

# Tapping into skeletal muscle biomechanics for design and control of lower-limb exoskeletons: a narrative review

Zahra S. Mahdian<sup>1</sup>, Huawei Wang<sup>1</sup>, Mohamed Irfan Mohamed Refai<sup>1</sup>, Guillaume Durandau<sup>2</sup>,  
Massimo Sartori<sup>1</sup>, and Mhairi K. MacLean<sup>1</sup>

<sup>1</sup> Department of Biomechanical Engineering, University of Twente, Enschede, Netherlands

<sup>2</sup> Department of Mechanical Engineering, McGill University, Montreal, Canada

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## **Correspondence Address:**

Mhairi K. MacLean

Department of Biomechanical Engineering

Drienerlolaan 5

Enschede, 7522 NB, The Netherlands

Phone: +31 5 3489 7699, Email: [M.K.MacLean@utwente.nl](mailto:M.K.MacLean@utwente.nl)

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## Abstract

Lower-limb exoskeletons and exosuits (“exos”) are traditionally designed with a strong focus on mechatronics and actuation, whereas the “human-side” is often disregarded or minimally modelled. Muscle biomechanics principles and skeletal muscle response to robot-delivered loads should be incorporated in design/control of exos. In this narrative review, we summarize the advances in literature with respect to the fusion of muscle biomechanics and lower-limb exoskeletons. We reported methods to measure muscle biomechanics directly and indirectly and summarized the studies that incorporated muscle measures for improved design and control of intuitive lower-limb exos. Finally, we delved into articles that studied how the human-exo interaction influenced muscle biomechanics during locomotion. To support neurorehabilitation and facilitate everyday use of wearable assistive technologies, we believe that future studies should investigate and predict how exoskeleton assistance strategies would structurally remodel skeletal muscle over time. Real-time mapping of the neuromechanical origin and generation of muscle force resulting in joint torques should be combined with musculoskeletal models to address time varying parameters such as adaptation to exos and fatigue. Development of smarter predictive controllers that steer rather than assist biological components could result in a synchronized human-machine system that optimizes the biological and electromechanical performance of the combined system.

### ***Keywords:***

musculoskeletal modelling, human locomotion, human-machine interaction, sensor based control

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## Introduction

Lower-limb exoskeletons and exosuits are worn in parallel with the body to assist, augment, or otherwise affect mobility. Collectively referred to as “exos”, exoskeletons and exosuits are often used in gait rehabilitation or as a mobility aid.<sup>1</sup> Exos deliver mechanical assistance to targeted biological joint(s) and thus interact directly with the wearer’s musculoskeletal system. To effectively unload or augment the biological joint, knowledge of joint biomechanics is typically incorporated into the design or control of the exo. Generally speaking, the research field has a good comprehension of lower-limb joint-level biomechanics including: dynamic (quasi-)stiffness,<sup>2–6</sup> distribution of work across the joints,<sup>7–9</sup> and how factors such as speed, terrain, and load change the joint dynamics.<sup>10–12</sup> However, skeletal muscles are the actual actuators that generate movement.<sup>13,14</sup> Therefore, there are clear advantages to movement support technology which interacts at the muscle level.

The quantity of published research, which combines muscle/tendon biomechanics with exos is small, but exhibits a slow upwards trends in recent years. Figure 1 illustrates the long-standing and increasing interest in muscle/tendon biomechanics research. The increase in exo research is comparatively more recent, likely due to technological advancements improving the feasibility of exo research.<sup>15</sup> Emerging in 2005, published research combining the fields of exos and muscle/tendon biomechanics has slowly increased, although it still trails behind both of its components.

Understanding of muscle-level biomechanics has improved with time, facilitated by improvements in technology and modelling. Well established techniques, like ultrasound, were able to capture muscle mechanics in intact humans *in vivo* during stationary tasks.<sup>16–18</sup> Improvements in technology allowed capture of muscle mechanics in dynamic situations such as

walking.<sup>19–21</sup> Advances in high-density electromyography (HD-EMG) and blind source separation enabled measuring the firing activity of contractile microstructures (*i.e.*, motor units) in human muscles *in vivo*,<sup>22,23</sup> which was critical to understanding how whole-body movement is accomplished via fibre contraction at the microscale.<sup>24</sup> Computational muscle-level models combined with a rise in open-source platforms and models, and an increase in computing power also served to advance our understanding of muscle-level biomechanics at macro- and microscale. Improvements in implementing trajectory optimization for musculoskeletal modelling facilitated faster modelling and simulations, which allowed researchers to more easily simulate and investigate numerous models.<sup>25</sup> In 2015, a modelling toolbox called CEINMS, integrated electromyographic (EMG) driven and EMG-informed algorithms into the musculoskeletal modelling environment of OpenSim.<sup>26</sup> The resulting open-source neuromusculoskeletal modelling platform was able to better simulate, test, and understand how muscle activity controls movement. Researchers have also developed tools to facilitate advanced optimal control (Moco in OpenSim) and customizable control (SCONE) in neuromuscular simulations.<sup>27,28</sup> Furthermore, recent advancements have combined computationally fast musculoskeletal models with reinforcement learning to explore muscle mechanics during real-life tasks. MyoSuite, an open-source framework with reinforcement learning capable musculoskeletal models, enables *in silico* design of robotic devices and controllers, thereby speeding up the design of personalized exos for *in vivo* real-world applications.<sup>29,30</sup> With a better understanding of muscle-level biomechanics we gleaned insights into the mechanisms of mobility and biomechanical principles about which exoskeletons can be designed and controlled.

Traditionally, the key players in exo design and control have been mechatronic and actuation aspects, while the human aspects have often been disregarded or minimally incorporated.

91 Many exoskeletons, both old and new, exclusively use techniques other than muscle-level  
92 biomechanics for their controllers and design. A number of review articles discuss the state-of-  
93 the-art for non-muscle-level exoskeleton control and design,<sup>1,31–33</sup> so we only briefly summarize  
94 them here. Generally, exo design and control focuses on the robotic part of the human-robot  
95 system, placing high importance on the output torque of the device (*Figure 2*). Oftentimes, exos  
96 use position or torque tracking to enforce a pre-defined kinematic or kinetic profile, and the human  
97 must yield and adapt to the robot's actuation rather than working symbiotically.<sup>34–37</sup> Impedance  
98 control considers the interaction between human and robot, resulting in a controller that is  
99 responsive to the human while still enforcing predetermined dynamics.<sup>37–40</sup> Volitional controllers,  
100 such as proportional myoelectric controllers, further shift the controller focus from the robot to the  
101 human component of the human-robot system by using human measures to inform the output.<sup>41–</sup>  
102 <sup>43</sup> However, proportional myoelectric controllers measure the emergent behaviour of the  
103 underlying muscle actions and therefore do not fully capture the muscle mechanics. Human-in-  
104 the-loop optimization acts to tune the exo parameters to optimize for a chosen output parameter  
105 which is often human energy expenditure or muscle activity.<sup>44–46</sup> Although a powerful and state-  
106 of-the-art technique, human-in-the-loop optimization can be time intensive and risks falling into  
107 local minima traps. Some consideration to muscle properties have also been included in design –  
108 most noticeably exos which employ contractile elements mimicking musculoskeletal properties,  
109 such as the McKibben pneumatic actuator (commonly referred to as an “artificial muscle”).<sup>41,47</sup>  
110 However, McKibben actuators require a compressed air source, thus limiting the locations the exo  
111 can be used in. In addition to little incorporation of muscle-level biomechanics in exo design and  
112 control, no exo has taken into consideration the short- and long-term response of skeletal muscle

to robot-delivered mechanical loads. Inclusion of muscle-level biomechanics may overcome some shortfalls in current exo design and control.

The design and control of exos has been increasingly inspired by muscle-level biomechanics over time. Earlier exoskeletons had heavy and bulky form factors, with a focus on providing enough power to compensate for 100% of biological joint torque-generating capacity.<sup>48,49</sup> Time and experience led to smaller, and less-bulky exos, with a wide variety of actuation methods. The development of light-weight yet strong materials, more compact powerful batteries and motors, and innovative design all contributed to reducing the bulk and weight of exos. Artificial pneumatic muscles which attempted to mimic biological muscle properties and were originally developed for prosthesis use, became a popular actuation method for exos.<sup>41,47,50,51</sup> Linear springs, acting in-line with muscle-tendon units such as the *triceps surae* complex, have also been used in exo design as a form of musculotendon mimicry.<sup>52,53</sup> Straps and cables, a more recent form of exo actuation, are often inspired by biological tendons.<sup>54,55</sup> While these techniques are guided by muscle properties, none of them rely on muscle-level biomechanics, which is the next logical step for exo development.

Inclusion of muscle-level biomechanics in exo design/control has the potential to break through some of the barriers to wide-spread exo success. Despite technological advancements, there is substantial room for improvement in exo design/control, particularly for real world environments. In this narrative review, we will discuss how muscle-level biomechanics has been and could be effectively implemented in exo control and design. We introduce the techniques and hardware used to understand muscle-level biomechanics and then discuss how muscle-level biomechanics can inform design and personalization. Next, we consider control choices and integrating real-time muscle-level biomechanics estimators within robotic control logics. After

presenting how muscle-level biomechanics affects the human-machine interaction, we end the review with recommendations and predictions of research within muscle-level biomechanics and lower-limb exos. Throughout the manuscript, we classified techniques as “Direct” if they measured a muscle property through sensors, and “Indirect” if the technique used a musculoskeletal model with or without sensor input to estimate a muscle property.

## Measuring muscle biomechanics

Incorporation of muscle biomechanics into exo design, control, or personalization requires a method to measure or estimate muscle biomechanics. The measurement or estimation technique usually needs to provide relevant biomechanical data *in vivo*, real-time (not for evaluation purposes), and during dynamic movement. Furthermore, sensors should be compatible with the physical structure of the exo. In this section, we reviewed muscle measurement methods and sensors to measure or estimate muscle biomechanics that meet the requirements for use with exoskeletons.

### ***Direct measures***

While various sensing methods measure parameters that can provide information about muscle-level kinetics and kinematics, the depth and accuracy of measurements are different. We presented the methods in order from the deepest to most superficial measurements.

#### *Sarcomere Microendoscopy*

Sarcomere microendoscopy can directly measure the second-harmonic frequencies of light generated in the muscle fibres to visualize muscle sarcomeres and their contractile dynamics. Llewellyn *et al.*<sup>56</sup> showed that second-harmonic generation with 920 nm illumination can effectively visualize sarcomeres in human extensor digitorum muscle *in vivo*. They showed that

visualizing sarcomere contractile dynamics in millisecond scale resolution can overcome cardiac and respiratory motion artifacts which is possible through high-speed data acquisition. As sarcomere length determines force production capacity in muscles, microendoscopy can reveal muscle biomechanics *in vivo* while being minimally invasive. Sanchez *et al.*<sup>57</sup> developed a wearable microendoscope to visualize sarcomere twitch dynamics in individual motor units of major skeletal muscles including *soleus* and *vastus lateralis*. Although sarcomere microendoscopy is still an invasive method and it has never been used in conjunction with exoskeletons, it is a potential measurement method which can deepen the knowledge of muscle biomechanics to inform design, control, and individualization of lower limb exoskeletons. For instance, because many movement disorders exhibit or originate from disruptions in sarcomere structure and performance, rehabilitative exos could be designed based on how they affect motor unit contractile dynamics and the structure of sarcomeres in short- and long- term. Similarly, different types of exos can take advantage of the evaluation of user adaptation and how adaptation results in desired or undesired remodelling in the muscle, which is advantageous for real-world applications.

Sarcomere microendoscopy demonstrated how joint angle affects sarcomere length and contractile dynamic. Cromie *et al.*<sup>58</sup> measured sarcomere length in *carpi radialis brevis* while wrist was in flexion and extension. The results showed substantial sarcomere length variability in an individual fibre. More studies addressed how joint angle changes sarcomere length and affects muscle force generating capacity in lower limbs.<sup>59,60</sup> As the changes in the sarcomere length at different angles were in the range of 2 to 4  $\mu\text{m}$  for the *soleus* and the measurement precision of the method is  $\sim 30$  nm, the measurement is therefore suitable for tracking the length of sarcomeres in lowerlimb movement.<sup>60</sup> Additionally, Lichtwark *et al.*<sup>61</sup> showed that fascicle length change can represent sarcomere length change.



Furthermore, sarcomere microendoscopy can equip research in the field of lower limb exos to investigate muscle adaptation. Pincheria *et al.*<sup>62</sup> determined how three weeks of eccentric exercise training changes sarcomeres in *biceps femoris long head*. They estimated sarcomere length and number as well as fascicle length before and after the training. The results showed an increase in the sarcomere length while the sarcomere numbers in series did not change, as well as a heterogeneous change in fascicle length.

#### *Ultrasound imaging*

Ultrasonography enables deriving muscle architectural (*e.g.*, volume, pennation angle, physiological cross-sectional area) and functional parameters (*e.g.*, fascicle kinematics), which are critical to understanding muscle biomechanics. As muscles are in series with tendons, other common biological measurements like joint kinematics and kinetics, or EMG cannot provide enough details to measure the separate kinetics and kinematics of muscles and tendons without many assumptions and models. Muscle-tendon biomechanics can provide useful information for individualization, fatigue recognition, real-time and overground joint torque estimation etc., which can enhance control and design in lower-limb exos.

Fukunaga *et al.*<sup>63</sup> used real-time ultrasonography to determine fascicle length and pennation angle of human *vastus lateralis* muscle *in vivo* and non-invasively at rest and during static contraction. Ultrasonography enabled *in vivo* measuring of parameters that can inform muscle level kinetics and kinematics such as physiological cross-sectional area of muscles,<sup>64</sup> investigating differences in longitudinal strain of the Achilles tendon,<sup>65</sup> as well as studying force-velocity behaviour of the *medial gastrocnemius* muscle-tendon unit.<sup>66</sup> Manual tracking of muscle architectures with ultrasonography is subjective and time-consuming, which led to algorithms developed for automated tracking of fascicle length,<sup>67</sup> for which the accuracy and repeatability is assessed,<sup>68</sup>

and the source code and standalone version of the semi-automated fascicle tracking algorithm was made open-source.<sup>69</sup>

Recently, studies used muscle ultrasonography during gait to estimate parameters like volitional motion or ability and muscle power, which can be useful for exo control. For instance, Nuckols *et al.*<sup>70</sup> used ultrasound imaging to estimate the onset of *soleus* concentric contraction just before push off, when the *soleus* begins to generate positive power, in real time during various gait conditions. They showed that an exo control strategy based on muscle positive power could adapt to the individuality of contraction timing (e.g., healthy and post stroke patient) and how it changed with changes in gait (e.g., speed and incline). Nuckols *et al.* also compared gait segmentation based on automated ultrasound detection of the *soleus* contraction onset with ground reaction forces and found the error was within 1% of the gait cycle. Other approaches to link human mechanics to exo control strategies include optimization and grid search (i.e. parameter sweeping) which explore and determine appropriate exo control parameters for a specific gait condition.<sup>71</sup> However, both techniques are time-consuming and not necessarily generalizable to differences in gaits and terrains. Direct EMG or matching to kinetics and kinematics of joints are also approaches that try to intuitively adapt to human gait, but their performance is not as good as optimization or grid sweep. One possible reason is that joint kinetics and kinematics and EMG cannot completely determine the dynamic state of muscles that are the real actuators of human gait.

Moreover, muscle architecture can be input into data-driven (e.g., using machine learning) or mechanistic (e.g., musculoskeletal modelling) models that can estimate motion intention. Jahnandish *et al.*<sup>72</sup> performed image enhancement and model fitting to extract ultrasound features of *rectus femoris* muscle, namely thickness, angle between aponeuroses, pennation angle, fascicle length, and image echogenicity. The echogenicity, defined as the ability to send and receive an

ultrasound wave, was measured by averaging the intensity of all pixels in the region of interest. Then, they estimated knee joint angle and angular velocity during non-weight-bearing knee flexion/extension based on the trained model with an average root mean square error value of  $7.45^\circ$  and  $0.262 \text{ rad/s}$ , which is close to a similar study which used sEMG. Muscle thickness and image echogenicity showed the highest correlation with both angle and angular velocity. Also, some studies showed that inputs from both s-EMG and ultrasound images (fascicle length and pennation angle) can increase accuracy of ankle joint moment prediction by machine learning<sup>73</sup> models or neural and musculoskeletal<sup>74</sup> models.

While studies used ultrasound B-mode probes to extract fascicle kinematics based on 2D images, Yan *et al.*<sup>75</sup> developed a measurement system to use ultrasound wearable A-mode probes (1D measurement) to estimate the acoustic nonlinearity parameter of skeletal muscles *in vivo*. The acoustic non-linearity parameter changes in tissues due to diseases or residual stress, which suggested that similar changes may occur with contraction in muscles. Yan *et al.* showed high correlation between the acoustic nonlinearity parameter of *biceps brachii* muscle and elbow joint torque, with an average coefficient of determination ( $R^2$ ) of 0.861. Hence, they proposed the acoustic nonlinearity parameter as supplementary information for force control of exoskeletons.

#### *Shear wave tensiometry*

An emerging research technique to directly and non-invasively measure superficial tendon and ligament kinetics is shear wave tensiometry.<sup>76</sup> The non-invasive device is placed on the skin, directly over the target tendon or ligament. A vibrational stimulus is delivered to the tendon (via the skin) which propagates through the tendon at a speed dependent on the tendon axial load due to real-time characteristics of the tendon modulating the propagation of the vibration. The shear

249 wave speed can be calculated knowing the distance between two miniature accelerometers placed  
250 along the tendon direction and measuring the arrival time of the propagated signal.

251 Shear wave tensiometry shows promising capabilities for applications in lower limb exos.  
252 First, it is applicable to lower limb exos, as the impulses are detectable throughout the gait cycle  
253 and can track dynamically varying wave speed.<sup>77</sup> Several studies used shear wave tensiometry to  
254 track the dynamics of standing balance and measure gait kinetics in clinical and able-bodied  
255 populations, including children, adults, and older adults<sup>78–82</sup>. Second, in more dynamic tasks like  
256 running and jumping, Schmitz *et al.*<sup>83</sup> proposed adding redundant accelerometers and using a  
257 Kalman filter to mitigate random sensor noise due to the high rate of loading and impact events.  
258 Harper *et al.*<sup>84</sup> developed a wearable shear wave tensiometer with dynamic range to track  
259 unconstrained locomotion. A later work combined this with inertial measurement units<sup>85</sup> to  
260 measure the work and power output of *Triceps Surae* outdoors. Schneebeli *et al.*<sup>86</sup> used intraclass  
261 correlation coefficient (ICC3.1) to test the test-retest (ICC3.1 0.87–0.99), inter-section (ICC3.1  
262 0.75–0.93) and intra-session (ICC3.1 0.85–0.96) reliability of shear wave tensiometry, which  
263 shows promising use in clinical and research settings.

#### 264 *High Density Electromyography (HD-EMG)*

265 Non-invasive and flexible or woven textile bi-dimensional grids of electrodes can measure  
266 muscle high density electromyograms (HD-EMGs).<sup>87</sup> HD-EMG is an interferent electrical signal  
267 generated by the superposition of action potentials generated by hundreds of skeletal muscle fibres  
268 during contraction. Because skeletal muscle fibres are directly innervated by alpha motor neurons  
269 (neural cells residing in the spinal cord), the HD-EMGs carry information about alpha motor  
270 neuron activity, which is directly associated to the control of movements.<sup>88</sup> Blind source  
271 separation can be used to disentangle the interferent HD-EMG and decode both discharge timings

of motor neurons as well as the resulting action potentials travelling along innervated skeletal fibres. HD-EMG holds great potential to explore the neuro-mechanics of movement in individuals wearing exoskeletons. Many studies have addressed HD-EMG in upper limb gesture recognition and exoskeleton controllers, but the literature in lower limb exoskeletons is scarce.

Some studies investigated HD-EMG during locomotion and demonstrated that spatial patterns of electromyograms can reveal how muscles adapt to different locomotion modes. Schlink *et al.*<sup>23</sup> compared different signal processing methods to reduce motion artifacts in HD-EMG during human locomotion and proposed canonical correlation analysis filtering during fast walking and running. Schlink *et al.*<sup>89</sup> also showed that spatial patterns of electromyograms are heterogeneous and differ among lower limb muscles and locomotion speeds, which could be due to preferential recruitment of faster motor units under greater loads. Moreover, they showed that fatigue alters spatial myoelectric patterns in the *medial gastrocnemius* during locomotion, while lower limb biomechanics remains similar, a potential strategy to avoid overuse injuries.<sup>90</sup> Exos can use HD-EMG to recognize fatigue or locomotion mode to tune assistance (e.g., timing and magnitude of torque). Also, HD-EMG can reveal muscle recruitment strategies, impairments, and adaptations of users as valuable information for exoskeleton design.

#### *Force myography (FMG)*

FMG refers to a broad category of methods that non-invasively measure muscle biomechanics by quantifying how muscle external geometry changes. FMG usually includes an array of sensors to detect muscle deformation or stiffness due to contraction, and methods that process the collected data to extract the desired parameters. FMG can vary in type of sensors (e.g., force or pressure sensors, strain sensors, bending sensors), sensor arrangement, and data processing method (e.g. signal processing and feature extraction, machine learning techniques),

with specific limitations associated with each technique.<sup>37</sup> However, sensor characteristics and device configuration can adversely affect the reliability of FMG signals. For instance, many researchers calibrated the pre-load forces when the device is donned based on the user's oral feedback.<sup>91</sup> Moreover, some methods are based on cross-sectional area increase of the muscles.<sup>92</sup> These methods can be used in some applications like gesture recognition but cannot estimate individual muscle force without making assumptions on the contribution of the individual muscles to the cross-sectional area increase. Also, some techniques are only applicable to static situations as they cannot handle motion artifacts.<sup>93</sup>

Some recent studies developed and used soft and wearable strain sensors to monitor muscle contractions.<sup>92,94</sup> Alvares *et al.*<sup>94</sup> used sensors based on strain-mediated contact in anisotropically resistive structures (SCARS) to measure changes in muscle deformation which correlate with muscle input and knee torque.

Many studies include FMG in hand rehabilitative and assistive exoskeletons to enhance user intention in upper body,<sup>95-99</sup> but FMG in lower limb applications is limited. Jiang *et al.*<sup>100</sup> proposed a wearable gait phase determination system based on FMG. The proposed force myography band could correctly detect more than 99.9% of gait phases over 12965 gait phase segments with an average temporal error of 55.2 ms. With upper limb applications motivating hardware and processing improvements in FMG, there is an increased likelihood of interesting applications for lower limb exos in the future.

### ***Indirect measures***

Aside from the direct measurements mentioned above, real-time musculoskeletal models have been used to estimate biomechanical parameters *in vivo*, such as muscle-tendon forces,<sup>101</sup>

kinematics, joint torques,<sup>102,103</sup> joint stiffness,<sup>5,6</sup> and compressive loads,<sup>104</sup> which can be used in exoskeleton controls,<sup>105–108</sup> without using invasive measurement sensors.

One research direction is to use optimization to estimate individual muscle forces from the net joint torques (often got from inverse dynamics<sup>109,110</sup>), named static optimization.<sup>111–114</sup> Specifically, researchers developed real-time computing platforms that utilize the static optimization method in estimating muscle forces.<sup>115,116</sup> However, optimization-based muscle force estimation for lower limbs often requires force plates to measure ground reaction forces, which limits this potential in out-of-lab applications. Trajectory optimization can avoid this issue by modelling the ground contacts, however, the objective function is normally movement-type specific and may not reflect an individual person or patient.<sup>25,117</sup> Furthermore, the computation time is long and prevented it from being used in the real-time control of wearable robotic devices.

To solve this problem, muscle force estimation using sEMG driven musculoskeletal (MSK) models have been developed, which requires joint angles and sEMG signals as input. At first, due to computational complexity, studies were focused on only one joint and its corresponding muscles<sup>118,119</sup> and an infinitely stiff tendon model was also used in the muscle models to save in computational time;<sup>120</sup> Later, these types of studies were expanded to multiple joints and muscles as well as incorporating an elastic tendon to cover more complex movements;<sup>102,121</sup> Recently, the open source Calibrated EMG-Informed NeuroMusculoSkeletal Modelling Toolbox (CEINMS) was developed to lower the entry to this field.<sup>26,103</sup> Furthermore, experimental EMG paired with inverse dynamics allowed for the personalization of muscle-tendon models to the user as they represent the inputs/outputs pair.<sup>26</sup> Not only can this method estimate muscle forces, but studies also demonstrated that it could accurately estimate joint torque and extrapolate results for unknown tasks (not used for the muscle-tendon model parameters personalisation), and even other degrees

of freedom.<sup>122</sup> Since musculoskeletal models were directly driven by the sEMG signals, calculated muscle forces and joint torques can be prior to the electromechanical delay of actual musculoskeletal systems, which provides a big advantage in exoskeleton control as it gives a windows of opportunity where optimal assistance can be provided to the user.<sup>106,107</sup> By knowing the force of each muscle that wraps over a joint, joint stiffness<sup>5,6,123,124</sup> and compressive loads can be estimated.<sup>104,125–129</sup> As these parameters are more closely relevant to either human-robot interactions or injury risks, they are more suitable to be directly used as control parameters in exoskeletons. Even though the above-mentioned studies have shown very promising results on reproducing joint torques, validating the actual muscle forces in vivo on human subjects poses ethical challenges, making it difficult to directly measure and validate these forces. However, experimental studies conducted on cats have provided valuable insights into the effectiveness of various approaches, such as static optimization, trajectory optimization, and surface electromyography (sEMG).<sup>130–133</sup> The similarities in muscle structures and types between humans and cats support the belief that these methods can be reliable in interpreting human movements as well. While there may be some species-specific differences, the fundamental principles underlying muscle mechanics and control are expected to be comparable. In general, indirect measurement methods provide very useful muscle biometric information using very simple sensor setups, compared to direct methods, which has advantages in real-life applications.

### **Muscle and tendon biomechanics for exoskeleton design or personalization**

A main objective of exos is to interact with the human wearing them. Thus, this interaction will influence the design and control of the exo. For a long time, the human neuromusculoskeletal system was ignored in the conception of exoskeletons resulting in devices that were powerful but bulky and with little to no benefit for the user.<sup>49</sup> To overcome this challenge, exoskeleton



emulators for iterative design were established; the most established of which is the human-in-the-loop technique.<sup>46</sup> Although emulators can result in the creation of optimal design and control,<sup>52</sup> they require a large amount of human data (3600 recorded conditions in the cited study).

### ***Direct measurements***

Direct measurements of muscle biomechanics can provide useful information to inspire novel designs or to help tune exoskeletons. Ultrasound imaging can reveal the effects of exo stiffness on force production in muscles and tendons. Farris *et al.*<sup>134</sup> evaluated the effect of parallel elastic assistance of ankle exoskeleton in hopping on *soleus* muscle-tendon-unit mechanics using *in vivo* ultrasound imaging. They showed that parallel assistance to *soleus* muscle reduces muscle force, but average positive fascicle power does not significantly change. This can help with tuning the stiffness of lower limb exos to optimize metabolic cost. Takahashi *et al.*<sup>135</sup> investigated foot-ankle interplay during walking by adding stiffness to the foot through shoes and insoles. They used ultrasound imaging to show that a stiffer foot results in decreased shortening velocity and increased force output in *soleus* muscle. The results suggested added foot/shoe stiffness as a potential design parameter to improve locomotion economy in tasks where muscles should generate more muscle force (e.g., walking with load carriage) or operate with less economy (e.g., fast walking speeds close to the walk-to-run transition). Also, Nuckols *et al.*<sup>136</sup> showed how exoskeleton stiffness alters *soleus* muscle contractile dynamics and affects metabolic rate during walking. They used ultrasound imaging to show that exoskeletons with higher rotational stiffness increase fascicle length and velocity and decrease fascicle force. However, the change in contractile dynamics results in a bowl-shape metabolic cost. Hence, measuring contractile behaviour can help to design or tune exos to steer more economical force production in the muscles. Moreover, Beck *et al.*<sup>137</sup>

showed how artificially fast balance-correcting exoskeleton torque can improve balance by 9% and how it affects fascicle mechanics.

Moreover, direct measurements can help exo personalisation through design and evaluation of assistance profile. Nuckols *et al.*<sup>138</sup> demonstrated that ultrasound imaging can measure muscle dynamics to develop exosuit assistance profiles that are tailored to the individual and adaptive to dynamic walking tasks. Also, Schmitz *et al.*<sup>139</sup> used shear wave tensiometer to directly measure force in the Achilles tendon during walking assisted with ankle exosuit while carrying load. They performed a pilot experiment in an unconstrained outdoor environment to evaluate nine different exosuit assistance profiles based on reduction in the peak force in Achilles tendon. The most efficient exosuit assistance profile could reduce metabolic cost by 9.6%.

### ***Indirect measurements***

Human-exoskeleton simulation can acquire the same benefits of emulators without requiring a high volume of human data. As previously presented, there is a wealth of literature on neuromusculoskeletal modelling based on cadaveric studies or human experiments. Nevertheless, one of the main and active challenges is the simulation of how human and mechanical devices interact. One of the main axes of simulation-research is based on predictive simulation using optimal control, which can reproduce the interaction between the human-exoskeleton system and the environment. Optimal control can also predict the effect of exos on humans or human biomechanical variables in unknown conditions. Fournier *et al.* began with a biomechanical simulation of healthy and spinal cord injury kinematics at varied walking speeds,<sup>140</sup> then added a simulated exoskeleton to the human neuromusculoskeletal system, which allowed them to predict ground reaction forces. Predictive simulation and optimal control can also be used to predict the effect of exos with different mechanical properties, for example Sreenivasa *et al.*<sup>141</sup> looked into

the optimal stiffness of an ankle-foot orthosis for reducing muscle effort in children with gait abnormality and Febrer-Nafría *et al.*<sup>142</sup> optimized parameters such as angle shape for the kinematic assistance delivered through an active knee exoskeleton to a spinal cord injury (SCI) patient. In both cases, after testing their simulation with pre-recorded human data, they created an optimization routine that tracked real kinematics or torque parameters and/or tried to minimize power, muscle activation or jerk.

Simulation can also be used to create a set of requirements for exos. Afschrift *et al.* investigated a capability gap (torque that a weakened muscle can produce against the torque task requirement computed using inverse dynamics), which allowed identification of the minimum level of assistance required for people with muscle weakness (reduction of maximal force capability in the muscle) to realise certain tasks.<sup>143</sup> This is an effective technique to determine the minimum power of the actuator in the exo for people with muscle weakness. Following the same philosophy, a study simulated ideal actuators to find the best single degree of freedom (DOF) or multi-DOF joint to actuate to minimize metabolic cost during running.<sup>144</sup> Results showed that at low running speeds (2 m/s) all joints provided the same metabolic reduction but at higher speeds, the hip could create better metabolic savings. For multi-DOF, a combination of hip, knee and ankle offered the highest metabolic reduction. Another interesting simulation study<sup>145</sup> showed how coupled joint assistance (using the same actuator/assistance on multiple DOF) had the same or similar effect on metabolic savings as multi-actuator assistance and provide better metabolic reduction than assisting only one DOF. This provided important guidelines in exoskeleton design to save on hardware components i.e., going from one actuator per DOF to one actuator crossing multiple joints thus providing cheaper devices.

There remains three main issues and challenges that delay the broad adoption of these simulation tools. The first one, which is common to not only neuromusculoskeletal modelling simulation but simulators in general, is the gap between simulation and reality which limits the transferability of simulation results to the real system. The issue of transferability was observed in a study<sup>146</sup> where results obtained in simulation promised a higher metabolic reduction (69%) than what was obtained in the real system (25.9%). Using simplified musculoskeletal models (3 DOF 9 muscles model<sup>146</sup>) can contribute to poor transferability. The second challenge is the idealization of exo components and structures. For instance, exoskeletons are usually modelled as a simplified mechanical structure that is rigidly connected to the human skeletal system, with the force produced by the actuator ideally transmitted directly to the skeletal system without loss due to friction, soft tissue connection, and shear forces.<sup>146,147</sup> An interesting study<sup>148</sup> tried to tackle part of this problem by implementing a spring and damper contact model between the human and the skeletal system, which resulted in accurately reproduced kinematics of the real exoskeleton system. Nevertheless, their model needed to be calibrated with multiple experimental recordings of the real human and exoskeleton. The third shortcoming is the current inability to simulate the change (or learning) of the neural system due to the exos assistance. The lack of modelled learning limits the ability to effectively design assistance for neurorehabilitation of patients such as stroke survivors. An interesting solution would be to replace optimization for simulating the neural command by a machine learning algorithm wherein a neural network trained on the simulation could adapt to the different assistances.<sup>149</sup>

### **Muscle biomechanics for exoskeleton control**

Muscle biomechanics can provide useful information to estimate valuable control signals for different applications including fatigue, volitional ability, and joint torque. Understanding

generation of joint torques is a useful for exoskeleton control. Direct or indirect measurement of joint torque can allow creation of a symbiotic system between the human and exo by providing assistance proportional to the force produced by the user (Figure 3). Although joint torque can be estimated through inverse dynamics, estimation through muscle biomechanics may be more suitable for exoskeletons applications, particularly applications in uncontrolled (non-laboratory) environments.

#### ***Direct measurements***

Despite attempts and innovations to directly measure muscle biomechanics during gait or other lower-limb movements to estimate useful control signals for muscle in the loop controllers (e.g., estimating joint torque or fatigue), we could find only one study that actually used a direct measurement of muscle biomechanics to estimate a parameter for the control parameter. Sheng *et al.*<sup>150</sup> used real-time ultrasound-based muscle fatigue assessment to robustly control their hybrid (functional electrical stimulation and electrical motor) knee exoskeleton to switch between its modes and avoid extensive stimulation of the fatigued muscle.

#### ***Neuromusculoskeletal modelling***

One indirect way of accessing joint torque is by using a neuromusculoskeletal model fed by EMG. Using neuromusculoskeletal modelling in combination with an exoskeleton is a recent technique, which was primarily delayed by the limitation of achieving real-time computation of the complex model (multi-DOF and multi-musculotendon unit).<sup>109,122</sup> Fleischer and Hommel<sup>151</sup> were the first to present the possibility of using a real-time neuromusculoskeletal model for the control of an unilateral knee exoskeleton. Durandau *et al.*<sup>105</sup> further developed the methods to apply it to a lower-limb exoskeleton for the knee and ankle and tested it on patients (SCI and stroke). The results showed the possibility of using this kind of system for rehabilitation purposes,

where muscle effort is reduced while also reducing neural control variability. Furthermore, the same system is used for a bilateral ankle exoskeleton during diverse walking conditions<sup>106</sup> showing the possibility to reduce the muscular effort in variable walking speed and showing better adaptability than the current state-of-the-art speed adaptative controller<sup>52,152</sup> although the metabolic reduction is less. Finally, neuromusculoskeletal models offer the possibility to compute biomechanical variables other than joint torque, such as stiffness, which can also benefit robotic control. Yao *et al.*<sup>153</sup> combined real-time muscle stiffness computation (*tibialis anterior*) and joint torque to control a non-ambulatory ankle exoskeleton. The joint torque estimation is used as an input command to the torque controller and the muscle stiffness is used to modulate the stiffness coefficient of the admittance controller used for the torque controller. Nevertheless, this method relies on EMG sensors which are subject to noise and muscle crosstalk as well as interference from electromechanical devices (i.e. an exoskeleton).

Neural control models can be used to drive musculoskeletal models for exoskeletons, which reduces reliance on EMG sensors. Ruiz *et al.*<sup>154–156</sup> explored the possibility of using a motor primitive-based neural control model for controlling leg exoskeletons together with musculoskeletal models. They conducted experiments to evaluate the performance of the neuromusculoskeletal model-based controller. A full-leg exoskeleton that had motors at the ankle, knee and hip was used as the hardware platform. Participants were asked to perform a locomotion track involving ground-level walking, ascending stairs, and descending stairs and several transitions between these tasks. They showed that the assistance significantly decrease time to perform tasks. Dzeladini *et al.*<sup>157</sup> showed that a reflex-based neuromuscular controller (NMC) for an ankle orthosis can reduce the net metabolic cost compared to the transparent mode without disturbing the walking dynamics at slow and normal speeds. Later, they extended the

neuromuscular control framework into a hip and knee robotic exoskeleton and tested it on SCI patients.<sup>158,159</sup> Their results showed that NMC enabled SCI subjects to walk at several speeds, including near healthy speeds, in a healthy-like manner. Shafer *et al.*<sup>160</sup> implemented a simple reflex-based neuromuscular controller for an ankle exoskeleton to study the effects of the reflex control parameters, such as the reflex gains and reflex time delay on users. They found that the reflex-based assistance could systematically reduce users' biological ankle moment, however, it didn't reduce their overall metabolic cost. Until now, most studies have looked at the immediate effect on the neuromusculoskeletal system, but long-term effects have not yet been investigated. The direct effect of assistance on the neural system has also been overlooked.

### **Changes to Muscle Biomechanics when using Lower-Limb Exoskeletons**

In this section, we summarized the changes to muscle biomechanics as a result of using exoskeleton assisted movement. Studies investigated these changes during actuation of lower-limb joints during either walking, seated knee flexion/extension, hopping, squatting, or sit-to-stand tasks. The influence on plantar flexion and dorsiflexion is commonly studied when using ankle exoskeletons, and are summarized in Table 1, whereas the following sections address actuation of either the knee or hip joints. We also briefly discuss the studies that used commercial lower limb exoskeletons or robotic gait trainers such as Lokomat and Lopes.

#### ***Active actuation of knee or hip joint***

Many studies showed that knee exoskeletons can reduce activity of associated muscles. Some studies that actuated the knee joint provided additional passive supports at either ankle or hip.<sup>161–168</sup> The results showed reductions in *soleus*,<sup>163</sup> *rectus femoris*, *tibialis anterior*, *gastrocnemius lateralis*, and *semitendinosus*<sup>162</sup> during gait, and during swing phase, the *biceps*

*femoris*,<sup>161</sup> *tibialis anterior*, and *semitendinosus*<sup>162</sup> when walking with powered as compared to minimal impedance mode. In minimal impedance mode, also called “free” or “transparent” mode, the exo attempts to be transparent to the user and minimally impact walking biomechanics either by providing no torque or actively controlling for minimal interaction torque. Active knee assistance with passive hip support reduced muscle activity of hip and knee extensors.<sup>166</sup> This general decrease in EMG activity was further associated with a decreasing trend over the time with assisted walking due to adaptation.<sup>166</sup>

Studies also evaluated knee exoskeletons in other tasks such as squatting<sup>167</sup> or knee flexion-extension.<sup>165,168</sup> A knee exoskeleton also reduced knee extensor muscle activity when using a controller that is capable of injecting the minimal amount of energy needed to support oscillations of the knee.<sup>165</sup>

Passive springs placed anteriorly on the hip stored and released energy thereby reducing plantar flexor activity during walking.<sup>169</sup> Actuated hip exoskeletons increased muscle activity of *tibialis anterior*, *rectus femoris*, and *gastrocnemius medialis* in the minimal impedance mode, whereas that of the *semitendinosus* reduced.<sup>164</sup> However, providing assistance reduced the muscle activity of the *tibialis anterior*, *rectus femoris*, and *gastrocnemius medialis* but increased activity of the *semitendinosus*.<sup>164</sup>

#### ***Actuation across multiple joints, and use of Robotic Gait Trainers, and commercial exoskeletons***

An exoskeleton with active knee and ankle actuation reduced muscle activity for both healthy and participants with stroke in the knee flexors and extensors, and ankle plantar and dorsiflexors.<sup>105</sup> Increased assistance reduced the variability of muscle activity in this study. Lower limb exoskeletons with hip and knee actuation and passive ankle support reduced muscle activity of the



*vastus medialis, gastrocnemius medialis,*<sup>170,171</sup> *tibialis anterior, rectus femoris, soleus*<sup>170</sup> when compared to walking with a minimal impedance mode. Activity of *semitendinosus* and *biceps femoris* increased when walking slowly with the exoskeleton.<sup>170</sup> Furthermore, muscle synergy patterns were shown to be altered when wearing such exoskeletons<sup>172</sup>. Otálora and colleagues<sup>173</sup> showed that actuation of the hip, knee, and ankle joints reduced activity in the knee flexors and extensors, and *tibialis anterior*.

Gait training devices such as the LOPES and Lokomat provide different degrees of actuation of the lower limb and, unlike exoskeletons, can also provide body weight support. Walking in the LOPES in zero-impedance mode showed a decrease in muscle activity of the muscles involved in push off whereas an increase in activity of muscles that contribute to acceleration and deceleration of the swing leg.<sup>174,175</sup> The activation timing was rather unchanged.<sup>174</sup> The virtual pivot point model implemented in LOPES II through admittance control also showed decreased muscle activity in *rectus femoris, hamstring, medial gastrocnemius, and gluteus maximus* muscles.<sup>175</sup> Literature about how the Lokomat impacted post training muscle activity has been inconclusive. The Lokomat imposes able-bodied joint trajectories through impedance control, with varying levels of exo guidance force. At higher levels of guidance force the joint trajectories are more rigid and it is increasingly difficult for the muscles of the user to influence or affect the trajectory of the Lokomat. The results depended on guidance level,<sup>176,177</sup> speed,<sup>176,178</sup> or body weight support.<sup>177,179</sup> Walking on the Lokomat increased the activity of *biceps femoris* in healthy participants,<sup>176,177,179</sup> *vastus lateralis*<sup>176,179</sup> *erector spinae, tibialis anterior,*<sup>179</sup> *tibialis anterior* and *rectus femoris*.<sup>177</sup> However, another study identified a general lowering of muscle activity compared to treadmill walking in participants with stroke as well as healthy walkers.<sup>180</sup> For participants with SCI, Lokomat training reduced *vastus lateralis* and *rectus femoris* activity during stance phase,

and increased *gastrocnemius medialis* during swing phase.<sup>181</sup> The Lokomat was also used to differentially assist either side during gait, and showed an inverse relation to muscle activity on the other side.<sup>178</sup> The activity in the trunk muscles during training with the Lokomat was similar to quiescent supine lying.<sup>182</sup> Using a robotic trainer that only assisted the hip increased activity of knee flexors.<sup>183</sup>

Commercially available exoskeletons have been rigorously studied in literature.<sup>182,184–194</sup> For instance, studies reported reduction in *rectus femoris*,<sup>186,187</sup> *gluteus medius*, *medial hamstring*, *tibialis anterior*, *soleus*,<sup>187</sup> *gluteus maximus*, *rectus femoris*, *vastus lateralis*, and *gastrocnemius* and an increase in *biceps femoris*<sup>186</sup> when walking with the Ekso GT, which assists the user in a predefined trajectory. However, the change in muscle activity depended on gait phase, whether the user had voluntary control in the exoskeleton, and the speed of reference walking without exoskeleton.<sup>186</sup> Voluntary control increased burst duration compared to fast walking.<sup>186</sup>

The Ekso has often used to train participants with neurological impairments.<sup>182,184–186,188–193</sup> Participants with multiple sclerosis showed a new muscle synergy when walking with the exoskeleton.<sup>193</sup> Incomplete SCI participants showed non-reciprocal firing patterns and reduced muscle activations especially that of the *rectus femoris*<sup>190</sup> and *tibialis anterior*.<sup>186</sup> A reduced variability in muscle activity was seen when walking with the exoskeleton.<sup>190</sup> Alamro<sup>182</sup> observed an increase in trunk EMG when walking with Ekso-assisted compared to the Lokomat for SCI participants. Trunk EMG activation remained similar between Ekso overground and treadmill walking.

Stroke participants were studied at all three phases; acute, sub-acute, and chronic with the Ekso.<sup>184,185,188,189,191,192</sup> Participants with acute stroke showed reduction in *soleus* and *rectus femoris* activity on affected side during stance phase with the exoskeleton.<sup>184</sup> *Vastus Lateralis* and

*rectus femoris* showed the largest dissimilarity in activation with the exoskeleton on the affected side.<sup>184</sup> Using the Ekso for training in sub-acute stroke improved bilateral symmetry of *tibialis anterior* and decreased co-contractions of the proximal muscles, suggesting improvement in proximal muscle activity.<sup>189</sup> Activation timing for the *semitendinosus* was improved in the paretic leg after training.<sup>191</sup> The Ekso trained group also showed more physiological motor control in the *semitendinosus* and *rectus femoris*.<sup>191</sup> Chronic stroke participants who trained with the Ekso showed reduced affected side *rectus femoris* activity during swing phase,<sup>188</sup> increase in *rectus femoris*, reduction in affected *biceps femoris*, increase in unaffected *biceps femoris*, reduced *soleus* and *tibialis anterior* activity was seen.<sup>185</sup> The synergy modules necessary to reconstruct lower limb muscle activities were more similar to healthy walking post Ekso training.<sup>192</sup>

This section overviewed the impact on muscles as a result of assistance provided by exos. In sum, we see a reduction in muscle activity across joints, and tasks, as well as changes to muscle synergies. This understanding must be accounted for when designing novel controllers that interact with the muscle directly.

## Discussion and future predictions

Exos have been designed with the goal of enhancing human movement. However, current technologies have shown only modest results in healthy individuals and limited clinical impact. A central element hampering progress is that exos do not interact directly with underlying skeletal muscles, but instead deliver external mechanical loads that directly influence the biological skeletal system. As such, current systems do not consider how biological muscles, tendons, joints, react to mechanically delivered torques. In this context, research in exos has overlooked the effect of robotic assistance, especially at extreme ends of the spatiotemporal scale (e.g., cell growth over months or years).<sup>88,195</sup> This is a critical aspect of human-exo physical interaction as skeletal

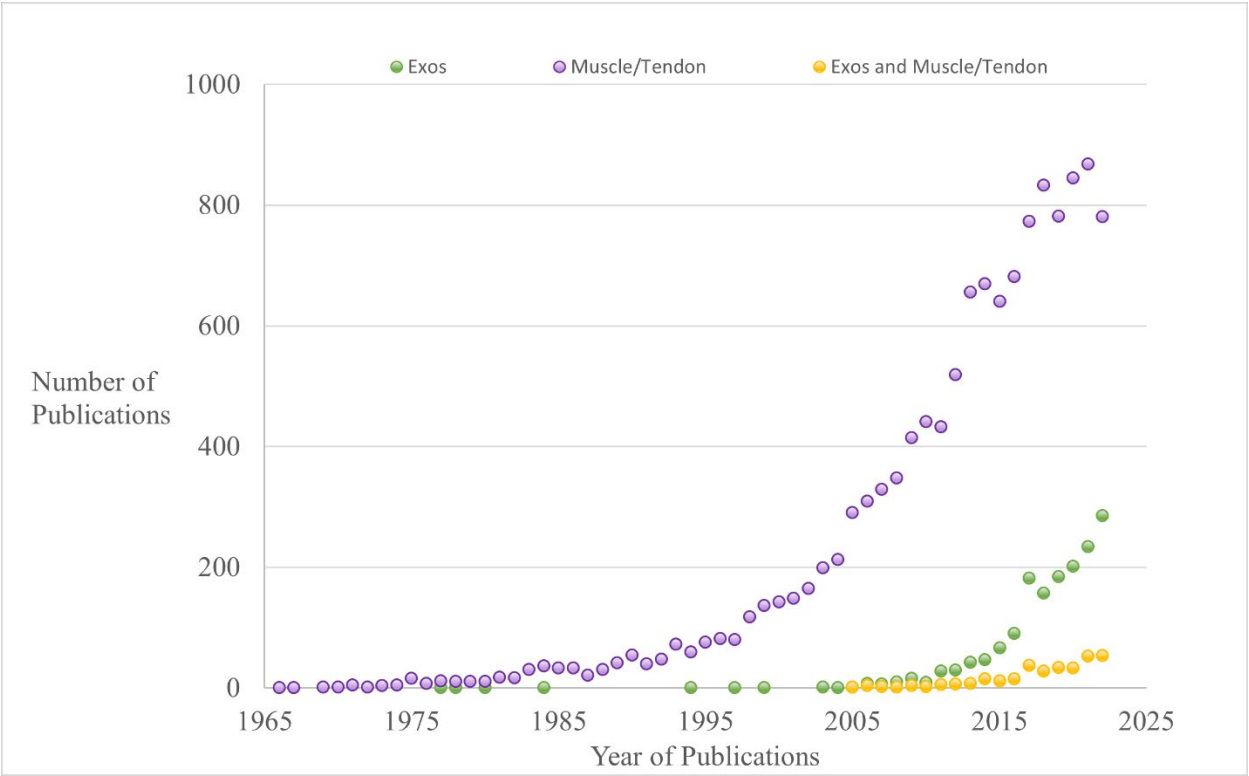
muscles will remodel new structural properties if exposed long enough to exo-delivered torques. The current inability to predict how exo assistance strategies would remodel skeletal muscle structurally hampers progress in longitudinal neurorehabilitation and in day-to-day adoption of wearable assistive technologies.

In the future we envision research advances aimed at ‘closing-the-loop’ between exos and human skeletal muscle biology.<sup>88</sup> In this context, we envision that future exos should be capable of delivering coordinated mechanical torques to alter, in a controlled way, skeletal muscle form and function over time scales ranging from seconds (e.g., a movement cycle) to months (e.g., the recovery stage following a neuromuscular injury) and beyond (e.g., across ageing stages).

We envision this will require developments in three key directions: (1) recording both neural and mechanical function underlying muscle contraction (e.g., motor neuron discharges and innervated skeletal fibre force) in the intact moving human *in vivo*, (2) fusing recorded neuro-mechanical data with numerical models to predict skeletal muscle adaptation in response to exos-delivered torques over time and (3) developing predictive controllers to steer skeletal muscle form and function with enough certainty to induce a targeted, positive change in the future. This will open to a new class of muscle-centred exos that directly respond to biological cues to maintain integrity of skeletal muscles over the lifespan.

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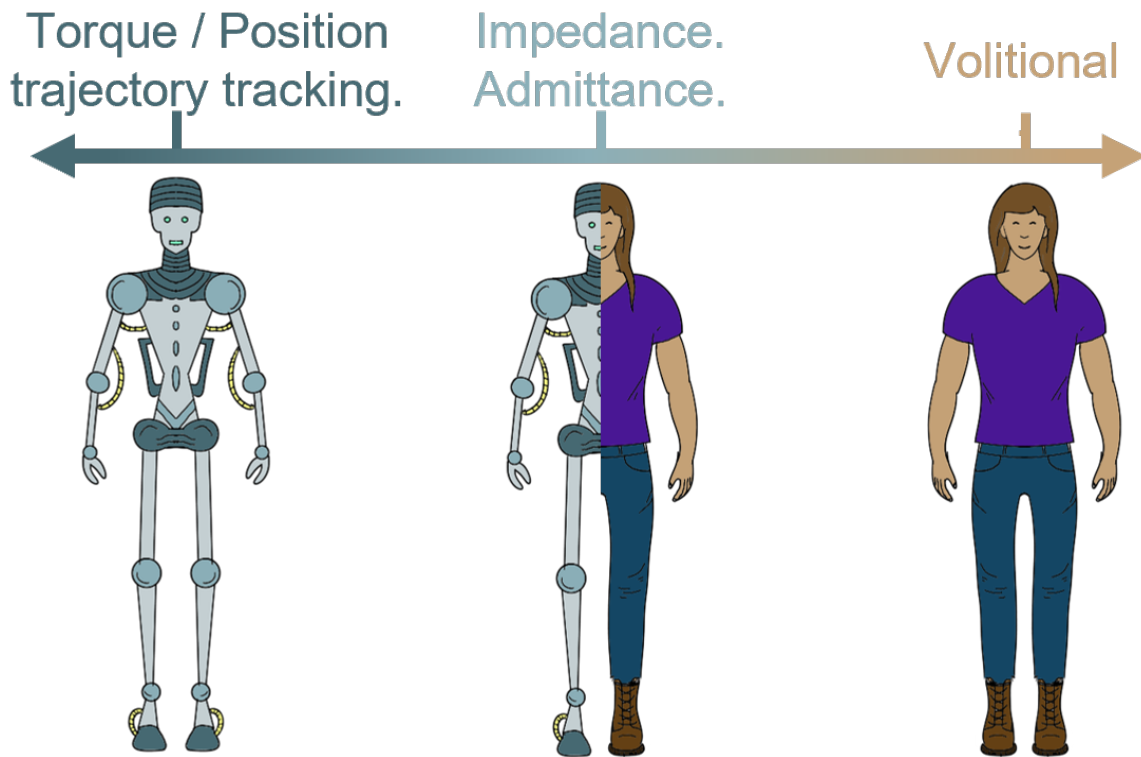
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Figure 1. The number of studies published over time on exos, muscle/tendon biomechanics, and both exos & muscle-tendon biomechanics from 1965 to 2022. The data were found through the PubMed database (<https://pubmed.ncbi.nlm.nih.gov>). All data searches were in English and for lower limb extremities (KEYWORD: gait OR walking OR (lower AND (limb OR extremities))) in human (KEYWORD: human OR participant OR patient). Specific data searches were: A) exos (KEYWORD: (exoskelet\* OR exosuit)), B) Muscle/tendon biomechanics (KEYWORD: (muscle mechanics) OR ((muscle OR tendon) AND (biomechanics))), and C) muscle/tendon biomechanics and exos (KEYWORD: (muscle mechanics) OR ((muscle OR tendon) AND (biomechanics)) AND (exoskelet\* OR exosuit)).



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650 Figure 2. Visual representation of the “focus” of high level exo controllers in terms of the robot-  
651 human system. Controllers on the left of the scale prioritize the robot part of the system, while the  
652 controllers to the right of the scale focus on the human part.

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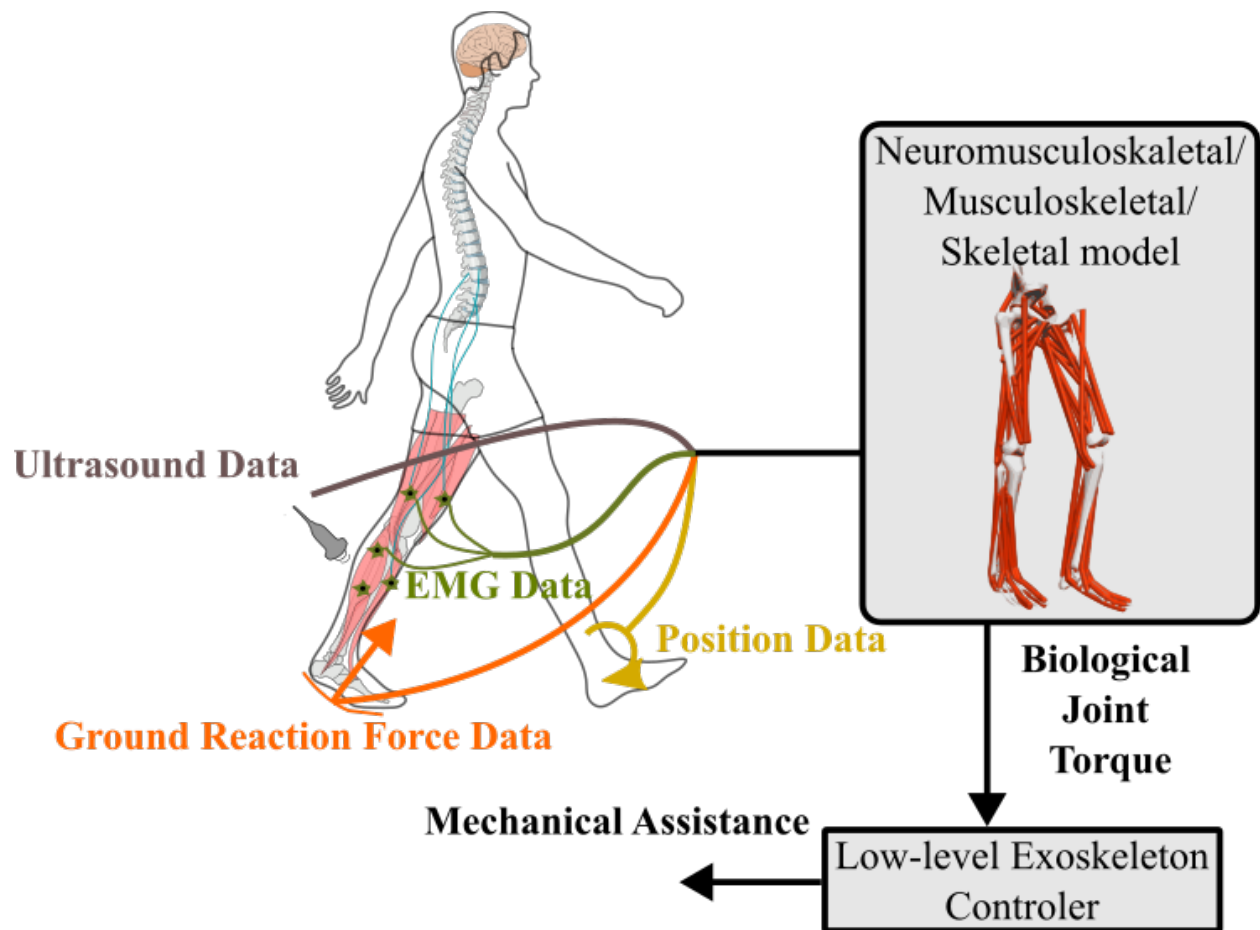


Figure 3. A general exoskeleton controller using a biomechanical model.

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## Tables

658 Table 1: Summary of changes to muscle-tendon biomechanics when participants wore an ankle  
659 exoskeleton.

Actuation Type	Task	Muscle/Tendon(s)	Condition varied	Changes to muscle biomechanics
Passive	Hopping	Plantar flexors	Ankle joint stiffness	Decreased activity, force, and force rate <sup>134,196,197</sup> Operating at less optimal fibre length and increased fibre velocity <sup>134,198</sup> Increased fascicle excursion, and overall no change in averaged positive fascicle power <sup>134</sup>
Active	Walking	<i>soleus</i>	Ankle joint Stiffness	Reduced muscle force, increased fascicle length and velocity <sup>136</sup>
		Plantar flexors	Inclination of walking surface	Increase in inclination results in lower reductions in muscle activity <sup>199</sup>
		Plantar flexors	Exoskeleton work	Increasing work reduced activity, and increased muscle synergy weights <sup>200</sup>
		<i>soleus</i>	Exoskeleton torque	Increasing torque reduced activity, and increased muscle synergy activations <sup>200</sup>
		Plantar flexors	Adaptation to walking with exoskeleton	Decreased activity <sup>201</sup>
		<i>soleus</i>	Controller type	Gait timing controllers are better than myoelectric controller proportional to <i>soleus</i> activity <sup>202</sup> myoelectric controller proportional to <i>gastrocnemius medialis</i> reduces <i>soleus</i> activity <sup>203</sup>
		-	Speed, step length, and walking incline	Increased apparent efficacy with increasing speed or step length <sup>204</sup> and drops when the surface incline increases <sup>199</sup>
	Walking with load	<i>Achilles</i> tendon	With and without exo, carrying additional load	Increase in tendon force with increase in load carried, but reduced with exo assistance <sup>139</sup>
	Walking in participants with chronic stroke	Bilateral <i>latissimus dorsi</i> , <i>erector spinae</i> , <i>external oblique</i> , hip flexors and extensors, knee flexors and extensors, plantar flexors and dorsiflexors.	With and without exo	Improved similarity of synergies in either side <sup>205</sup>

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