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AI-Powered Lower-limb Assistive Devices: Future of Homecare Technologies

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Healthcare systems are burdened by mobility impairments resulting from aging and neurological conditions. One of the recent advances in robotics is lower-limb assistive/rehabilitative devices that can make independent living possible. Nonetheless, some limitations need to be addressed before robotics can be used in home-based applications. This paper describes the current state of the art in intelligent motion planning and control of lower-limb assistive devices, which have addressed some of these challenges. Adaptable central pattern generators and the divergent component of motion are introduced as methods for personalized motion planning based on physical human-robot interaction (pHRI). Uncertainty analysis for neural networks is introduced to increase safety in motion planning based on pHRI. For the case that a user cannot apply physical interaction, a reinforcement learning-based approach is introduced to switch among different modes of walking based on the user's input via a push button embedded in a walker. Moreover, a smart walker is introduced as a device that can be synchronized with the lower-limb exoskeleton to assist users with their daily activities. Also, we introduce a roadmap for future steps that can make lower-limb assistive/rehabilitative devices a good fit for home use.

1 Introduction

Human gait can be affected by neurological impairments such as spinal cord injury, stroke, and multiple sclerosis. Assistive and rehabilitative wearable devices (e.g., exoskeletons and smart walkers) have the potential to help millions of people with these conditions manage their daily needs independently and also improve their physical activities. Several powered exoskeletons such as Indego [1], Exo H3 [2], ReWalk [3], HAL [4], and Ekso GT [5] (see Fig. 1), and smart walkers such as JARoW [6], *i-Walker* [7] and *FriWalk* robotic walker [8] (see Fig. 2) have been developed in recent years for user assistance and/or rehabilitation in the clinics. The devices are able to provide a variety of sensory and actuation systems, making them perfect candidates for homecare applications. From the software perspective, several studies have tried to employ artificial intelligence (AI) in their controller to improve their performance. Table 1 summarizes the state of the art in AI-powered lower-limb assistive devices.

1.1 Potentials of lower-limb assistive devices in home-based assistance

Lower-limb assistive robots have demonstrated strong potential for home-based assistance and rehabilitation [20]. These systems are usually equipped with many sensors and actuators and can integrate additional modules as required to extend their potential use cases. Actuators are components of exoskeletons and smart walkers that are capable of generating various movements. While electromechanical motors are the primary source of actuation for most assistive devices, some exoskeletons use electrical muscle stimulation as an additional source of actuation.

Model Type	Kinematic Parameters	Intention Detection
Neural Network	Active torque of hip and knee [9], Hip and knee joint trajectory [10]	Level of walking (stairs or ramp) [11], Standing or transition in level of walking [12]
Fuzzy Logic	Joint torque estimation [13]	Uphill/Downhill walking [14], Ascent/Descent stairs walking [15]
Support vector machine (SVM), Principal component analysis (PCA)	Joint trajectories [16], Joint trajectories of affected limbs [17]	Sitting/Standing/Walking [18], Walking with/without exoskeleton [19]

Table 1: Review of state-of-the-art methods in AI-powered lower-limb assistive devices

These devices can also be equipped with different sensors, making gait analysis possible [21]. These analyses can facilitate early diagnosis, specifically for elderly people and people with injuries [22–24]. Feeding these sensory inputs to the artificial brain of the lower-limb assistive devices, valuable evaluations can be provided for users, decreasing the risk of catastrophic events, e.g., falling [25, 26]. Gyroscopes, accelerometers, kinetic and kinematic sensors, such as torque, pressure, inertia, force and tilt sensors, can all be used for recording user's walking behavior that can be employed for gait analysis and also providing feedback to ensure the device maintains its stability and follows the intended movement. Furthermore, recently the idea of using infrared distance sensors [27, 28], head-mounted cameras [29], chest-mounted RGB camera systems [30], and ultrasonic devices worn on the waist [31] are under investigation for developing intelligent systems with the capability of detecting terrain changes and accordingly evaluating users response to the changes.
Body-worn sensors can record also biosignals. Signals acquired from those sensors can be used for analysing user's gait and adjusting the rehabilitation and/or training routines of users. Electromyography (EMG) signals can provide valuable information about how much power the user generates through their muscle contractions to determine whether or not underlying neural connections are improving.Flexible and stretchable electronics can be incorporated as skin-mounted sensors to monitor the health conditions in areas such as electrophysiology, dermatology and sweat diagnostics [32]. Advanced Carbon materials are an example of the flexible wearable electronics that can be used in conjunction with the exoskeletons. These materials have shown promising potential due to their electrical conductivity, inherent flexibility, excellent chemical and thermal stability, and possible mass manufacturing [33]. The next generation of these devices are advancing in utilizing AI and machine learning technologies to raise the bar for connection quality, intelligence and users' comfort and convenience. Examples of these devices can be seen as 3D hand motion tracking and gesture recognition with a Data Glove, Glove orthosis for VR systems and wearable motion sensors using Gallium thin films [34–37]. Such recorded signals can also be used as a

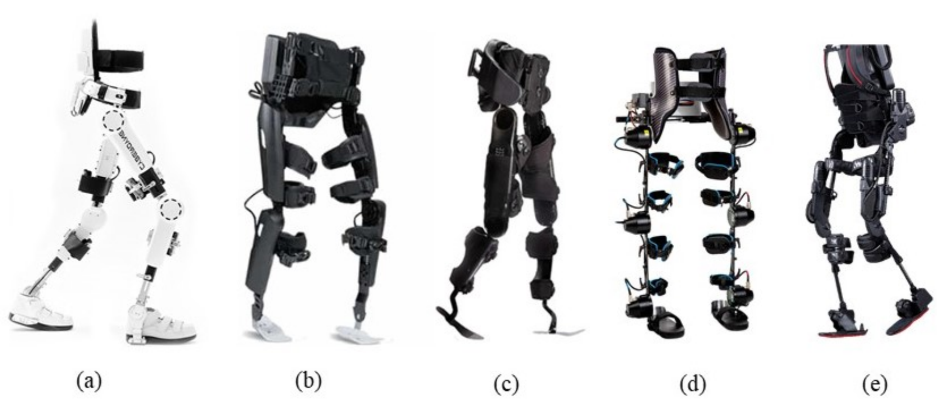

Figure 1: Some of the commercially available exoskeletons: a) Hal [4], b) ReWalk [3], c) Indego [1], d) Exo H3 [2], and e) Ekso GT [5]

reference or training set for developing advanced intelligent controllers [18, 38].
The available actuators and sensors have made lower-limb assistive devices an excellent framework for homecare. Given sensors like EMG, inertial measurement units (IMUs), and torque sensors, it is possible to develop intelligent control methods to understand the user's intention. Also, the environment can be actively monitored using sensors like light detection and ranging (LiDar) and head-mounted cameras. Furthermore, the available actuators also provide a viable structure to assist users in actively reaching their desired locomotion goals and protecting users in unsafe situations. All of these are critical requirements of home-based assistive devices.
Exoskeletons can also be used for rehabilitation to maximize the effectiveness of the treatments. As an example, in the Indego exoskeleton [39], controlled functional electrical stimulation (FES) allows for stimulating the leg muscles producing contractions in a controlled manner to create leg motion, although a possible downside is accelerated muscle fatigue. Recent studies have demonstrated the potential of hybrid actuation (FES combined with exoskeleton joint motor torque) in walking rehabilitation which substantially reduced muscle fatigue [40]. Using hybrid actuation can also reduce the weight of the exoskeleton motors. The above characteristics make lower-limb assistive devices good candidates for home-based assistance; however, these devices will need improvements in their software and control algorithms in order to provide functional home-based assistance.

1.2 Limitations of commercially available lower-limb assistive devices

Although lower-limb assistive devices have much potential for home-based assistance, some limitations need to be resolved before they can be used as a homecare device. Some of the limitations are a result of hardware design; however, the majority are software-related. Most of these devices take advantage of pre-defined fixed trajectories that force users to follow certain walking patterns. Rigidity in gait trajectories can result in incompliant and uncomfortable interaction between the user and the robot and can lead to less appeal for long-term use. In addition, a lack of intelligence in the control method can decrease interest in lower-limb assistive devices in homecare. Since the home environment that the robot interacts with is dynamically uncertain, there is a very high chance of facing mission failure. In order to provide home-based assistance, these systems must have sufficient intelligence to predict and prevent unsafe situations. Commercially available assistive devices must also be able to detect the user's intent. When walking at home, the user needs to switch between various modes; e.g., sitting, standing, turning, ascending and descending stairs, which requires a robotic system to recognize the user's intention.
Some of these challenges have been addressed in our recent studies. Adaptable central pattern generators (CPGs) can provide flexibility in the exoskeleton gait trajectory by understanding the user's intentions based on interaction torque (Sec. 2) [41, 42]. Further, divergent component of motion (DCM) can help to predict loss of postural stability and to prevent it by adjusting the position of the upper-body (Sec. 3) [43]. We also proposed a method that detects potentially unsafe actions in the interaction between the exoskeleton and the user during task execution—the method results in a safer collaboration between humans and assistive devices Sec. 4. When a user is unable to apply interaction forces, reinforcement learning-based smart switches can be used to change the walking mode for exoskeletons via

(a) (b) (c)

Figure 2: Several practical smart walker prototypes: a) JARoW [6], b) *i-Walker* [7], c) *FriWalk* robotic walker [8]

push buttons embedded in the walker (Sec. 5) [44]. Additionally, a smart walker with the capability of detecting falls is introduced in Sec. 6, which can be used with alone or in conjunction with an exoskeleton [45].

2 Personalized locomotion planning

In this section, a method is being reviewed for reshaping exoskeleton trajectory based on users' physical interaction. The motivation for this research is the considerable differences exists in walking patterns among different people. Even for one person, walking can vary within one day and over time for a variety of reasons, including aging, fatigue, load-carrying, etc. [46]. As discussed in Sec. 1.2, pre-defined trajectory usage is one of the significant shortcomings of commercially available exoskeletons, limiting their use in homecare. For exoskeletons to be used at home, the systems need to be automatically adapted to the user's locomotion patterns. In this section, we discuss the adaptable central pattern generators (CPGs) method, which we introduced to address this problem [41].

CPGs function as connected modules that are capable of generating oscillatory movements with organized patterns in response to non-periodical inputs [47]. Because CPGs are capable of producing time-continuous rhythmic motions synchronized with adjacent joints, they are an appropriate method for motion planning for exoskeletons. Our adaptable CPG method [41] is capable of adjusting the walking pattern based on the user's intention, which includes two parts: Learning-based pHRI estimation, and CPG-based gait motion amplitude and frequency adaptation on a user-specific and individualized basis.

The dynamics of the human-exoskeleton system were described by:

$$M_q(q)\ddot{q} + C_q(q)\dot{q} + G_q(q) - \tau_{hum_{pas}} = \tau_{mot} + \tau_{hum_{act}} \tag{1}$$

where q is the vector of exoskeleton joints' position, and $M_q(q)$ and $C_q(q)$ are the inertia matrix and matrix of Coriolis, centrifugal and damping terms, respectively. $G_q(q)$ represents the vector of gravitational torques, τ_{mot} is the exoskeleton's motor torque, and $\tau_{hum_{pas}}$ and $\tau_{hum_{act}}$ are the passive and active portions of the human torque vector, respectively.

For the learning-based pHRI estimation, a neural network (NN) was employed in a supervised fashion to learn the combined dynamics of the human-exoskeleton (human user wearing a exoskeleton) system and estimate the active HRI torque $\tau_{hum_{act}}$. Learning was based on experimental data collected when the user wore the exoskeleton and the entire system was driven by motors with minimal active torque generation (as a result of the user relaxing the lower-limb muscles). A human-exoskeleton system recorded joint position, velocity, torque, and frequency for various locomotion patterns (amplitudes and frequencies). These data were used to train and evaluate the NN, with joint velocity and position used as inputs and motor torque used as the output. Given this, the network learned the human passive torque and the motor torque ($\tau_{mot} + \tau_{hum_{pas}}$). It estimated the human active torque based on the torque measurements from the exoskeleton torque sensor ($\tau_{tot} = \tau_{mot} + \tau_{hum_{pas}} + \tau_{hum_{act}}$). The schematic of the human-exoskeleton interaction torque estimation is represented in the pHRI estimation part of Fig. 3. Given the estimated HRI torque, the human exoskeleton interaction energy was determined as the time integral of the product of HRI torque and joint velocity.

$$E_i(t) = \int_0^t \tau_{HRI_i}(t)\dot{q}_i(t)dt \tag{2}$$

The pHRI energy (E) is positive if the applied torque and joint velocity are in the same direction and negative if they are in opposite directions. Our adaptable CPG dynamics used this energy value to tune the walking frequency and amplitude based on the locomotion pattern of the user. Therefore, if the user applies positive interaction energy, the adaptable CPG increases the amplitude and frequency of walking, which results in higher speed and longer steps. Conversely, negative energy is interpreted by the algorithm as the user's desire for a slower walking speed and a smaller step length. This adaptable structure enabled the exoskeleton to refine its locomotion pattern based on the user's demand and comfort, which is critical in a non-clinical environment (Fig. 3). Furthermore, for use in the home, due to the

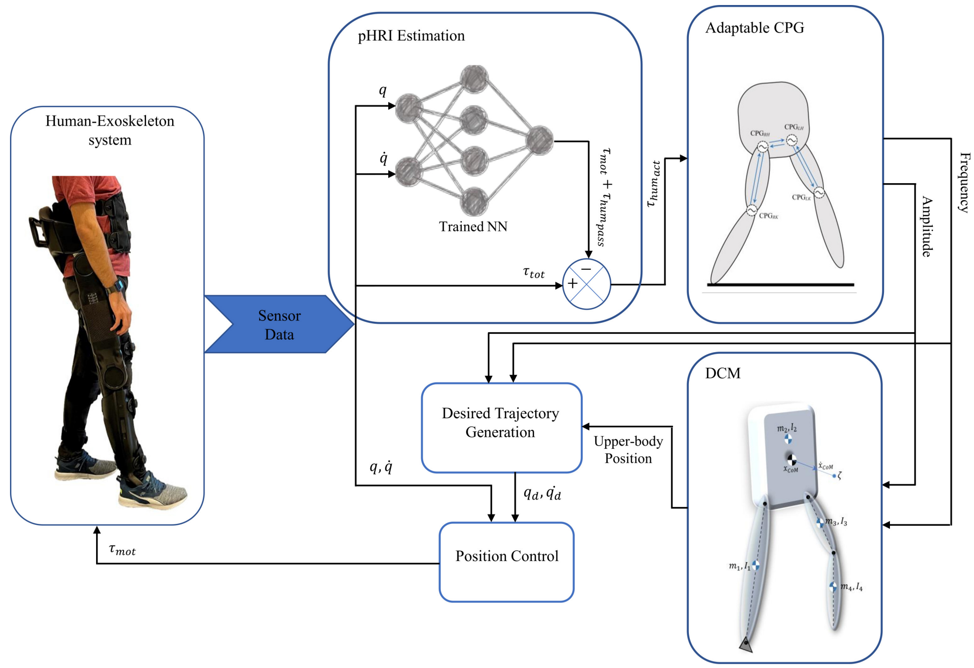

Figure 3: Schematic of the proposed intelligent control of lower-limb exoskeleton using NN-based pHRI estimation, adaptable CPG, and DCM methods.

many uncertainties about the surrounding environment; e.g., surface conditions and obstacles, the possibility of adjusting the walking speed and step length can provide a higher level of safety for the user. The results of employing this approach on the Indego lower-limb exoskeleton (Parker Hannifin Corporation) are depicted in Fig. 4. The user applied interaction torque (τ_{HRI}) in the same direction as the velocity vector ($\dot{q}$) which increased the interaction energy based on Eq. 2. This increase in the interaction energy level was translated to a 13% increase in stride length and a 71% increase in walking velocity based on the developed ACPGs dynamics [41] (see [41] for more details and results).

3 Postural stability enhancement

In the past section (Sec. 2), a method introduced which can reshape exoskeletons walking pattern to be fit with users. Although it can solve one of the major issues with the commercially available exoskeletons, the algorithm also needs to monitor postural stability while letting user to change exoskeleton's trajectories. To address this challenge, in this section we introduced the divergent component of motion (DCM) for lower-limb exoskeletons [43]. While walking with the exoskeleton, the DCM method monitored the position and velocity of the exoskeleton's center of mass (CoM) and adjusted the upper-body position to maintain postural stability (Fig. 3). Therefore, the exoskeleton had the authority to ensure postural stability and viability of locomotion while the user reshaped their gait pattern with pHRI.
It is necessary to plan a stable trajectory for the CoM to maintain postural stability for the human-exoskeleton system. To this end, the dynamics of CoM were divided into convergent and divergent components (see [43] for more details). The convergent part is always stable; thus, it did not require specific control strategy. Planning a stable trajectory for the divergent part (DCM) however, was necessary to ensure postural stability. The DCM was defined as

$$\zeta = x + \frac{\dot{x}}{\sqrt{\alpha}} \tag{3}$$

where x is the position of the CoM and α is a constant value being determined based on the user's body characteristics.
Our nervous system has naturally learned to adjust our upper-body position when walking at different

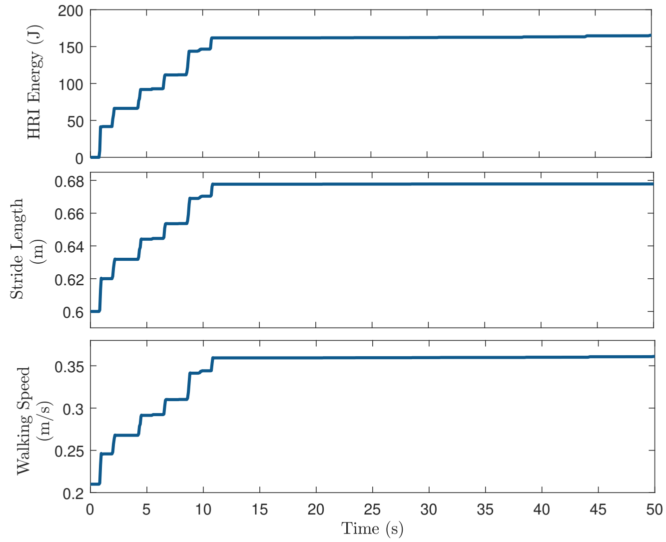

Figure 4: Stride length and walking speed changes due to the pHRI

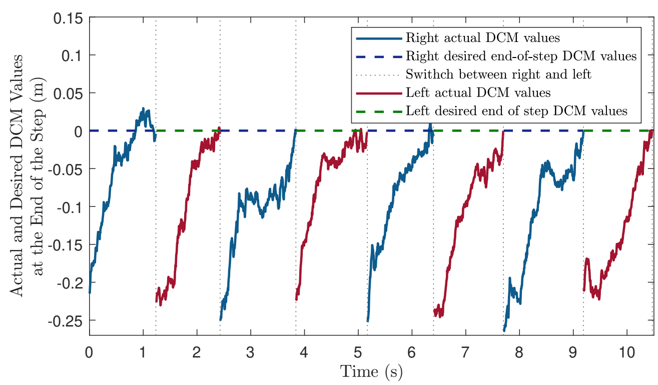

Figure 5: DCM trajectory in the presence of upper-body position adjustments

speeds. Therefore, the exoskeleton's walking speed had to be taken into consideration when governing the desired trajectory of DCM. The desired DCM position at the end of each step was defined based on the exoskeleton's walking speed and step length as [48]

$$\zeta_{d_T} = X_{CoP} + \frac{L}{e^{\sqrt{\alpha}T} - 1} \tag{4}$$

where X_{CoP} is the position of the center of pressure, L is the step length and T refers to the walking period.

To calculate the optimal torque that needed to be applied to the upper body, the optimization problem was defined based on the desired position of DCM at the end of each step. The upper-body position was adjusted to reach the desired DCM position at the end of the step by applying this torque. By applying this method, the exoskeleton can enhance postural stability and viability of locomotion in the pHRI while allowing the user to adjust walking speed and step length through CPGs. The results of applying the DCM method on the Indego exoskeleton are shown in Fig. 5. The positive physiscal interaction from user's side has increased step length (L) and decreased walking period (T). Due to these changes, the desired DCM at the end of step has been changed based on Eq. 4. In response to the changes in the desired DCM at the end of step, the proposed CDM analysis algorithm [43] has adjusted the upper-body position in order to minimized the error between actual and desired DCM at the end of each step (see [43] for more results).

4 Improving Safety Using Uncertainty Analysis

Over the past decades, deep learning has been successfully applied to many medical applications, powered by a large amount of available data and data-driven system development paradigms. Deep neural networks (DNNs) have also been used in our proposed approaches to estimate the human-exoskeleton interaction torque (Fig. 3). As discussed in Sec. 2, passive torque estimation plays a vital role because it affects the calculation of HRI torque and controls exoskeleton speed. Therefore, if there is uncertainty in calculating the passive torque, the resulting control algorithm may fail to control the exoskeleton. This fact emphasizes the necessity of considering model prediction uncertainty in control strategies of exoskeletons.

Lower-limb assistive devices are safety-critical systems where a thorough safety analysis is required, especially when data-driven artificial intelligence (AI) is integrated as part of the robot control system as a decision-maker [49]. A typical data-driven AI model (e.g., DNN) learns the decision logic to handle future unseen data that are dissimilar to the distribution of training data. A safety concern is that deep learning does not guarantee reliable performance for a wide range of input scenarios, and has limited capabilities in handling data outside of the learning distribution [50]. For instance, an autonomous driving system that uses a visual perception module to comprehend the environment can be trained on a limited number of scenarios even if the visual system has encountered many different scenarios during training. In order to avoid actions based on uncertain predictions that could have catastrophic safety repercussions, it is important to know when an input data point is out of the boundary of the DNN that has been trained. This is the same for medical assistive devices which may have even greater safety-critical concerns as AI-enabled lower-limb assistive robots also rely on imagers and sensors to feed a decision-making DNN. In a situation where the robot is used for homecare, where the user interacts with the robot in the absence of an expert such as a medical professional, uncertainty analysis becomes even more critical. Making unsafe decisions in such a scenario could be catastrophic. This fact motivates the idea of using prediction uncertainty estimates in the control loop of the robot to make it safe for applications such as home-care applications. A schematic of the safe human-exoskeleton collaboration when a DNN is integrated into the control loop is presented in Fig. 6.

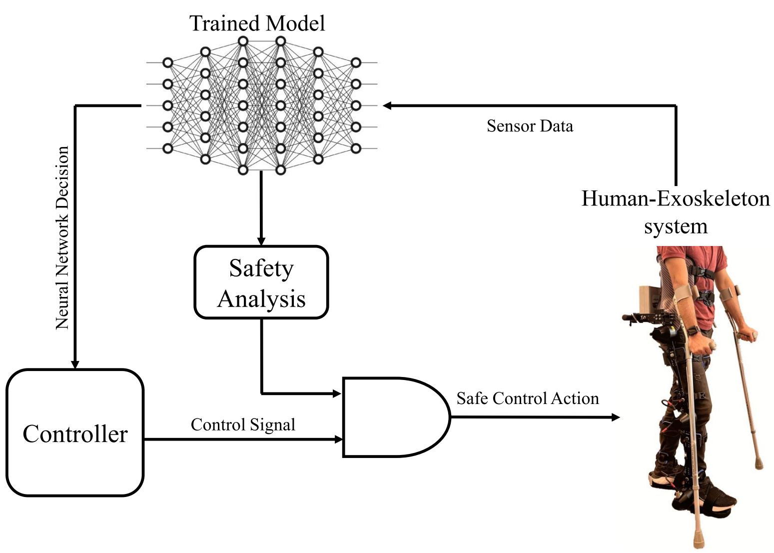

Figure 6: Schematic of safe human-exoskeleton physical interaction

As of now, there are two main categories of uncertainty analysis techniques widely used for measuring the level of uncertainty in DNN predictions. The first category learns model uncertainty along with its prediction in the DNN's feedforward path, which means that a well-trained DNN should have a prediction label and its corresponding uncertainty of the prediction result vector [51]. The second category of methods considers the uncertainty introduced by the development of DNN, such as from different architectures of DNN, which can be managed by simulated methods such as including additional layers to estimate the uncertainty of predictions [52]. In addition to these two categories, out-of-distribution (OOD) detection is a widely used safety analysis method and can be considered an uncertainty analysis technique. In [53] OOD detection and uncertainty level estimation are based on the distance between the test sample and training data.

Incorporating uncertainty analysis in the control loop of assistive robots can be challenging since it needs to operate in real-time. Also, due to safety requirements of homecare applications, the proposed method needs to have reliable performance. By taking these facts into account, we propose an algorithm for calculating the uncertainty of the predictions using the deep learning algorithm's training and testing phases. As a case study focusing on the use of a lower-limb exoskeleton to assist the walking of people with disability, we learn the passive human-exoskeleton system's dynamics ($\tau_{hum_{pas}} + \tau_{mot}$ in Eq. 1) using Random Forest Regression (RFR) and quantify the uncertainty level of its prediction. The proposed method leverages the knowledge of the model predictions' uncertainty levels into the adaptable CPGs to ensure safety in pHRI. Our proposed framework for uncertainty-aware control of medical robots finds the similarities of labels and predictions in the training set using Kullback-Leibler (KL) divergence between input and training distributions, and detects OOD data using Mahalanobis distance between test feature and training set. We have tested the proposed method on the ExoH3 (Technaid S.L. , Madrid, Spain) lower-limb exoskeleton. The experiments were conducted to evaluate the performance of the uncertainty analysis technique.

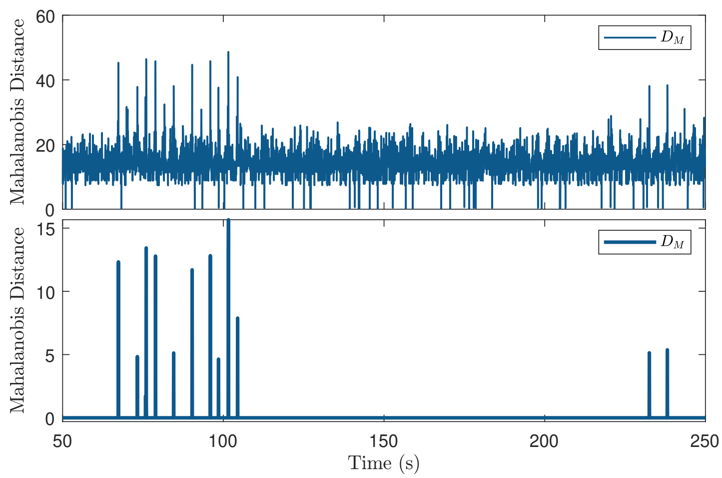

Figure 7: Performance of uncertainty detection algorithm when robot makes an unsafe decision.

The distance between the test sample and the training data is the measure to revisit the initial estimation of the reliability of deep learning's prediction. First, KL divergence is used as an initial estimate of uncertainty, and then the distance is used to revisit the initial estimate for each test sample in real-time. The results shown in Fig. 7 present the performance of the uncertainty detection algorithm using Mahalanobis distance as an uncertainty indicator. When the controller of the exoskeleton faces the out-of-distribution input, which results in an unsafe decision, the distance function becomes more significant. Therefore, the maximum value can be isolated and used to control the gain of the CPG to mitigate the effect of unsafe decisions in changing gait trajectories.

5 Smart switching in exoskeletons using reinforcement learning

Methods discussed so far (Secs. 2, 3, and 4) were applicable for exoskeleton users who are capable of applying a detectable amount of force and have active physical interaction with the exoskeletons. However, for scenarios where users are not able to apply forces by themselves; e.g., people with motor complete spinal cord injury, there is still a need for a smart system to predict users' intention. The presence of underlying similarities in the performed movements, especially in the homecare robots where similar daily activities are performed, can provide a framework for utilizing machine-learned models. In the case of employing lower-limb exoskeletons for home-based assistance, different walking modes/decisions can be learned and predicted using novel machine learning techniques. General walking modes can consist of straight walking with different gait speeds, turning left/right, stair ascending/descending, sit-to-stand, stand-to-sit movements, walking with different step lengths, etc. Desired joint trajectories can be predefined for each of these walking modes. Upon switching from one mode to another, these desired trajectories can be smoothly altered using the CPG concept discussed in Sec. 2, by considering underlying differential equations of motion.

The gold standard method for switching between different available walking modes in lower-limb exoskeletons is using a switch button or voice-control [54–56]. Usually, there is a fixed switching list, containing the available walking modes, where the users need to hit a single switch button many times to get their desired mode. This makes users feel uncomfortable in performing their daily routines, increases the cognitive task and the likelihood of user errors during demanding tasks or when many walking modes are available to switch to [54]. Alternatively, several buttons are used for selecting modes where each button is allocated to a specific mode; however, this approach limits the capacity of utilizing many modes and is undesirable for users [54].

Recently, the idea of using supervised learning approaches (pattern recognition techniques) for predicting users' intention has been widely investigated. These methods, despite their promising outcomes, face many practical issues; they require a large amount of training data for training a model. Training data can contain several signals [such as EMGs, electroencephalograms (EEGs), joint angles, pressure signals, etc.] chosen based on the users' needs and the control strategy of the device. Due to the high variability among different user signals, these systems cannot be fully generalizable [57]. Moreover, users are required to perform a training routine for adaptation of the device. Performing this routine at different limb positions or different walking modes can lead to a long and extensive training period, which is not desired and can be cumbersome for users [57].

A qualitative study involving therapists and users of myoelectric multi-function upper limb prostheses assessed the utility of conventional (manual) switching between functions and pattern recognition-based switching [58]. The results emphasized that although the pattern recognition controller had several advantages (in terms of requiring less effort, and being faster and more natural), it still was not considered a strategy that can be applied to daily routines. In addition to the training duration that was reported as an important limitation, the model needed to be trained in laboratory/clinical environments and could not perform as expected in new environments where noise and unexpected situations are present. As an example, prosthesis users had issues when they were holding heavy bags after grocery shopping [58]. These issues are all indicative of a need for a new technique that requires no training routine and could be adapted to users' specific needs in each new situation.

Reinforcement learning (RL) is an area of machine learning specialized for sequential decision making under uncertainty and has shown potential for prediction and learning. One of the major differences between RL and supervised learning techniques is that the RL systems require no previous knowledge (no need for a training set of labelled examples) and can learn from interactions with the environment along the way by trial-and-error. Moreover, RL methods are built based on maximizing a reward signal. The reward signal is accumulated using a value function and takes the future actions into consideration while generating the reward magnitude [59]. One of the distinguishing methods in RL domain is called temporal-difference (TD) learning [60]. This method is specialized for prediction learning, and uses previously obtained estimates (previous guess) of the value function to generate new estimates (new guess). It learns the value functions directly without a need for a model using bootstrapping [59]. Recently, a new concept has been introduced by Sutton et al [61] in the RL domain called general value functions (GVFs), where the goal is to predict values of arbitrary signals over a window in the future, rather than trying to maximize the value function (future reward), using TD learning and eligibility traces [62]. This is advantages where many signal are needed to be predicted by the system.

Generalized value functions can be implemented to provide smarter ways of pHRI and reduce the effort and cognitive load that was present in traditional switching actions. Utilizing GVFs, we can introduce, for a single switch, an adaptive switching list that changes the order of the modes in the switching list at each instant, according to the users' previous choices and representations of the system [44, 63]. Therefore, instead of trying to hit the switch button many times, a single hit can provide the desired mode to the users. This method was previously tested and verified on the myoelectric prosthesis users [63] and is currently under investigation for lower limb exoskeletons [44]. We have shown that by using the user's positional information (in 2D space) and LiDAR sensors mounted on 3 sides of a smart walker, the system can leverage the similarities in the movements being performed and update the switching list at each time-step [44]. Each mode was assigned a GVF and those GVFs were learned and predicted during walking in different experimental scenarios. The modes were then ranked in the allocated switching list according to their GVF values in a descending order. The mode that the user was using at each instant was always ranked least, regardless of its GVF magnitude. The modes used and a comparison between traditional and adaptive switching are shown in Fig. 8. Figure 9 represents the GVF values for each mode in a specific experiment [44], where at the times of switching (vertical dashed lines), the desired mode selected by the user (filled area) had the highest magnitude in comparison to the other modes, except for the mode that was used before the switching action. This method can reduce the users' effort, cognitive load and switching duration in switching actions and has the capability of predicting an unlimited number of walking modes. This can be especially useful for the home environment, where users' preferences in different situations can be quickly learned and predicted.

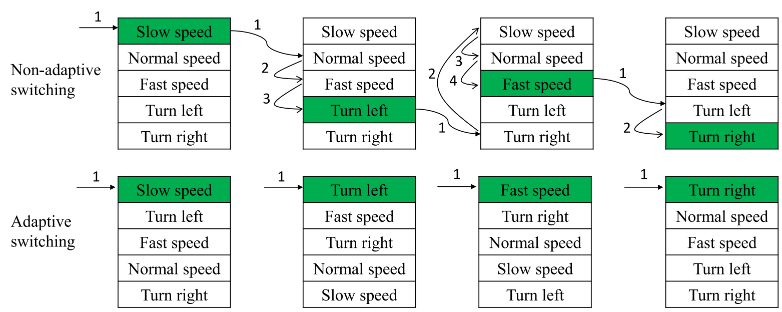

Figure 8: A comparison between adaptive and non-adaptive switching actions. Numbers are indicative of the total number of required switching actions at each switching instance.

6 Smart assistive walkers

Smart assistive walkers are another group of lower-limb assistive devices that can be helpful in home-care. These devices can be employed collaboratively with exoskeletons to support the postural stability and provide a higher level of safety while walking. A smart walker can contribute to the control loop of an exoskeleton by providing additional sensory input (as described in Sec. 5). A smart walker can also be employed solely to intelligently improve the stability and mobility of people with lower-limb weakness or poor balance. In this section, a learning-based control approach was introduced for smart walkers. The method learns users' walking pattern while assisting and utilize an admittance-based method to detect walking variations. Furthermore, the developed method monitors users' interaction force in all directions to prevent some catastrophic conditions, such as falls.

The main goal in the development of smart walkers is to provide a compliant interaction between human and robot. In this case, the robot needs to measure the forces being applied by the user and then determine the desired locomotion based on that. We proposed a strategy that takes advantage of the cooperative dynamic movement primitives (DMPs) method to assist the user's walking [45]. The algorithm can learn user-specified walking pattern over one gait cycle using cooperative DMPs, where a variable admittance control (VAC) approach is used to update the smart walker's desired path to reach the desired locomotion pattern. The VAC approach employs the interaction force in all directions to adjust the

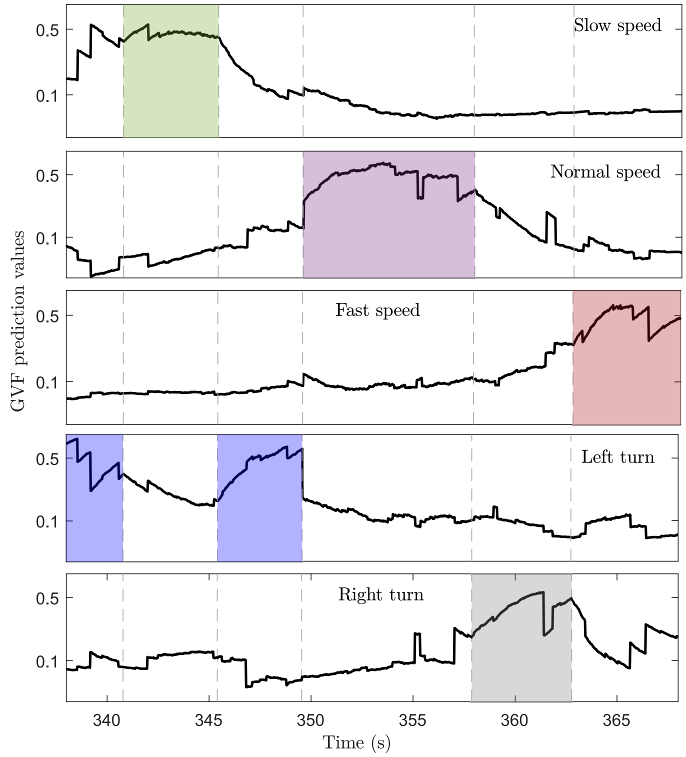

Figure 9: GVF prediction values (solid lines) for different modes in the switching list. Dashed vertical lines are indicative of a switching action and filled area present the selected mode at each instant.

velocity of walking. Force applied the in horizontal direction results in acceleration along the same direction. Force applied in the vertical direction results in acceleration/deceleration along the current walking direction. Also, taking advantage of the cooperative DMPs, the algorithm can detect and respond to emergency conditions; e.g., large unintended force or fall (large vertical force), and provide support for the user in these cases.
The performance of the proposed approach was demonstrated with a custom-built smart walker, which was equipped with a force/torque sensor to measure interaction force/torque [45]. The performance of the VAC method in detecting user's walking intention is presented in Fig. 10. The applied vertical force (f_z) resulted in acceleration in the horizontal direction. A larger vertical force exerted at about 9.8 s in Fig. 10(a), resulted in deceleration of the motion. The deceleration can be seen as tilt angle change, shown in Fig. 10(b) ($\theta_a > \theta_b$). This characteristic could be very beneficial in homecare applications, when the user wants to walk faster/slower.

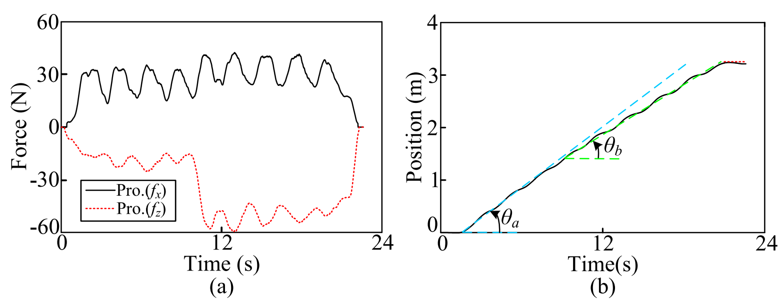

Figure 10: Performance of the VAC method in detecting a user's walking intention. (a) demonstrates the applied forces, and (b) shows the resultant trajectories

The performance of the cooperative DMPs in handling an emergency was tested and the results are shown in Fig. 11 [45]. An applied unsafe force by the user (e.g., as a result of falling) is detected and the dangerous situation is avoided using our proposed method. Specifically, when a large vertical force (approximately 52 N) was applied at 8.03 s, the walker stopped with a reaction time no longer than 150 ms. The walker also gradually stopped at 18 s and 27.54 s after the user stopped applying any force.

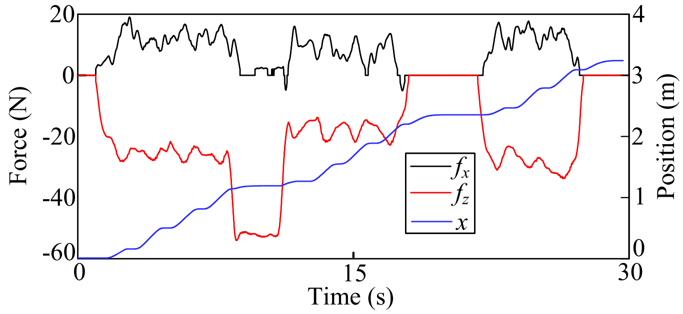

Figure 11: Performance of the cooperative DMPs in handling an emergency

7 Conclusions and Future Vision

The huge demand caused by the aging population for healthcare service has made the employment of advanced technologies necessary. Lower-limb assistive robotic systems are one of the recent advancements that have shown a great capacity to help the healthcare system to provide more effective service. The ability of robots to repeat tasks without getting tired or bored, a precise sensory system that can monitor users during working with the system, and also the capacity to record data for future assessments are capabilities that make them interesting for healthcare applications. However, to use these systems in the home environment, they need to be sufficiently intelligent to adapt to the user and also provide a safe pHRI.

Our proposed adaptable CPG method estimates the HRI torque and refines the gait trajectory based on the user's intent. By employing this method, users do not need to comply with the exoskeleton's trajectory and can contribute to shaping that based on their desired walking pattern. Although refining the gait trajectory is an essential step in making the robots usable at home, safety and postural stability are other issues that need to be addressed. The DCM analysis we proposed may be a way to addressing this challenge. Taking advantage of this method, we actively monitor the CoM of the human-exoskeleton system and adjust the upper-body position to maintain postural stability.

DNNs are used to estimate human-robot interaction torque, which can detect the user's intent; however, failure to estimate the correct values can result in unsafe action from the exoskeleton. We have a random forest regression model to estimate the passive torque dynamics for pHRI estimation. However, there are uncertainties in the model prediction that need to be considered because of the sensitivity of pHRI calculations. We developed an uncertainty analysis method to address this issue by estimating the uncertainty in the model predictions and applying that information to the controller of the assistive robot to refine the trajectory generated by adaptable CPGs.

The methods mentioned above can provide user-specific safe assistance, but they require force or torque from the user to modify the behaviour of the assistive device. Therefore, they will not be appropriate for people who can not apply interaction torque/force; e.g., people with motor complete spinal cord injuries. To address that, we need to think of alternative ways to update the robot trajectory, and an adaptive switching approach. For that, we mounted the smart walker with a button for switching among different walking modes. To use this button efficiently, the order of the modes needed to be updated based on the sensory data (distance from obstacles) and the history of users' actions. To do that, we developed an adaptive switching approach based on reinforcement learning that can learn the users' behaviour over time and predict their desired mode of walking based on the upcoming situation.

Smart walkers are another type of assistive device that can be beneficial in home environments in addition to exoskeletons. Our developed smart walker can capture the user's walking intention based on the applied force from all directions to the handles. The applied force in the horizontal direction sets both the direction and velocity of walking. However, the vertical force contributes to acceleration/deceleration

in the current walking direction. The proposed algorithm can also detect unsafe situations and help to protect users by adjusting the walker's speed. These features make the smart walker a useful assistive device for home users.
Although the proposed approaches could resolve some of the existing issues with lower-limb assistive devices, there is a need for more work to meet the requirements of homecare applications. From the software perspective, increasing the controller intelligence in several aspects can be very beneficial. Most of the existing methods have focused on one mode of locomotion; e.g., walking or ascending stairs. To be fit for home-based assistive applications, the device needs to understand the user's intention and switch among these different modes. Moreover, the transition between these modes needs to be done in a very smooth way to guarantee the user's safety.
In addition to the software, improvement in the hardware can also contribute substantially to increasing interest in using the lower-limb assistive devices in the home environment. In the case of the exoskeletons, mechanical rigidity and high weight are two of the main problems. Soft robotics can help solve these problems. The lack of actuation in the lateral plane is another challenge for currently available commercial exoskeletons. Users' comfort can be enhanced significantly by adding degrees of freedom (passive or active) in the lateral plane. Figure 12 depicts a roadmap for future studies in design and development od lower-limb assistive devices. With the ongoing and future technological advancements, assistive lower-limb devices will hopefully play an essential role in home-based assistance in the near future.

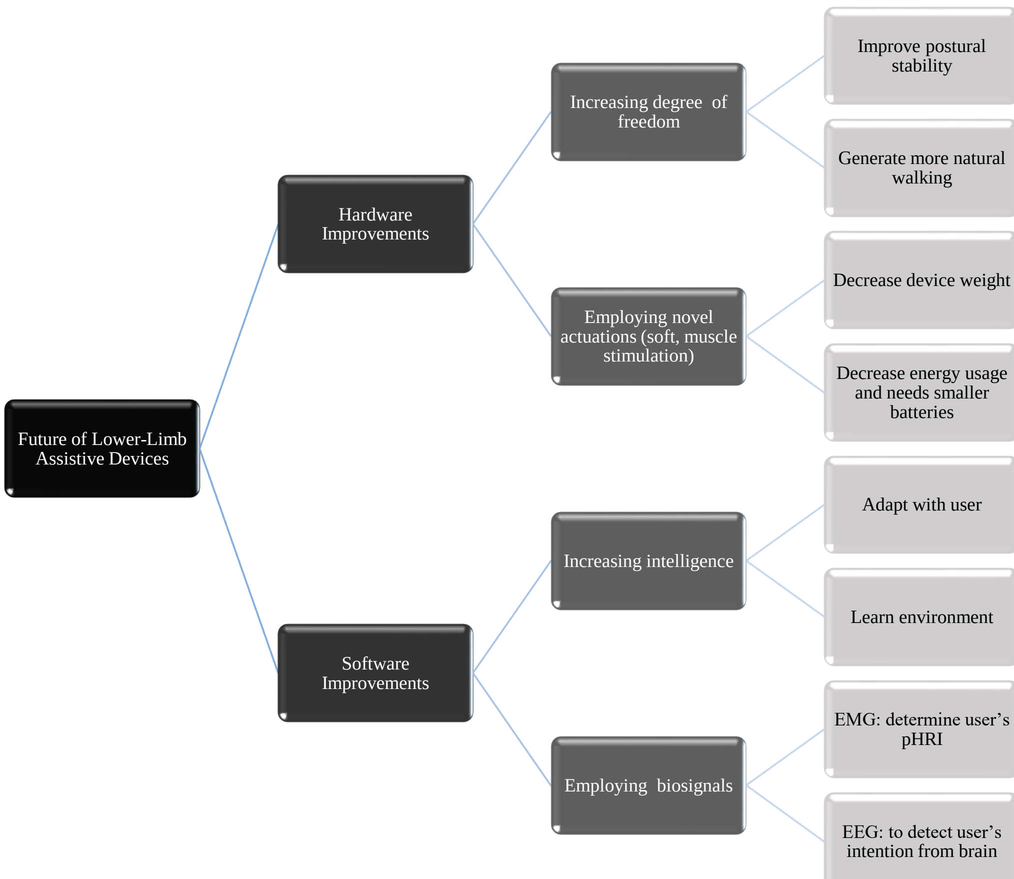

Figure 12: Roadmap for future works on lower-limb assistive devices to make them better fit for homecare

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