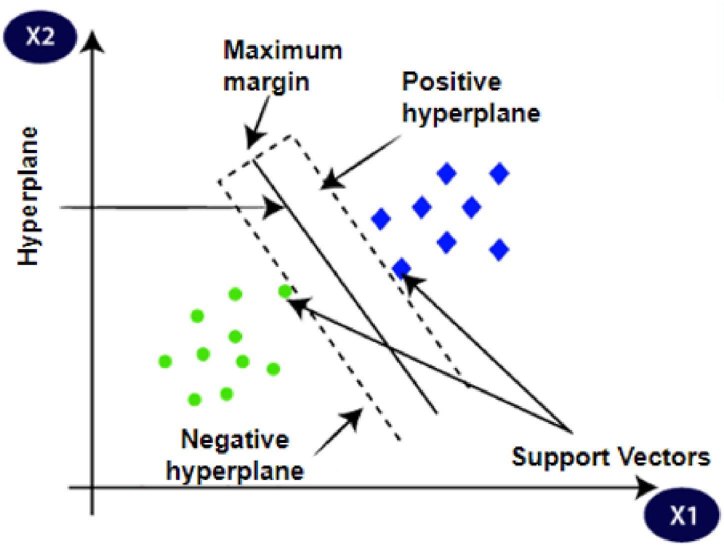

Figure 13: Illustration depicting the ideal classification utilizing SVM for enhanced comprehension.

For linearly separable data, the equation of the hyperplane is presented as:

$$\mathbf{w}^T\mathbf{x} + b = 0 \tag{10}$$

- w is the weight vector perpendicular to the hyperplane.
- x represents the input feature vector.
- b is the bias term.

The decision function aiming to classify new data points x_{new} is:

$$\text{Prediction} = \text{sign}(\mathbf{w}^T\mathbf{x}_{\text{new}} + b) \tag{11}$$

If $\text{sign}(\mathbf{w}^T\mathbf{x}_{\text{new}} + b) > 0$, x_{new} belongs to class A, otherwise it belongs to class B.

When dealing with non-linear data for classification, SVM employ a technique called the *kernel trick*. This technique allows SVM to handle data that is not linearly separable in the original feature space. The *kernel trick* effectively transforms input data into higher-dimensional spaces without explicitly calculating the transformed coordinates. This transformation enables the creation of nonlinear decision boundaries, facilitating complex classifications.

By utilizing Kernel (K) functions, SVM computes relationships between data points in the transformed space, avoiding computational complexities associated with explicitly working in higher dimensions. The proper adjustment of crucial hyper-parameters significantly influences SVM's performance for achieving high classification accuracy. Among the essential hyper-parameters, two hold particular importance [13]:

- **Choice of K**: The selection of kernel types, such as linear, polynomial, radial basis function, profoundly impacts the model's performance. Different kernels are suitable for varying types of data and problems.

– **The C parameter**: This regularization parameter regulates the trade-off between maximizing the margin and minimizing classification errors. The C parameter can take any value within the interval $0 - \infty$. Smaller values of C encourage a larger margin but may lead to wrong classification results, whereas larger C values may result in a smaller margin but good classification results.

The dataset used in this project is linearly separable, allowing for straightforward differentiation between classes. For this reason, the parameter K is configured to a *linear* setting, while the value of C is set at 1.0. In the realm of SVM, a lower C value, such as one approaching zero, signifies stronger regularization. This regularization strategy widens the margin between classes, potentially permitting a slight margin of error in classification on the training data. However, it results in a more straightforward decision boundary, simplifying the model.

Finally, to calculate the classification accuracy of the model the following formula is used:

$$\text{Accuracy Score} = \frac{\sum_{i=1}^{n} 1(y_{\text{test}_i} = y_{\text{pred}_i})}{n} \tag{12}$$

– n is the total number of predictions.
– y_{test_i} represents the true label of the ith sample in the test set.
– y_{pred_i} represents the predicted label of the ith sample in the test set.
– 1 is the indicator function which returns 1 if the condition inside the parentheses is true and 0 otherwise.

4.2.4 Act

In essence, the myoelectric signal captured by the EMG sensors (*Sense*) undergoes processing for filtering and classification using SVM (*Plan*). The resultant output from this classification model serves as commands transmitted to the myoelectric system, regulating the motors (*Act*).

This integrated myoelectric control system within the AFES enables the manipulation of the exoskeleton arm solely through the subject's bicep muscle activity. It operates in real-time, providing an immediate response from the exoskeleton arm upon the subject's muscle contraction.

The SVM model undergoes offline pre-training on a diverse range of signals, encompassing both muscle contraction and relaxation states. Predicted values derived from the continuous online EMG signal feed into the motor control system as inputs. Consequently, the motor control system executes commands to modulate the motors, facilitating the desired control and corresponding response to predicted movements.

To control the system in the prototype exoskeleton software implementation, the classification output consists of binary values that represent commands used to control the motors. When the predicted values are set as '1' the motor positioned at the elbow rotates in a counterclockwise (CCW) direction at a constant speed, thereby aiding in the arm's upward movement. Conversely, when the predicted values are '0' the motor rotates clockwise (CW), allowing the arm to descend parallel to the body. If neither '1' nor '0' is transmitted, the motor is turned off. The majority of the predicted values from every set of three values is considered to decide the final command sent to the motor as either '1' or '0'. Figure 14 illustrates the final step of the myoelectric control system. This procedure determines the speed for rotating the motors when the subject contracts his or her bicep muscle.

While lacking safety features or feedback control information, this prototype control system serves the purpose of demonstrating the real-time application of controlling the exoskeleton exclusively through the subject's muscle activity.

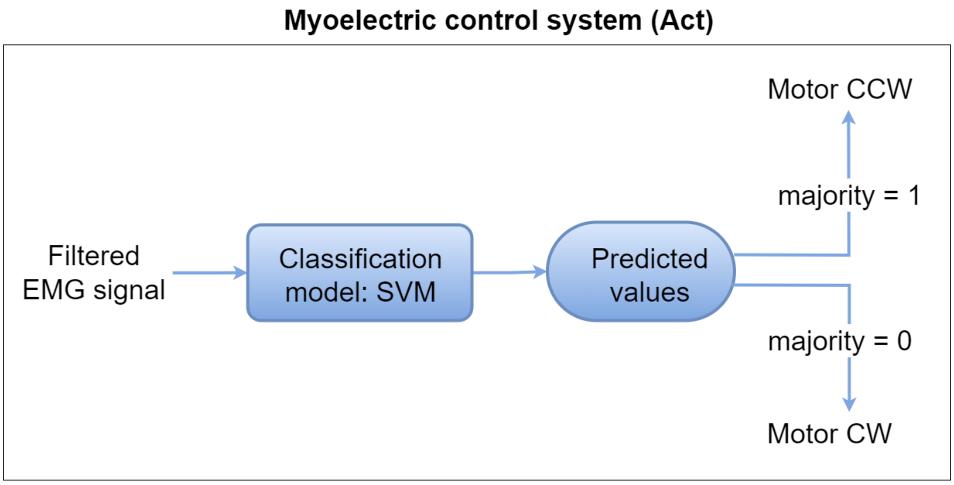

Figure 14: Brief workflow diagram of the process Act.

4.2.5 Software Programs Utilized:

The programs used to develop the software solution are presented in the list that follows:

- Visual Studio Code
- Python 3.12.1
- Consensys V1.6.0 (64bit)

5. Ethical and Societal Considerations

When delving into the development of a project like the AFES, it becomes essential to thoroughly examine numerous ethical considerations.

The most essential areas this project addresses is the user safety, since the final product will be mounted onto a human being. With this in mind comprehensive risk analysis have been in focus through the entire design phase. This led to implementations such as end switches and hardware stops that stop the motors to ensure that the arm does not go beyond its designed range of motion, the addition of worm gears to ensure that the arm can not be backwards driven without motor support, and joint positions that follow the ergonomics of a real arm to ensure no muscle tear. In the final product, there will be more implementations in regards to safety in the software area to shutdown the system when anomalies appear. Additionally, in the future more operational safety will be implemented, such as maintenance checks, user training programs, and continuous monitoring during use.

Another area of importance is accessibility. Currently the design is made to fit a smaller built individual. However, in the future this needs to be accessible to a broad range of users, including those of varying physical abilities and body types. This could include adjustable straps, modular components, and customisable settings.

The AFES system relies on gathered offline data to ensure that the SVM can effectively classify live data. For the system to be precise in its motor activation it needs to have individual offline data for each user. This opens this project up to two kinds of issues. Data has to be collected from a wide range of individuals to assure satisfactory functionality for all kind of different users. Furthermore, this data needs to stored. This data would need to be protected and comply with privacy regulations. In this project current state, nothing have yet been implemented to ensure data privacy, but later on with this project being ready for commercial use, it is of most importance to implement privacy regulations, encryption, and clear policies regarding data usage and sharing.

Additionally, some more minor ethical areas this project touches are listed below:

1. Ethical use: Establish guidelines for the ethical use of the exoskeleton, preventing its use for harmful or malicious purposes.
2. Informed consent: Obtain informed consent from users, clearly explaining the capabilities, limitations, and potential risks associated with using the exoskeleton.
3. Affordability: Consider affordability in the design process to make the technology accessible to a wide range of users.
4. Regulatory Compliance: Adhere to existing regulations and standards related to medical devices and assistive technologies.
5. Transparency: Be transparent about the functionality, limitations, and potential risks of the exoskeleton to users, healthcare professionals, and relevant stakeholders.

The ethical topic of AI in technology will not be covered in this work.

6. Results

Figure 15 shows a live demonstration of the exoskeleton. In this demonstration, the individual undergoes a testing protocol involving cycles of relaxation and active engagement of the bicep while the Shimmer sensor captures the EMG signal in real-time. The AFES adjusts the motor orientation based on the contraction or relaxation of the bicep muscle.

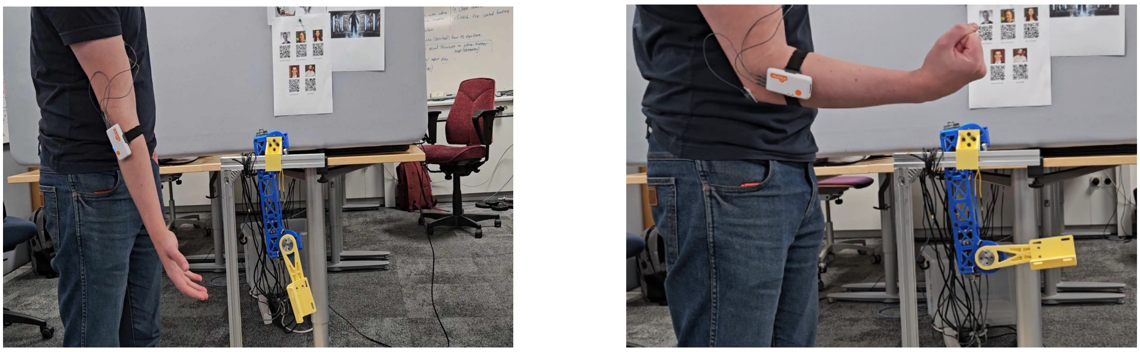

Figure 15: Live demo that shows how the arm reacts when the subject rest or flex

6.1 Hardware

Following an examination of the hardware procedures, it is crucial to evaluate whether the achieved results align with the intended objectives. This evaluation is a crucial step in determining how effectively and successfully the hardware has been implemented. The prototype arm was constructed by 3d-printing the structural parts and assembling all of the components, a stand was also constructed with extruded aluminium profiles to test the arm without mounting it to a person.

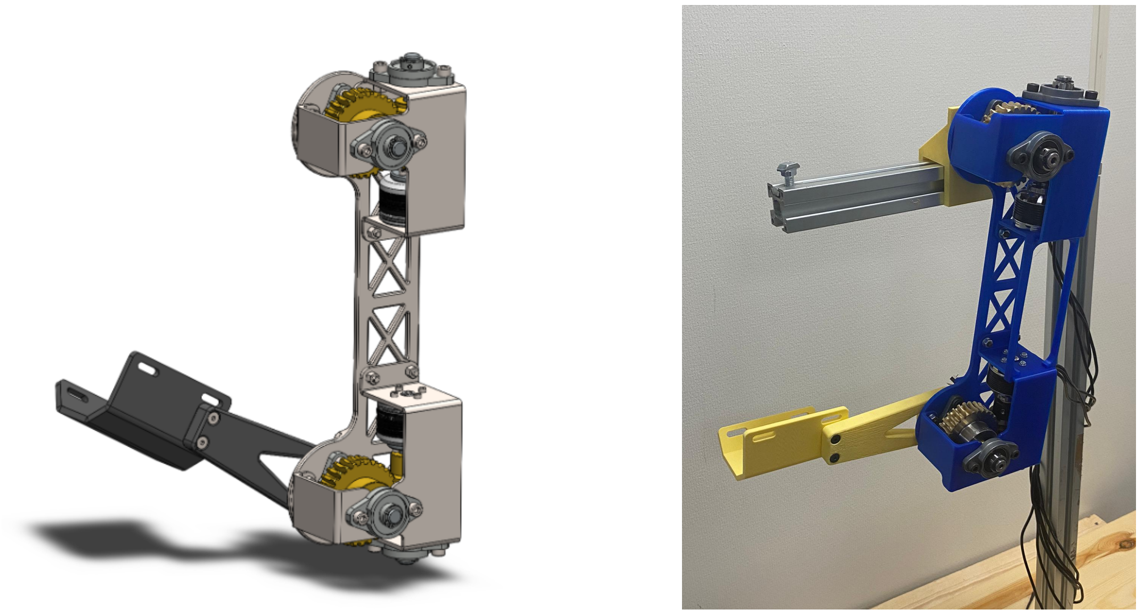

Figure 16: This figure illustrates the final design for the AFES. The image on the left displays the ideal theoretical design, while the image on the right shows the end product. A clear difference is in materials, were in the ideal one parts would have been made of metal, but in the end product several of these parts was made in plastic instead. This compromise occurred for several reasons, some being cost, time and supplier issues.

6.2 Software

Upon reviewing the results obtained from the software method, it is essential to assess their alignment with the desired outcomes. To conduct this evaluation, the results are categorized into the same components as outlined in the method: Sense, Plan, and Act.

6.2.1 Sense

The successful establishment of Bluetooth communication between the EMG Shimmer sensor and the Python script. This achievement enabled online data streaming during the subject's live actions. Figure 17 illustrates a part of the obtained raw signal, which was continuously streamed online into Python.

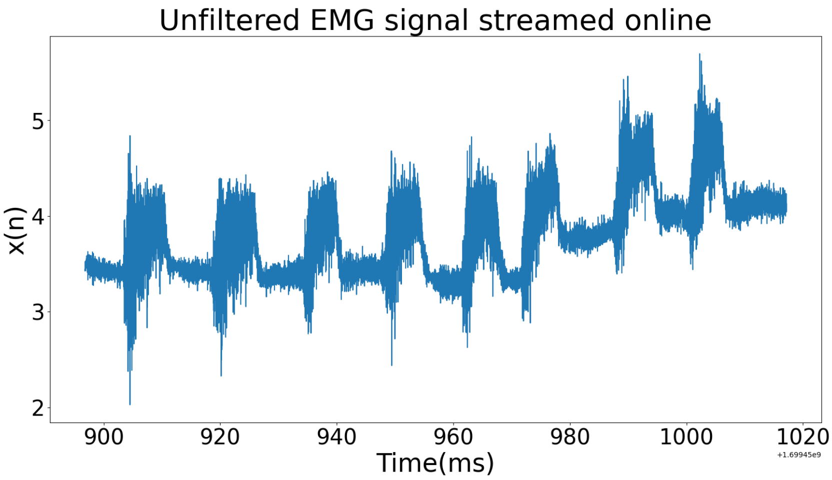

Figure 17: The successful communication between the Shimmer sensor and Python results in the online streaming of muscle activity.

6.2.2 Plan

The procedure's outcome is depicted in Figure 18, where the red dashed line represents the estimated threshold value for this signal segment. The green shaded areas indicate moments when the model detects muscle contractions; otherwise, muscle relaxation is shown. Furthermore, the performance of the classification model is presented. During offline testing, the trained SVM model attained an accuracy rate of 98%, while in online scenarios, it sustained a commendable accuracy level of 93%.

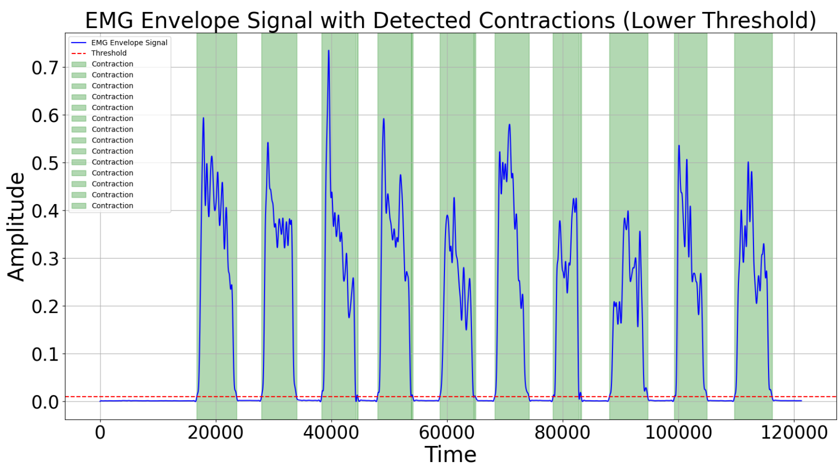

Figure 18: SVM model detection of muscle contraction and muscle relaxation.

Additionally, it is pertinent to highlight a conducted experiment depicted in Figure 19. In this experiment, EMG data of the bicep muscle were measured while the subject carried various loads of dumbbells. The subject executed the dumbbell curl task, focusing on contracting the bicep brachii muscle. A notable observation emerged by comparing the EMG amplitude relative to the weight the subject held. When the subject held a dumbbell of 1.25 kg (colored in orange), the signal's amplitude measured approximately 0.6, whereas with a 10 kg dumbbell (colored in purple), the EMG signal amplitude increased to approximately 0.9. This experiment highlights that varying amplitudes, correlating with different levels of muscle contraction, can offer data to regulate the exoskeleton motor, allowing for percentage-based motor activation and rotation control. This stands in contrast to the prototype exoskeleton model device, which only identifies muscle contraction and provides a constant motor speed.

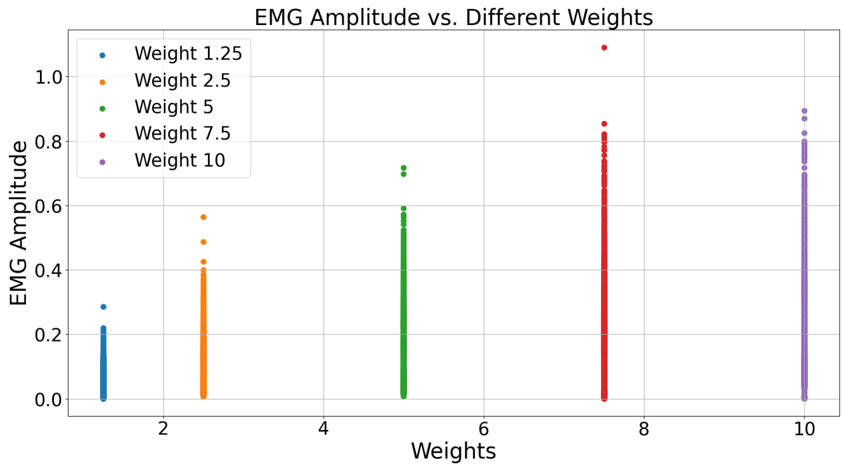

Figure 19: Experimental Results. Recorded data points obtained under different loads.

6.2.3 Act

During the final stage, commands are dispatched to regulate the motors based on inputs from the classification model, ensuring motor control. However, this process encounters a delay between the moment the subject contracts his muscle and the transmission of commands to regulate the motor. This delay is attributed to several known factors:

- The Shimmer sensor primarily operates via Bluetooth connectivity, typically optimized for offline applications where signals are analyzed rather than streamed online to instantly command a system.
- Python, the programming language used in this application, exhibits limitations in speed and efficiency compared to faster languages like C/C++ that are more suited for such real-time applications.
- The code implementation, while functional for this prototype system, prioritized proving the motor's functionality based on muscle activity. Therefore, optimizations for code efficiency and reduced running time were not part of the project plan.

Despite these limitations, the procedure demonstrated the functionality of the software system, as evidenced by the exoskeleton arm moving in the correct direction upon muscle contraction, despite with a noticeable delay.

7. Discussion and Future Work

The results showcase the success of this project, which is ensuring the motor responds appropriately to the EMG activity of the bicep. In addition to this achievement, the project contained a total of 78 specified requirements essential for the practical implementation of the AFES system. However, given the limitations of a student project, only 32 of these requirements were feasible within the defined project scope. Despite these constraints, the project managed to meet 25 out of the 32 requirements. The main factors contributing to the seven unmet requirements were time and budget constraints, hardware incompatibility, and miscommunication.

The constraints on time and budget for this project originate from the expenses associated with building a system of this magnitude. The budget of approximately 20.000 kr, was entirely allocated to hardware components, leaving no room for software development. These budget limitations made us use plastic for our main modeling efforts, a cost-effective strategy aimed at minimizing the potential complexities and expenses associated with remodeling metal parts, which would involve additional time and financial commitments from suppliers. In addition, our desire to achieve slower yet more powerful arm movements was lost by the considerations of cost and the size of required motors and gears. We had to find a balance with a solution that was not only feasible but also mindful of constraints and weight considerations. However, with the current selection of gears we managed to achieve additional fail-safes in the form of worm gears, with the special property of not being able to be driven backwards without assistance from the motor. Thus, ensuring safety in the system even when turned off.

Throughout the project, a significant challenge consumed a large amount of time, an issue from hardware incompatibility. The original concept involved integrating a Raspberry Pi into the system to acquire EMG data from sensors and execute the software model for motor orientation. However, the setback occurred due to communication issues between the EMG sensors and the Raspberry Pi. Since the system operated wirelessly, the data needed to be trough Bluetooth connections. The complication arose from the fact that the EMG sensors used Bluetooth classic, while the Raspberry Pi utilized a modern version. This difference in Bluetooth versions resulted in substantial packet losses, rendering the control of motors via EMG difficult with sizeable amounts of errors. Faced with this challenge, a compromise was needed. Instead of using the Raspberry Pi, a computer was integrated into the system. This adjustment ensured compatibility, as both components now operated on the same Bluetooth version, thus ensuring good data transmission. While this computer solution is temporary and not suitable for the final product, the constraints of the time frame and budget made us use this approach. An alternative solution would involve using different EMG sensors with compatible Bluetooth versions or opting for wired connections. However, acquiring such EMG sensors was deemed economically impractical, as the cost of new sensors exceeded the current total budget of the project.

Within this project, an additional challenge made us chose another direction, the challenge to attach the shoulder component of the AFES system to an actual human. During the project's design phase, we struggled with the attachment of the shoulder part. While it might seem straightforward to attach something over the shoulder, the essence of the AFES lies in providing an ergonomic solution. Typical exoskeleton designs redistribute weight to the back and hip, making a simple shoulder attachment impractical. Unfortunately, a suitable solution was not reached within the project timeline. While we played with the idea of attaching the shoulder part to a "alice pack frame" but we could not implement this idea in time. Therefore, we sought an alternative method to demonstrate the system's functionality. This led to the creation of a stand showcased in the results section, serving as a temporary solution to display the arm's movement within the designed DOF.

As previously mentioned, the current iteration of the AFES is mainly modeled with plastic. While the existing model is fully functional in its present state, future development involves changing the current plastic components to metal. This transformation not only improves the model's functionality but also provides insights into critical factors, including weight, compatibility, general design feedback, and more. This data would be useful in shaping future parts of the design, such as the shoulder connection part or the addition of a second arm. Additionally, it serves as a valuable resource for any potential redesigns.

In the future development of the AFES it is essential that there is multiple designs made for the purpose of being available for divers users. This also includes the need for individual trained EMG data to ensure that the AFES behaves accordingly to the user. With multiple tests it was proven that the system could work with separate subject data for offline and online. However, for the final product it is crucial that the motors only activates in the right moments, thus individual offline data would be necessary for ensuring safety. Furthermore, the AFES requires additional safety features that align with the initial exoskeleton requirements. These safety measures need to be integrated into both the hardware and software components of the AFES. Research focusing on suitable EMG sensors applicable for real-time procedures is imperative. These sensors should be capable of capturing multiple output signals simultaneously, aiding in reducing latency within the system's functionality. Implementing programming languages like C/C++ is essential for minimizing system delay and enhancing code efficiency.

One limitation of the system is that motor orientation changes are restricted to when the user is either relaxing or actively engaging the bicep. This introduces a certain lack of flexibility, raising questions about the current effectiveness of carrying objects with the AFES. To enhance system flexibility, a promising improvement involves the integration of additional sensors, such as IMUs. IMUs could provide crucial data on the x, y, z orientation, velocity, and acceleration of the arm. This additional data can then be used to make more accurate power assessments when the user is tasked with carrying objects, enhancing the overall functionality and adaptability of the AFES.

An essential aspect involves exploring artificial intelligence methods tailored for EMG signal classification. Expanding the exoskeleton's sensor array can enhance system predictability and adaptability to its surroundings. This augmentation could encompass various sensors, including those measuring additional physiological signals or those interpreting environmental cues, such as Lidar.

Additionally, acquiring EMG data from diverse muscle groups is crucial for building a robust dataset required to train supervised classification models. However, considering alternative approaches like reinforcement learning warrants exploration for future investigation. Moreover, this underscores the necessity of implementing a robust control system for the exoskeleton. Such a system should furnish feedback data, including temperature and torque metrics, vital for comprehending and stabilizing the device's control system.

8. Conclusion

In conclusion, the group's work on an AFES has revealed compelling insights into the possibilities and challenges associated with EMG data and wearable hardware. Throughout this project, a deeper understanding of exoskeletons, data processing and prototyping has been attained.

In the following section, the authors will delve into the implications of this projects findings, propose recommendations, and identify potential avenues for future research to foster continued advancement. As a reminder, the goal of this work was the development of a AFES with the purpose of supporting workers in physically demanding jobs and lowering the negative impact their work has on their health.

Within the limitations of the project, the team was able to build a working prototype of a single-arm AFES. Processing the data properly is essential for success when working with EMG. Therefore, succeeding in this laid the foundation for any further work that might build on this.

On the hardware side of this project, weight and dimension of all parts was a reoccurring problem throughout this project. Since in a system like this, every gram has to be carried and moved, making parts as light as possible is crucial. By simulating forces that act on different components, the team was able to make them significantly lighter without affecting their structural integrity. On the other hand, certain improvements can and should be made. The used gearing should be improved to achieve a slower speed but higher torque on the driven gear. Two hardware tasks that could not at all be addressed during this project due to time limitations are the shoulder attachment to the torso and the power supply. Both of these should be developed in a future project. On the software side, while the team was successful in running a single sensor, there was no time to also integrate sensors on the triceps and shoulder muscles. Those and the respective changes to the motor controller need to be made in a future project.

In conclusion, the research goals are revisited to provide a comprehensive overview of the project's accomplishments. Firstly, in pursuit of **RG1** *(To design and build a prototype single arm exoskeleton that fulfills the given medical and industrial requirements.)*, the team successfully engineered a lightweight, stable, and easily manufacturable prototype for the single-arm AFES. Although constraints in time hindered the inclusion of the power supply and shoulder attachment in this iteration, meticulous consideration was given to their incorporation in the design, paving the way for future project enhancements.

Moving on to **RG2** *(To acquire, analyse and process online and offline EMG signals to control the exoskeleton.)*, the achieved milestones are vividly presented in the results section, particularly evidenced in Figure 15. The figure aims to show how that the exoskeleton functions to move exclusively by muscle activity. This visual representation underscores the real-time control of the exoskeleton through the utilization of EMG signals. The signal analysis results, whether conducted offline or online are shown in both Figure 18 and Figure 19. These figures illustrates the results of filtering and classification of the signals which serve as input to the exoskeleton controller. This successful execution establishes a strong foundation for further developments in this area, as discussed in section 7.

Lastly, with respect to **RG3** *(To integrate a motor controller that controls the exoskeleton based on the EMG signals.)*, the team successfully developed a motor controller capable of regulating the installed motors based on the captured EMG signal. Despite facing time constraints, the team was unable to implement advanced methods to achieve more human-like behaviors. Addressing this limitation is identified as a priority for future projects, where further exploration and implementation of sophisticated approaches will be pivotal to enhancing the overall functionality and naturalistic behavior of the exoskeleton system.

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A Appendix

An outline of the individual contributions made by the authors towards the completion of this report is summarized in Table 2.

Table 2: Individual Contributions

Author	**Section**	**Section title**
Jalal Taleb	3	State of the Art
	4.2	Method-Software
	6, 6.2	Result-Software
	7	Part of Discussion and Future Work
Irini Provatidis	2.2	Software Related Background Concepts
	3	Part of State of the Art
	4.2	Method-Software
	6, 6.2	Result-Software
	7	Part of Discussion and Future Work
Albin Gustafsson		Acknowledgments
	4, 4.1	Method-Hardware
	6.1	Results-Hardware
Moritz Schmidt		Abstract
	1	Introduction
	2.0, 2.1	Hardware Background
	5	Ethical and societal considerations
	8	Conclusion
Sebastian Ahlström	3	State of the art
	5	Ethical and societal considerations
	6, 6.1	Results-Hardware
	7	Discussion and future work