Exoskeleton Technology: State-of-the-art and -practice of Physical and Cognitive Human Robot Interface

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Exoskeletons and orthoses are wearable mobile systems providing mechanical benefits to the users. Despite significant improvements in the last decades, the technology is not fully mature to be adopted for strenuous and non-programmed tasks. To accommodate this insufficiency, different aspects of this technology need to be analysed and improved. Numerous studies have been trying to address some aspects of exoskeletons, e.g. mechanism design, intent prediction, and control scheme. However, most works have focused on a specific element of design or application without providing a comprehensive review framework. This study aims to analyse and survey the contributing aspects to the improvement and broad adoption of this technology. To address this, after introducing assistive devices and exoskeletons, the main design criteria will be investigated from a physical Human-Robot Interface (HRI) perspective. The study will be further developed by outlining several examples of known assistive devices in different categories. In order to establish an intelligent HRI strategy and enabling intuitive control for users, cognitive HRI will be investigated. Various approaches to this strategy will be reviewed, and a model for intent prediction will be proposed. This model is utilised to predict the gate phase from a single Electromyography (EMG) channel input. The outcomes of modelling show the potential use of single-channel input in low-power assistive devices. Furthermore, the proposed model can provide redundancy in devices with a complex control strategy.

Index Terms—Assistive technology Exoskeleton Human Robot Interaction Intent detection Machine Learning

I. INTRODUCTION

Assistive technologies can help individuals with a particular task in an environment associated with pain or injury. In the last 30 years, advancements in assistive technology have experienced a significant improvement in design and application within field use. However, most systems still struggle to accommodate slight variations in tasks other than the initially planned application. This can become a critical issue as most strenuous jobs are not singular and often involve different movements.

The concept of exoskeletons goes back to 18th century when Vangestine conceptualised a wearable device for people with disabilities to assist them with walking, jumping and running [1]. This concept became a reality by the design of the first exoskeleton in 1936 [2]. One of the firsts active devices is the full-body exoskeleton developed by General Electric in 1965 to handle heavy loads [3].

Wearable assistive devices can be generally categorised into prostheses and orthoses. The first one aims to replace a missing body part’s functionality, whereas the second one is to support or augment the functionality of the existing part [4]. The orthoses can be designed to operate either along the human joints and limbs known as exoskeletons [5]–[7] or adjust the user’s end-effector [8]. Exoskeletons can also be divided into different groups based on their application, whether they are powered or not, the body part they are assisting with, design type (rigid or soft), control system, user interface, and mobility [9].

Exoskeletons show many advantages over traditional wheeled devices like wheelchairs. These benefits include: First, the user can perform tasks outside paved surfaces. Second, their interface is usually more transparent and intuitive as they follow the user’s motion [10]. And third, they can provide the user with haptic feedback [11]. One limitation here is energy efficiency. Wheeled devices only require energy for the initial acceleration and friction compensation. In contrast, exoskeletons and orthoses require constant acceleration and deceleration in addition to the required energy for supporting against gravity [12].

Assistive systems can be either passive or active. Passive systems allow the user to carry loads that they may not usually be capable of without additional support. This may expose users to a risk when the system is not transferring the load to the ground during movement. Additionally, the rigid nature of passive systems’ design causes lost mobility and transparency and often discomfort. On the other hand, active systems rely on empowering the joints with actuators that can provide additional torque. The added torque allows minimal activation of the muscles and thus reduces muscular fatigue, allowing for prolonged tasks. Fig 1 shows an example of the classification of wearable assistive devices.

To the authors’ best knowledge, most published surveys in this field are either on a specific type of exoskeleton, e.g. active lower-limb exoskeletons [13], or are focused on a particular area related to these devices, e.g. control [14], pattern recognition [15] classification [16]. This survey aims to investigate the design background and development of state-of-the-art exoskeleton technology regardless of their intended use [17]–[22], utilised technology [16], [23], or target body parts [13], [16], [19]. As part of this research, several examples will be provided to support the discussion on the design and technical aspects of this technology.

The rest of this paper is organised as follows: In Section 2, the biomechanics aspects for exoskeletons will be explored and the mechanical solutions, including the mechanism, actuation and energy source, will be covered. In Section 3, the well-known existing systems are classified into passive, semi-passive and active systems, and a detailed discussion on each

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system is provided. In Section 4, the human-robot interface for wearable assistive devices is investigated. Furthermore, following a discussion on intent detection and the relevant subsystems, including sensors, signal processing and data fusion, different approaches for intent interpretation will be reviewed. Section 5 discusses the control strategies integrating intent detection and interpretation components to provide an intuitive performance for the exoskeleton. In Section 6, an intent prediction model will be proposed to predict the gait phase from a single EMG channel. Moreover, the processing and AI training techniques are discussed in this section along with the results. Section 7 shows the outcomes of the study.

II. EXOSKELETON DESIGN

The design and implementation approaches of exoskeleton systems are getting converged despite the difference in their applications [24]. These systems should be aligned with human biomechanics [1], wearable and portable [25]. Moreover, the power consumption, control subsystem, accuracy and robustness of them play a key role in the design requirement [26]. Overall there are several aspects associated with the design criteria of exoskeleton systems. These include structural and material design, human-robot interaction, hardware including sensors and actuators, energy source, and software or control system. In this section, the biomechanical design aspects of these devices are discussed. Then, we will cover the physical human-robot interaction (pHRI) criteria, i.e. mechanism, actuators and energy sources.

A. Biomechanics

The exoskeleton should be designed around the human body’s biomechanics, i.e. anthropomorphism and ergonomics. To make them fully compatible with the human body, the degree(s) of freedom (DoF) [27] and the placement of actuators [28] of the exoskeleton shall be aligned with human anatomy. This means that simple yet accurate human kinematic models are essential to developing an efficient control algorithm for these assistive devices. Such a model should involve DoF of the assisting joints and all possible body parts movements and their limitations. Figure 2 shows the possible motions of human upper limbs. Modelling the accurate functions of human upper limbs can be complicated; therefore, usually, a set of pre-determined movements will be used [14]–[16], [23], [29]–[31]. These models can be simpler for the lower limb as there are 3 DoF in the hip and ankle and 1 DoF in the knees. These models shall be aligned with the appropriate biomechanical parameters to accommodate the body parts’ kinetics and kinematics. This is also necessary for understanding the power requirement of the active systems. For instance, Dollar and Herr showed that the power at the hip, knee and ankle in level walking is evenly distributed in both the positive and negative sides [32]. Another example is weight-climbing, which presents more significant biomechanical challenges as the body’s centre of mass (CoM) needs to be raised [19]. Other than that, these parameters help with studying the exoskeleton’s impact on the user. There are several ways to measure the effectiveness of a exoskeleton, e.g. average maximum load [19], joint moment [33], muscle torque reduction [12], [33], muscle activity [20], [34]–[37] and metabolic cost [7], [19], [25], [38]–[41] (Tab. 1).

B. Mechanism

The main mechanical criteria in the design of an exoskeleton are: ergonomics and comfort, manoeuvrability, weight, structural strength, adaptability and safety [49]. The importance of these criteria differs depending on the application and focused limb, affecting the structural design and optimal solution [4]. Moreover, an exoskeleton needs to be adaptable to the wearer’s characteristics, e.g. body shape and limb size [50]. Also, it has to deal with the changes in the body motion’s characteristics. This is essential to minimise the misalignment between the human and robot’s joints and limbs. However, achieving this alignment is challenging as biological joints’ centre of rotation are not fixed [51]. For example, the instant centre of rotation (ICR) at the shoulder and elbow alters with joint motion [52]. To solve this problem, MEDARM uses additional joints so it can move the centre of rotation [53]. Another approach is to consider the shift of the centre of the rotation in the design. An example of this approach is the upper limb exo by Kiguchi and Fuku [14].

Misalignment can also occur during motion between the human and robot’s joint axis. The resulting high contact pressure and cognitive loads can cause discomfort for the user [54]. Jarrassé and Morel proposed a hyperstacticity solution to prevent these undesired interaction forces [55]. Vitello et al. avoided this misalignment issue in NEUROExos using a compliant actuation system [56]. Furthermore, self-aligning systems like decoupling joint rotation [57] and ASSISTON-SE [58] are alternative approaches to align the robot and user’s joints. However, these solutions come with the detriment of
Ankle exoskeleton [42]:
- Uses artificial pneumatic muscles to help with ankle push-off.
- Reduce walking metabolic cost by up to 21%.

Passive-elastic knee-ankle exoskeleton [44]:
- Stores knee extension energy in a spring and releases it during ankle push-off.
- Reduce the metabolic cost by 11% compared to wearing disengaged exoskeleton.

Autonomous hip exoskeleton [46]:
- Uses BLDC motor to help hip rotation in uphill walking
- Demonstrated 15.5% metabolic cost saving at 10 grade slope.

Multi-joint soft exosuit from Wyss Ins. [43]:
- Reduces the muscle activity of the vastus lateralis and soleus by 4.7 and 8.4% during walking
- 14.2% reduction in metaboloc cost.

Powered bilateral hip exoskeleton [45]:
- Achieved reduction of 6% in gait energy cost in it’s optimum setup.

Passive arm exoskeleton [47]:
- Showed 62 and 49% reduction in Medial Deltoid and Biceps Brachii’s muscle activity while holding a 2Kg load [48].

TABLE I
THE BIOLOGICAL EFFECT OF EXOSKELETON ASSIST WITH SPECIFIC TASKS

| Exoskeleton Type | Description |
|------------------|-------------|
| Ankle exoskeleton | Uses artificial pneumatic muscles to help with ankle push-off. Reduce walking metabolic cost by up to 21%.
| Passive-elastic knee-ankle exoskeleton | Stores knee extension energy in a spring and releases it during ankle push-off. Reduce the metabolic cost by 11% compared to wearing disengaged exoskeleton.
| Autonomous hip exoskeleton | Uses BLDC motor to help hip rotation in uphill walking. Demonstrated 15.5% metabolic cost saving at 10 grade slope.
| Multi-joint soft exosuit from Wyss Ins. | Reduces the muscle activity of the vastus lateralis and soleus by 4.7 and 8.4% during walking. 14.2% reduction in metaboloc cost.
| Powered bilateral hip exoskeleton | Achieved reduction of 6% in gait energy cost in its optimum setup.
| Passive arm exoskeleton | Showed 62 and 49% reduction in Medial Deltoid and Biceps Brachii’s muscle activity while holding a 2Kg load.

The added mass and complexity. That is why most systems focus only on one joint like knee [59], [60] or ankle [38]. Table II shows some solution approaches for misalignment in exoskeletons.

Structural integrity or strength is the other aspect of mechanical design. Material property and mechanism design are the key influencers of the structural integrity. In order to maximise the system’s movability, they need to utilise materials with high strength to weight ratio. Light metals alloys like Aluminium have been widely used in many designs like HAL-3 [24], [61]. Titanium has a 67% better strength to weight ratio than Aluminium [62]. Fibre-reinforced composites have gotten popular in recent years due to their high strength, lightweight, and ability to shape different designs [7], [25]. However, they cannot perform efficiently compression and connection strength.

The most common exo designs are rigid robotic mechanisms designed around the human body. They connect to the user’s limbs and help them with parallel to their muscles and joints. PKAEExo [19], H-PULSE [63], BLEEX [28], RoboKnee [59] and HAL [5] are examples of a rigid design. Their downsides are the added bulk and weight, which may undermine the ease of application and increases the energy consumption. For lower limb’s devices, more actuation energy is required by moving the mass towards the foot and ankle [64]. For example, adding 4Kg mass to the centre of mass of a person will increase their metabolic cost by 7.6%, whereas this number can rise to 34% if the mass moves towards the feet [7]. One possible approach to prevent this added mass is to use passive systems that store and release kinetic energy in elastic parts [19], [38], [40].

An alternative solution is soft design inspired by invertebrates [65]. This design solution can assist the user through flexible structures [22] and increases the system’s flexibility. The lightweight elastic fabrics used in these systems help with reduced inertia and power consumption and increased comfort and transparency. An emerging field in soft systems is soft pneumatic gripper technology. Kai et al. developed a soft hand exoskeleton based on variable stiffness actuators embedded in a glove [66]. The proposed system is lightweight and easy to use, and the variable stiffness would allow for different finger profiles and movements. Another benefit of these designs is that precise control becomes less of a priority due to the forgiving nature of the system. In cable-driven soft exoskeletons, torque can be provided on multiple joints simultaneously. This reduces the number of actuators and, in turn, weight and efficiency [25], [39]. Another example is the soft exosuit developed in WySS institute that helps with ankle moment [7]. The proposed design does not have rigid parts to help with compression, so human muscle and bone support the load which may limit the load-carrying capacity.

C. Actuators

The actuator should provide the required mechanical strength while having minimal weight and transparency. Most of the popular robotic actuators cannot pass the high torque and high-speed required for exoskeletons [50]. In general, size, weight, and actuation efficiency can affect the system’s range and maneuverability [71].

Among electric actuators, servo motors are best suited for applications that require precise position control. This includes almost all assistive devices aiding with disabled or injured body part, e.g. injured spinal cord [24]. These motors can be set up in direct drive actuator mode, series with reduction gears or cable drive transmissions. While the first approach leads to an expensive, bulky, ungainly set-up, the gear set-up increases friction and reflected inertia. On the other hand, pulley transmission needs a lot of space for large pulley set-ups to get the desired reduction ratio [11].

Load cells can be used in closed-loop control systems to avoid friction and inertia problems with geared solutions. The load cell measures the amount of force that the actuator is applying. At the same time, the feedback controller uses the the difference between the applied force and the desired one. The downside is that they are susceptible to shocks, e.g. when
the foot touches the ground. A solution to this problem is using Series Elastic Actuators (SEA) [11]. As shown in Fig. 5, SEA works fundamentally like the traditional linear actuators coupled with load cells in a closed-loop system. The difference is that instead of load cells, it uses spring deflection to measure the force. This flexible part can also help with energy-saving similar to passive devices. High fidelity force control, backdriveability, low impedance and low energy consumption are some of their advantages.

Brushless dc motors have high torque to weight ratio and can be a perfect candidate for applications that do not require precise position control. Honda Walking Assist [72] and ankle exoskeleton by Mooney [73] are examples of this type of motor. In case of heavy lifting, hydraulic systems could be a good replacement for electric and pneumatic actuators [74]. Sarcos exoskeleton is an example using hydraulic rotary motors [50]. However, in the design of BLEEX, Zoss et al. found that rotary motors suffer from friction problems and oil leakage [28].

These hydraulic actuators, however, may not be suitable for compact designs [24]. Instead, artificial muscles can be used for the mentioned systems. These artificial muscles can be electroactive, memory alloy or pneumatically controlled. An example of these actuators is Flat Pneumatic Artificial Muscles developed by Wyss institute [75]. Their 2D design and fabric sleeves makes them compact and lightweight. Table III shows the actuator choice in some exoskeletons.

D. Energy source

Exoskeletons require a source of energy that can provide the required range of motion for a specific duration of task, yet light enough not to adversely affect the mobility of system. Other than the designs tethered to an external power source, the exosystems can use batteries, small internal combustion engines, electrochemical fuel cells, or wireless energy transfer [79]. Lithium batteries have a relatively high energy to weight density, which makes them popular in exoskeletons. With the current technology, most active exoskeletons can function between one to five hours [24]. A solution to this limitation can be regenerative braking, e.g. Ankle Foot Orthosis by Oymagil et al. [80]. Overall, this aspect may impose limitations on exoskeletons and their application. To overcome this, more efficient and advanced energy transfer and storage as well as processing and actuation techniques are required.

III. TYPES OF EXOSKELETONS

Exoskeletons can be categorised based on their application, structural design or power consumption. The most common classification is based on passive, semi-passive or active mechanism.

A. Passive exoskeletons

Passive exoskeletons work by saving muscle energy in a spring or other elastic element and releasing it when needed. This type of exoskeleton does not need actuator and has fewer moving parts than active or semi-passive ones, making them a less complicated, lightweight, and economical option [19]. One of the first models of these passive wearable assistive devices is Yagn’s walking aid which utilises two leaf springs parallel to the legs [84]. Passive exoskeletons can significantly reduce muscle load and metabolic cost if they are designed optimally [12].

There are different approaches to designing a passive exoskeleton. A common way is to transfer a rotating joint’s

| TABLE II | REPORTED SOLUTIONS TO MISALIGNMENT IN EXOSKELETONS |
|----------|----------------------------------------------------|
| MEDARM for rehabilitation [53]: | NEUROExos [56]: |
| - Aims to improves the replication of human motion. | - Poststroke elbow rehabilitation exoskeleton. |
| - Uses additional joints to move the centre of rotation to solve the misalignment issue. | - Passive mechanism allows the elbow to align with robot’s axes during motion. |
| SPEXOR [67]: | - Fixing the misalignment and eliminating contact pressure in exoskeletons by translating axis [57]. |
| - Stores energy during bending and releases for back extension: | - The implementation is by using two extra link and the elbow joint. |
| - Revolute-Revolute-Revolute (RRR) [68] misalignment compensation method for the hip. | Cable-Driven Arm Exo (CAREX) [70]: |
| Double-Layered Elbow Exoskeleton [69]: | - Uses cable lengths and joint angles to calculate the glenohumeral joint rotation centre to improve achieving desired forces on the hand. |
| - Uses 3-PRR planar parallel mechanism to solve the axis misalignment. | Soft exo suit for hip assistance during walking and running [25]. |
| Quasi-passive leg exoskeleton [41]: | - Soft material used in the design imposes no restriction on hip movement, solving the problem of misalignment altogether. |
| - Load carrying augmentation. | |
| - Uses a cam mechanism for hip misalignment compensation. | |

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- Revolute-Revolute-Revolute (RRR) [68] misalignment compensation method for the hip. |
- Uses 3-PRR planar parallel mechanism to solve the axis misalignment. |
- Load carrying augmentation. |
- Uses a cam mechanism for hip misalignment compensation. |
kinetic energy into an elastic element. Collins et al. developed a passive ankle assistive device that helps the wearer with calf muscles activity [38]. It uses a spring to connect the shank to the calf for energy storage. A clutch engages the base on the ground and disengages when it is on the air. The results show a 7.2 ± 2.5% reduction in healthy human’s metabolic walking cost. Another example is the passive knee assist exo (PKAExo) for weight climbing [19]. Its eccentric pulley design allows for a nonlinear increase in the assist ratio with knee angle and showed a decrease of 21% in the average number of the knee extensor’s maximum load.

Another approach to passive exoskeletons lies in exotendons. In some animals, muscles connect multiple joints [85] which helps in energy saving when one joint requires acceleration, and the other needs deceleration [86]. Needless to say that the elasticity of the muscles and tendons helps with storage and release of the energy [87], [88]. This can help animals to use only 50% metabolic energy compared to humans [85]. Single leaf exoskeleton (SLE) from MIT utilities this concept and demonstrates a reduction of 24% in metabolic cost during hopping [40].

Another solution is using pulleys and more complicated setups. Bogert developed a passive exoskeleton concept with elastic cords and pulleys that spans multiple joints [12]. The idea was to assist with walking by transferring the saved energy into different joints. In simulations, in the most straightforward setup with only uniarticular exotendons at the ankle, a muscle torque reduction of 21% was achieved. By replacing the exotendons with triarticular ones, spanning the ankle, knee and hip, this reduction increased to 46%. It has been shown that a maximum of 71% muscle torque reduction could be achieved by using multi exotendons in complex configurations. Based on this concept, XPED2 was designed to assist with lower-limb [33]. In this system, a cable connects a leaf spring at the foot to the pelvis through a pulley at the knee. Change in the hip and ankle joint angle results in the spring’s deformation, thus force in the cable. The experimental result showed 12.1% assistance and a slight increase in the metabolic cost. Dijk and Kooji concluded that the 71% assistance in Bogert’s is probably unlikely to achieve [33]. Table IV shows some of the most renowned passive exoskeletons in the literature.

### B. Semi-passive exoskeletons

One of the drawbacks of passive devices is their fix assist ratio defined by the stiffness of the elastic parts, limiting
their adaptability to different situations. Semi-passive devices use low-power actuators to control the assistive ratio while maintaining low complexity and lightweight. Jams’ek et al. developed a spinal exoskeleton that uses electrical clutches to engage the elastic part during lifting and disengage during other tasks [89]. H-PULSE uses an “active tuning mechanism” to automatically adjust the assistive torque using a servomotor, a spindle drive and a hierarchy control system [63]. Walsh et al. optimised a quasi-passive design of a leg exoskeleton with linear springs in the ankle and hip and variable damper in the knee [41]. It finds the gait phase through knee angle and force and adjusts the variable-damping mechanism to help with negative mechanical power. The system managed to decrease the metabolic cost by 11% when fully engaged compared to zero-impedance design.

When it comes to ground level walking, the knee shows the highest springy behaviour compared to other lower limb joints [60]. To get the best results with minimum effort, researchers from Yale University worked on a quasi-passive knee exoskeleton that uses a finite-state machine to control the engagement [60]. It determines the gait phase based on toe sensors to engage the assistance spring during the weight acceptance phase and disengages it otherwise. Table V describes principles of some examples of semi-passive devices in the literature.

C. Active exoskeletons

While passive assistance can significantly help in preventing muscle fatigue in repetitive works, it may not be sufficient for some applications like power augmentation [28], rehabilitation [104] or for weak and impaired users [5]. Active exoskeletons use various sensors paired with complex computing units to control the joint movements in real-time. They are mechanical structures whose joints are aligned with the user [27]. The idea is to combine the robot’s strength with human intelligence [27], [105].

A breakthrough in the development of active exosystems was the concept of human-robot interaction (HRI) [106]. The interaction between the exoskeleton and the user is either physical or cognitive [4]. Physical human-robot-interaction (pHRI) determines the suitability of the exosystem, whereas cognitive human-robot-interaction (cHRI) consider intelligence for controlling the system [1]. pHRI, which include Degree of freedom, actuation, kinematic, transmission, and dexterity, directly affects safety and comfort aspects [52]. In contrast, cHRI is crucial for intuitive and real-time control of the system. An in-depth discussion of cHRI will be presented in the next section.

Exoskeletons require different control scheme compared other types of robotics [27]; The generated motion must follow the user’s intention with minimum error [79]. Thus, an elaborate "human-in-the-loop" control system is required to synchronise the robot’s movement with the user’s intention based on HMI input. The major ordeal is predicting the user’s intent and reacting to it in real-time [107]. The intention will act as the system’s input, and the output will be the exoskeleton’s movement. The human will sense this movement as a motion feedback which makes the user optimise their intention [27]. Furthermore, human’s learning ability and motor adaptation plays a crucial role in this synchronisation
This will raise the concern for cross adaptation in which the exoskeleton and the user shall adapt themselves to each other. One approach here is to calculate the joint torque to do a task and help the user with a pre-determined fraction of that torque, called assist ratio.

There are different ways to control the exoskeletons and HRI. Berkeley Lower Extremity Exoskeleton (BLEEX) minimises the force interaction between the human and robot by shadowing the user’s movement. However, the problem here is to meet the sweet spot for the system’s sensitivity to the interaction force. This is essential to balance the system’s response time and its robustness. High sensitivity can cause losing stability as well as decreasing the robot’s precision to its dynamic model. In BLEEX, the gait cycle has been divided into load support and swing phase, where position control and positive feedback control systems have been applied to them, respectively. The controller does not need direct input from HMI in the sensitivity amplification and only uses built-in accelerometers and encoders.

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In recent years, use of biological signal has been trending in intent prediction in human-robot collaboration. The most common signals are Electromyogram (EMG), Electroencephalogram (EEG), Electrooculogram (EOG), Electrocorticogram (ECoG) and Magnetoencephalography (MEG). Electromyogram intent detection is categorised into classification and regression models. The system can estimate the joint torque and help with a fraction. The EMG signal starts 20-80ms before muscle activation making it useful for real-time processing. Another advantage of EMG-based control methods is that they can compensate for the patient’s inability to produce adequate joint torque. In other words, as long as the patient can produce the neuromusculoskeletal signal, in theory, they should be able to control the assistive device. However, it cannot be extended to people with motor injury. There is a correlation between EMG signals and muscle force or intended joint torque. The output depends on the instrument, user’s anatomy, sensor placement, muscle crosstalk, and internal/external noises.

One of the most known myoelectrically controlled exoskeletons are the Hybrid Assistive Limb (HAL) series. The development of HAL started in 1992 by Sankai et al. HAL-1 was designed to help the user with the joint torque while walking, utilising DC motors and ball screws. HAL-3 used myoelectricity to implement the assist torque and sequence control. Phase Sequence control divides
walking into different phases for assistance based on muscle force conditions. Floor reaction forces can help with the transition between phases. Assist torque control, on the other hand, utilises a feedback controller to maintain the assistance ratio. "Cybernetic Voluntary" and "Autonomous Control" are the two complementary parts of the system. The former helps with physical support based on the user’s intention extracted from the biosignal. The latter utilises different input types to control the system seamlessly, e.g., position-based and force-based inputs. In HAL-5, the shift of the centre of gravity helps to determine when to assist with walking [5].

The active exoskeleton’s design differs based on its application; performance augmentation [25], [39], [61], [105], rehabilitation [66], [104] and individuals with disabilities [5], [24]. Assistance-as-needed knee exoskeleton developed by Lyu et al. is an example of robotic therapy [104]. It connects the knee exoskeleton to a screen game in which the subject controls the game by their knee angle and muscle activity as in Fig 3. The inventors used AI agents based on modular pipeline and deep Q-network to help with assistance as needed and enhance the exoskeleton’s autonomous control.

An example of a soft active exoskeleton is the autonomous multi-joint soft exosuit developed by Wyss Institute [39]. It helps the wearer with the plantarflexion and hip flexion/extension using iterative force-based position control and Bowden cables. By optimizing control parameters for each individual, up to 15% reduction in metabolic cost compared to not wearing the suit and 22% compared to wearing the unpow- ered suit can be achieved. In another version of Wyss exosuit, only hip assistance was targeted to reduce the equivalent metabolic cost of 7.4 and 5.5 Kg of payload for walking and running, respectively [25]. Table VI highlights some famous active exoskeletons in the literature.

### IV. HUMAN ROBOT INTERFACE

The human-robot interface plays a key role in the wearer’s comfort and safety. This subsystem can vary significantly from one design to another. For instance, Sarcos exoskeleton utilises
direct input from the wearer through force sensors interfacing human body to the robot [50]. BLEEX, on the other hand, does not interface any sensor to the user and relies on accelerometers, encoders and load distribution sensors to calculate the user and robot’s state and predict the intention and control the system [32]. HAL utilises surface EMG for its Cybernic Voluntary Control along with position-based and force-based sensors for its complementary Autonomous Control [5]. The advantage of EMG is that even patients with weak muscles, as long as they produce neuro-muscular signals, can utilise it as the input for the robot [120].

Human-robot interaction is “a field of study dedicated to understanding, designing, and evaluating robotic systems for use by or with humans” [121]. This collaboration allows the robot and the human user to perform shared tasks. The interaction between the human and the robot is bidirectional. The robot receives the human movement intention and, in return, provide them with mechanical help as well as feedback information [122]. While the robot’s output is the outcome of mechanical design or pHRI, the intent interpretation should be implemented at the controller level or cHRI.

The control structure of the active exoskeletons should be designed with the human-in-the-centre or human-in-the-loop consideration. Figure 4 shows the structure of a human-machine intelligence: In the first layer, both the human and machine sense the information from each other and the environment. Next, the information from the previous layer will be processed in the human brain and the robot’s processing unit. Lastly, the user initiates the intended movement, which the machine will detect, and activates the actuators to contribute. The actuators’ feedback will be sensed by both the human and robot in the first layer to correct the decision and helping ratio in a closed-loop system. In other words, the robot will act based on either user or the system’s command generator, then senses the environment’s response and provides the user with feedback so that they can intuitively execute the task.

A. Intent detection

Intent can be defined in many ways depending on the scenario. In some cases, like whether the human wants to control the robot or not, the intention can be defined in binary terms. In controlling a lower limb exoskeleton, they can be defined as a set of possible movements. In continuous systems, intent can be defined as velocity, position trajectory [123], force [123], or torque [107]. It can be more complicated in the upper limb systems, which include more poses and functions. Well defining the intent can help accurately measure the engagement of the patients undergoing neurorehabilitation [124].

Measuring the pre-defined intent can be done in a variety of neural ways like EMG and EEG as well as kinetic and kinematic based methods such as FMG, somomyography, load cells and position encoders to determine the gait phase and assist accordingly [125]. Another approach to intent detection in mechanical systems is to measure the robot’s position and estimate the indented force or vice versa. Ge et al. developed a method that estimates the human intention in the pre-defined limb trajectory by measuring the position, velocity and interaction force of the contact point using neural networks [126]. In another study, the interaction force in the handles of the intelligent walker is used to forward the path trajectory [127]. BLEEX minimises the force interaction between the human and robot by shadowing the user’s movement [105].

1) Sensors

Sensors play essential roles in assistive devices. Their primary use is to gather data on the operator or patient’s kinematics during a task [128]. They help the exoskeleton to interact with the user and the environment and regulate the output. An example is using position encoders to modulate torque output of a joint by providing the phase variable [24]. They can also help with safety regulation and calculating the system cycles stride’s joint angle trajectory. Another widely used sensor is load cell. They can be highly accurate [129] and are commonly used in lower limb devices [130]. A typical lower limb application is to measure the contact force between the user and the ground. In some cases, this measurement can be replaced with a binary on/off switch [24]. Series elastic actuators (SEA) can be an alternative to load cells. They measure the deflection of the spring that is installed parallel to the linear actuator and calculate the actuator’s force [59].

Figure 5 shows the schematic of SEA.

In recent years, neural command sensing technologies like EMG [131] and EEG sensors [96] became popular in exoskeletons. These sensors read the user’s intention from the peripheral or central nervous system [132], [133]. EMG signal is a bio-electric signal caused by the neuro-muscular activity collected directly from the target muscle. The time delay between the neuro-muscular activity and actual movement makes it perfect for real-time applications. Surface EMG sensors collect neuro-muscular electrical signals from the skin surface. As the muscle signal is not collected directly from the targeted muscles, the signal strength will decrease, resulting in a decreased signal to noise ratio (SNR). Other than that, the other muscles’ activity can affect the quality of the recorded signal known as cross-talk. If the targeted muscle is hidden behind other muscles, it will become harder to record a clear muscle activity signal.

In surface EEG, electrodes collect the local field potential (LFP) signals from the scalp non-invasively. This can help to predict the user’s intention 500ms before their motion [134]. In another more invasive approach named electrocorticography or intracranial EEG, electrodes will be surgically placed on the
The movement artefact and electromagnetic noise could be noises. For instance, increasing the electrode size will reduce strategies can be implemented to minimise the effects of these artefacts.

Sensor signals carry noises from different sources. For instance, EMG signals have electrode inherent noise, movement artefact, electromagnetic noise [140], muscle cross-talk [141]–[143] internal body noise and electrocardiographic (ECG) artifacts for upper-chest recording [144], [145]. Different strategies can be implemented to minimise the effects of these noises. For instance, increasing the electrode size will reduce the impedance and give a high signal to noise ratio (SNR). The movement artefact and electromagnetic noise could be minimised by using a high and low pass filter, respectively.

After filtering noises, the signal needs to be processed before feeding into the intent prediction model. The raw signals are usually large [146], so using them directly for classification can reduce the efficiency of the classifier [147]. Extracting features from the raw signal can reduce dimensionality while maintaining the most important information. This improves the performance and allows real-time computing. Feature extraction can be done in time-, frequency-, or time-frequency domains [112], [148]. The advantage of time-domain features is that they are easier to calculate with less computational effort [16]; hence they are popular in engineering and medical practices [148]. To process signals in the frequency domain, Fast Fourier Transform (FFT) helps to shift from the time domain into the frequency domain. The common frequency-domain characteristics include mean frequency (MNF), mean power frequency (MPF) and median frequency (MDF).

3) Data fusion

Data fusion is the combination of information from multiple sources to increase the intent detection performance and accuracy [149]. This information can be either redundant to increase reliability or complementary to decrease uncertainty. Data fusion could happen in measurement, features extraction or classification and decision making [150].

The intent can be acquired through multiple sensors of either the same or with different modalities. An example of the first one is the knee exoskeleton developed by Lyu et al., which uses 16 EMG sensors on the thigh to predict the knee movement’s intention [104]. The latter has been implemented by Krausz et al. in which they fused EMG signals with gaze data to control prosthetic arms [139]. Researchers at the University of Espírito Santo combined IMU and intensity variation polymer optical fibre to develop a highly reliable angle measurement system [151]. Young et al. studied the effect of combining EMG signals with position, load, and inertial sensors to increase pattern recognition accuracy [138].

B. Intent interpretation

For many scenarios, the direct measurement of the intent is impossible; however, we can measure the related parameters [125]. The interpretation, then, relies on the modelling and simplification of assumptions [130]. Either pattern recognition or continuous effort mapping can help with this mapping [125]. Pattern recognition uses AI algorithms to map the input signals or their reduced features to a set of functions. Some of the widely used algorithms in the field are linear discriminant analysis (LDA) [30], support vector machine (SVM) [16], artificial neural networks (ANN) [23] and fuzzy neural networks (FNN) [14]. The general approach here is feature engineering or machine learning (ML), in which the data shall be pre-processed and standardised. Then the features

Fig. 4. Human-machine intelligent structure.

Fig. 5. Schematic diagram of Series Elastic Actuator.
should be extracted and reduced in dimensionality and fed into the model to do the classification [15]. Figure 6 shows the intent interpretation schematic of a wearable assistive device.

With the increasing number of available data as big data in recent years, deep learning (DL) has become popular in the field. Compared to general ML methods like shallow learning, DL can extract high-level features from low-level inputs [31]. For instance, Convolutional Neural Networks (CNN) performs exceptionally good at finding local features. Geng et al. used CNN on sEMG data to recognise finger motions and achieved up to 99.5% accuracy [29]. Recurrent Neural Networks (RNN) uses feedback connected into previous layers to store prior inputs to model the problem in time. The most popular RNN models are long short-term memory units (LSTM) and gated recurrent units (GRUs). To take advantage of both RNN and CNN, a combination model (RNN + CNN) has been proposed [152]. Laezza showed that RNN performs the best myoelectric signal classification among RNN, CNN and RNN+CNN [153].

Unsupervised pre-trained networks (UPN) are another category of DL models, which can be stacked auto-encoders or deep belief networks (DBN). The first one comprises multiple auto-encoder neural network layers to find the hierarchical features. The DBN uses restricted Boltzmann machines layers to find the joint probability distribution of the training data. Shim and Lee achieved 88.6% classification performance using DBN, which was 2.9 and 7.6% higher than the support vector machine (SVM) and linear discriminant analysis (LDA) [154]. UPNs have also shown the potential to replace traditional unsupervised feature projection methods. Said et al. developed a DL model for EMG and EEG signal classification, showing that multimodal autoencoder has less distortion, and outperforms unimodal algorithms in classification accuracy [155]. Chen et al. used DBN to estimate joint angles of the hip, knee and ankle, reached 50% reduction in root mean square error (RMSE) compared to principal components analysis (PCA) method [156].

Continuous effort mapping can be categorised into model-based [116] and model-free [162] approaches. Model-based approaches help map the inputs to the desired outputs using dynamic, kinematic or musculoskeletal models that are precisely developed around human biomechanics. Koike et al. used ANN to build a dynamic model of arm movement using EMG signals [163]. Wang and Buchanan were the first ones to use the Hill-type model to calculate muscle forces [164]. On the other hand, model-free approaches use machine learning techniques to learn the relationship between the input and the desired output known as “black box” or “unknown”. Some popular methods are ANN, fuzzy approximation, Bayesian network, hidden Markov model, and Kalman filter. Loconsole et al. utilised a time-delayed neural network for an exoskeleton to estimate the shoulder and elbow torque of the robot from the mean absolute value of the EMG signal [157]. Nielsen et al. estimated contralateral limb force by multilayer perceptron ANN from four features of 100ms EMG signal episodes to control multi DoF prostheses [158]. Table VII highlights some recent efforts in intent prediction.

V. CONTROL STRATEGIES

Effective and efficient control systems are necessary to maximise the exoskeletons’ performance and achieve stability and safety. The most popular control schemes are kinematic-based and position-based controls [24]. The latter is more useful for people with disabilities, i.e. when the user cannot interact with the robot properly [119] by the patient in a set of pre-determined movement trajectories. However, it will decrease the user’s manoeuvrability.

Another categorisation of control systems is whether they are open- or closed-loop. The open-loop controller applies a pre-determined force/torque, depending on the calculated position. The advantage of this method is that it is easy to embed other variables like step length or walking speed in the gait cycle. However, it is not adaptable to different conditions, e.g. walking on uneven terrain, climbing stairs, jogging. The closed-loop applies force/torque by processing the input from sensors. Unlike the open-loop ones, these controllers are adaptable to different situations. However, they are more complicated when it comes to implementation [24].

There are several approaches or strategies to control assistive devices:

**Model-based control**: It is one of the most popular assistive strategies in which the desired joint position or torque will be calculated directly. However, it requires an accurate model of...
TABLE VII
SOME APPROACHES FOR INTENT PREDICTION

| Body part/ Aim | Input | Methodology | classes | Results | Ref |
|----------------|-------|-------------|---------|---------|-----|
| Ankle          | EMG   | Finding walking style deviation from optimum/ adjusting EMG features | 4       | 77.2% prediction accuracy | [30] |
| Gesture recognition | EMG   | SVM and majority voting | K binary class | 86-99% accuracy | [16] |
| Gesture recognition | EMG   | CNN on high-density eEMG | 8       | 89.3% accuracy | [29] |
| Motion intention | EEG    | LDA | Binary | 92% accuracy | [134] |
| Brain-machine interfaces | eCoG, Eye tracking, computer vision | Hybrid Augmented Reality Multi-modal Operation Neural Integration | Complex task | Up to 92.9% accuracy | [135] |
| Giips prediction | FMG   | LDA | 11 | 70% accuracy | [136] |
| Hand Motions prediction | Ultrasound imaging | nearest neighbor classification | 15 hand motions | 91.92% accuracy | [137] |
| Arm Prosthesis control | EMG and gaze | Two SVRs for x and y position | Continuous 2D | RMSE = 6.94 cm | [139] |
| Brain Computer Interface | EEG    | LDA | Binary | 63-84% accuracy | [124] |
| Intention Estimation | Interaction force, position, velocity | NN | desired trajectory | Verified by simulation | [126] |
| Wrist muscles | EMG | deep belief networks | 5       | 88.6% accuracy | [154] |
| Multimodal data | EEG-EMG | deep autoencoder architecture | binary | 78.1% accuracy | [155] |
| Shoulder and arm | EMG | Recurrent CNN | 3D motion | $R^2$ value = 90.3% | [152] |
| Shoulder and elbow | EMG | Time delayed neural networks | joint torque | tested/ validated | [157] |
| Upper limb | EMG | ANN | estimate force | Performance = 0.9 [158] |
| Knee | inertial and fiber optic sensors | Kalman filter of two IMUs and variation-based POP curvature | angle measurement | $1 < \text{RMSE} < 4^\circ$ | [151] |
| Lower Limb Prostheses | EMG and sensor | time-based features extraction | 3 | 100% accuracy | [159] |
| AAN Control | EMG | Model Predictive Control (MPC) | torque | RMSE = 3.1e-2 | [97] |
| Spinal Exoskeletons | IMU | Gaussian mixture and state machine | Q-Passive assist | 86.7% accuracy | [89] |
| Upper limb | EMG | Hill model/ Genetic algorithms | joint moment | RMS = 3.8 N.m | [160] |

the coupled human-robot dynamic system, which depends on a series of sensors to validate the kinematics and dynamics variables. An example of this control strategy is Hybrid Assistive Limb (HAL) [5]. It uses a model-based strategy to control the knee joint in which EMG signals detect the user’s intention to apply assistive torque, damping or gravity compensation based on the human-exoskeleton model [165]. Teramae et al. developed an MPC controller to enhance the rehabilitation of motor muscle functions in patients with torque deficiency in their joints [166].

Sensitivity amplification control: It is based on the inverse dynamic model and is popular with increasing the wearer’s load-carrying capacity. The user’s exerted force will be set on a positive feedback loop and can be scaled down, depending on the situation [105]. Naval Aeronautical Engineering Institute Exoskeleton Suit (NAEIES) [167] and Berkeley Lower Extremity Exoskeleton (BLEEX) [28] are examples of this strategy.

Predefined gait trajectory control: In this control technique, the joint trajectory is obtained from either gait data analysis or will be recorded from healthy participants. The aim of this system is to help patients in normal voluntary movements. ATLAS [97], HAL [168], and ReWalk [169] are examples of this implementation. This assistive strategy seems more straightforward to implement; however, the patient has to walk in an unnatural reference gait.

Adaptive oscillators-based control: This controller predicts the limb’s future posture based on the periodicity of the gait pattern [170]. It captures the phase, frequency, amplitude and offset of the periodic locomotion. This strategy is mainly used in rehabilitative walking and cyclic exercises [171].

Fuzzy models: The adaptive controllers based on fuzzy-logic layers are practical when an accurate dynamic model is hard to construct. The downside is that many parameters shall be tuned according to each motion and person [172]. To do so, the fuzzy controller need three main blocks: fuzzification to interpret the inputs; fuzzy-rules block to hold the control knowledge of the system; and defuzzification block to convert the results to the desired output signals. EMG-based neuro-fuzzy controller by Kiguchi is an example of this method [14]. In another effort, a neuro-fuzzy model was used to make an upper-limb exoskeleton adaptable to different users [173].

Predefined action-based control: This technique utilises the recurrent gait phase transition to regulate the actions in flexible interactions [7]. In other words, it works by activating physical impedance and compliance, e.g. spring or pneumatic cylinder and act in sync with the expected gait task [174].

Hybrid assistive strategy: This strategy utilises multiple assistive strategies to deal with different situations with increased adaptability. It splits the controller into sub- control states that can kick in depending on the gait cycle phase. For instance, BLEEX’s controller is divided into positive feedback sensitivity amplification force and position controller for swing and stance phase [6]. Moreover, HAL uses two complementary control algorithms to control the robot based on human intent command and physical body situation [5].

A. Arbitration

Arbitration is an integral part of the human-robot interaction that determines how control is divided between the robot and the user. There are different types of arbitration. One common approach is to put the human in charge of position control of the end effector, while the robot assists with the orientation [125]. Alternatively, both the human and robot could control
the position and orientation with different influence levels. The human and robot roles in an exoskeleton can be co-
activity [159], master-slave [70], teacher-student [175], or collaboration [176].

B. Communication and Feedback

Human body parts get the intent orders from the central nervous system and provide them with feedback information. The same concept applies to wearable exoskeletons or prostheses. This feedback information should include sensory details such as interaction forces and the action, and future intention [125]. The most common modalities of sensory feedback are haptic, aural and visual. The implementation of motion-force coupling in haptic is similar to the way the human body utilises the peripheral nervous system to monitor the task and environment and adjust the action force of the muscles [125]. The haptic feedback can be divided into kinesthetic and tactile feedback. The first one applies force to the muscles and joints, whereas the latter stimulates mechanoreceptors in the skin.

VI. PROPOSED METHOD

In this section, we propose some classification models based on ML algorithms to recognise the gait phase of human walking using data collected for other purposes. This system can help activate the appropriate control system like the one implemented in BLEEX [28] based on the cycle phase. The aim here is to evaluate the possibility of using the vast amount of data collected by other researchers for different purposes to train intent detection models. Also, only one input channel will be used to test the limits of the proposed models. We will evaluate the possibility of gait phase recognition using just EMG signals related to the rectus femoris activity. This can help build simpler models or be used as a redundant system for multi-channel systems.

The unidentifiable EMG dataset in Lower Limb collected by Sanchez et al. is used here [177]. Gaussian Naive Bayes (NB), Gradient Boosting (GB), Random Forest (RF), Decision Tree (DT), Support Vector Machine (SVM) and K-Nearest Neighbors Vote (KNN) algorithms have been used to find the best performing model based on the Area Under the ROC Curve (AUC) performance metric.

A. Data preprocessing

The dataset has been collected to study the pathological abnormalities [177]; however, only the data related to the gait exercise could be used to train our models. We exclude the data from unhealthy patients to prevent the physiological effect on the models. Knee angle position has been used to extract the gait phase of the target leg over time. In Figure 7, blue plot shows filtered and normalised position of the knee over time. The gait cycle phases have been recognised in between the local maxima and minima as shown orange plot. In this figure, zero demonstrate the swing phase, and one is for stance phase.

EMG signals have been filtered by a bandpass filter between 10 and 300Hz. Then, we normalised them to compare the visual pattern of the RF activity in regards to the gait phase with other subjects. As it is obvious in Fig. 8, the RF activity of subjects 5 and 8 seem to have chaotic orders. The 90 and 95 percentile of the absolute values of RF EMG signals for subjects 5 and 8 in Tab. VIII shows that the sensors were probably not recording the signals properly. A robust model might compensate for these kinds of flaws in one channel if it uses multi-channel input. But since we aimed to use only a single channel signal for our classification to test the limits of our model, the signal quality can significantly affect the results. Hence, we decided not to use data from these subjects.

The moving window method has been used to divide the data into standard window sections for training and evaluation. The data has been prepared with different sizes of 50 to 400ms to find the optimum window size for the sake of accuracy and real-time computation. The corresponding labels have been shifted with various time delays from 0 to 100ms to compensate for the time delay between the neuromuscular activity and the actual movement.

B. Feature extraction

The windowed data have high dimensionality, and using them directly for classification will significantly increase the computation cost and degrade the real-time performance of the classifier. To address this issue, we extract four features from each channel of the time series data to use as the input to ML algorithms. These features are extracted from the previously
separated window sections, representing the features of each specific time. The four extracted features for this study are zero crossing (ZC), mean absolute value (MAV), standard deviation (σ) and mean absolute deviation (MAD). Equations (1)-(4) show the calculation of features:

$$ZC = \frac{1}{2} \sum_{i=1}^{n-1} |\text{sgn}(x_i) - \text{sgn}(x_{i+1})|$$  \hspace{1cm} (1)

$$MAV = \frac{1}{n} \sum_{i=1}^{n} |x_i|$$  \hspace{1cm} (2)

$$\sigma = \frac{1}{n} \sum_{i=1}^{n} (x_i - \bar{x})^2$$  \hspace{1cm} (3)

$$MAV = \frac{1}{n} \sum_{i=1}^{n} |x_i - \bar{x}|$$  \hspace{1cm} (4)

where:

- n is the number of values in each window,
- $x_i$ is the dataset value,
- $\bar{x}$ is the population mean.

After extracting these features from each window section, we passed the results through a standard scalar to map the data to zero mean and unit variance.

C. Training

All combinations of window sizes between 50 to 400 ms with 25ms interval and delay times between zero to 100 with 10ms interval have been used to train the proposed ML models. Random search method has been used to tune the hyper-parameters in each step and reach the best performing model. For evaluation, k-fold cross-validation has been chosen, with k as the number of subjects. The division was based on subjects to prevent the data leakage from training to testing datasets due to overlapping windows in the data regarding each subject. AUC was used as the performance evaluation metric.

D. Results

NB model showed the lowest AUC of 0.81, whereas SVM reached the highest score at 0.91. All other models showed AUC of around 0.88 to 0.89. However, the optimal points for different models are not the same. Table IX shows the highest achieved AUC for each model along with its optimal point. Figure 9 depicts the changes in the AUC of the SVM model for different window sizes and delay times. It is apparent that the window size has a higher effect on AUC than delay time. This is because the larger window size allows for broader and more complex patterns. Moreover, a predetermined delay time does not always work best across the board. The larger the window size, the shorter the delay time should be to achieve the optimal point. For real-time applications, smaller window sizes are preferred, tilting the delay time towards 60 or 70ms. This increase in delay-time decreases the gap between the starting point of the data window and task execution, helping with real-time computation.

These results, considering the small amount of data used for this study, are promising. First, they show the potential of using already existing data to develop more accurate and versatile systems. Second, they prove the reliability of single-channel systems that can either be used in low-power systems or help as redundant systems in devices with more powerful computation capability.

VII. DISCUSSION AND CONCLUSIONS

Human assistive technologies need multiple areas of science to work together to effectively and efficiently perform their mission considering the human body physiology. One of the fundamental fields in this area is the study and understanding the human motion’s kinetic and kinematic. Human limbs are complex systems, and their modelling differs for different joints and individuals. This is essential as these devices need to be anthropomorphic and adapt to the limbs characteristics and motion.

An exoskeleton should be able to assist the user in the desired direction with precise timing. Furthermore, it should not restrict or impede the users motion. It means that the system’s DoF should be similar to the human. Its joints and limbs must stay aligned with them as any misalignment can impose unnecessary forces on the user’s body and cause discomfort and fatigue.

The most primitive aim of assistive devices is to help with muscle engagement or joint torque. This can assist with performing a task, motor skill training, rehabilitation, or augmenting capabilities. The muscle activation and metabolic cost are useful tools to measure the effectiveness of the exoskeleton, and in a general sense, to study the effect of external assist on human limbs. While this assistance reduces the task strain on the body, it should be restricted, so the user can still feel in charge of performing the tasks. The position and orientation of forces exerted to the human user should be as if there is no external assistance. Furthermore, the exoskeleton itself should not impose additional resistance to the motion and be as transparent as possible.
Exoskeletons can be categorised based on their intended use, structural design or power consumption. However, the most common classification based on the actuation, control system and level of complexity is passive, semi-passive and active devices. Passive devices are the less complex, lightweight and economical solutions: they use an elastic element to save the motion energy and release it when required. Semi-passive exoskeletons use simple control components and light actuators to control the assistance ratio based on the situation and task. An active assistive device uses an elaborate human-robot interaction (HRI) to actively monitor the user and environment’s status and control the powered robot’s joints in real-time.

For an intuitive control of an active exoskeleton, both the physical and cognitive HRI should be optimised. For instance, the mechanism should be lightweight, actuators and transmissions should be able to provide high torque and speed, and at the same time, do not add to the angular and linear momentum of joint motion. An intent detection system is responsible for extracting the commands for intuitive control of the exoskeleton. Different approaches for intent detection/interpretation has been suggested in the literature, from sensors combination and their positions to signal processing and intent prediction.

Intent interpretation is the act of mapping input signals from sensors to the desired intention. It can be achieved using either model-based or model-free approaches. With the increasing popularity of artificial intelligence (AI) and using data-based techniques in recent years, AI model-free approaches have become popular. These systems can be developed to be more versatile and adaptable to different individuals, situations and tasks. Following surveying renowned attempts for both methods, we proposed a model to identify the gait cycle phase from only one EMG input signal. The modelling results showed up to 0.91 Area Under the ROC Curve (AUC) performance despite the small size of the data and lack of redundant signals. As part of our future work, we will consider increasing the number of input channels and training the extended dataset. We anticipate that this leads to more sophisticated models with better accuracy and consistency.

### Table VIII

| Subject | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 |
|---------|---|---|---|---|---|---|---|---|---|----|----|
| 50      | 0.0055 | 0.0050 | 0.0024 | 0.0033 | 0.0026 | 0.0025 | 0.0229 | 0.0018 | 0.0031 | 0.0019 | 0.0235 |
| 90      | 0.0242 | 0.0229 | 0.0113 | 0.0275 | 0.0067 | 0.0138 | 0.1116 | 0.0059 | 0.0217 | 0.0326 | 0.2043 |
| 95      | 0.0354 | 0.0337 | 0.0176 | 0.0436 | 0.0086 | 0.0228 | 0.1562 | 0.0089 | 0.0401 | 0.0542 | 0.3240 |

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### AVAILABILITY OF DATA AND MATERIALS

The data used in this research are publicly available on UCI repository:

http://archive.ics.uci.edu/ml/datasets/emg+dataset+in+lower+limb

### ETHICS APPROVAL AND CONSENT TO PARTICIPATE

The data used in this study has been collected by researchers in Universidad Militar Nueva Granada and Universidad Autonoma de Manizales which have deindetified and published in UCI repository [177]

### COMPETING INTERESTS

The authors declare that they have no competing interests.

### CONSENT FOR PUBLICATION

Not applicable.

### AUTHORS’ CONTRIBUTIONS

All authors were involved in the conception and design of the study. FN searched the literature and did the majority of the drafting. NM contributed to the manuscript’s academic language and the paper’s structural design. DN helped with approaches and methodologies. FN and AK were involved in designing and evaluating the AI models. SN was involved in revising the content and presentation of the work. All authors read the final manuscript and approved it.

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