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Human Modeling in Physical Human-Robot Interaction: A Brief Survey

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***Abstract*—The advancement and development of human modeling have greatly benefited from principles used in robotics, for instance, multibody dynamics laid the foundations for physics engines of human movement simulation, and the robotics and control theory were used to contextualize human sensorimotor control. There are many common interests and interconnections between the fields of human modeling and robotics. In recent years, as robots have become safer and smarter, they actively participate in our lives and help us in various scenarios. Roboticists need tools and data from human modeling to build next-generation robots that better assist humans. In this survey, we focus on the connections between physical human-robot interaction and human modeling. On one hand, human neuromusculoskeletal and sensorimotor control models provide novel insights into the human response that robots can utilize to improve human performance. On the other hand, robots are becoming instrumental in quantifying the performance of the (neuro)musculoskeletal system. Thus, the combined use of human modeling and robotic methods in physical human-robot interaction can lead to both improved human understanding and functional assistance.**

***Index Terms*—Physical human-robot interaction, modeling and simulating humans, human-centered robotics.**

I. Introduction

ROBOTS are entering our lives and interacting with us more frequently. This trend is only increasing and robotics is inevitably becoming more human-centered. For seamless physical human-robot interaction (pHRI), the robot has to understand human performance and intentions to be able to provide effective and transparent assistance. Robot control systems need insights into the human, which can be obtained from human models. On the other hand, human modeling research can benefit from robotics as a tool to discover new insights into human behavior. For that, robotic systems can be used to build special interacting environments and platforms to study new human models or validate existing models.

Human models offer unique insights into the human biomechanical responses to robot actions, yet only recently has pHRI begun to integrate human models to provide real-time feedback [1], [2], [3], as opposed to offline planning based on normative responses. On the other hand, only recently have studies in human biomechanics started to exploit advanced pHRI methods as a standardized tool for testing model responses for improved quantitative results [4], [5], [6]. Therefore, now is an ideal time to push the state of the art of both fields in a direction of extensive interconnection and cross-pollination, and to stimulate dialogues and collaboration between the communities of robotics and biomechanics.

The central issue of pHRI is how robots can leverage human models to understand and manipulate human performance and in turn, how robots can improve human modeling to facilitate new insights and understanding into the structures/behavior underlying human biomechanics. This should be seen as a loop where the outputs of each element feed into the other element, gradually improving both robot control and human understanding. Therefore, this letter aims to examine what information biomechanists and neuroscientists can gain from robotics technology to improve their understanding of the neuromusculoskeletal system, and how neuromusculoskeletal models can be used to extract measures of human performance and be used to improve the control and benefits of pHRI.

The search method involved scanning research databases for keywords related to pHRI and neuromusculoskeletal and (sensori)motor control modeling. In the research selection, we had a preference for papers that involved both robotics and human modeling, and for those that provided computational human models. While pHRI has social aspects [7], [8], our scope is limited to physical interactions. There are several relevant survey papers that examined pHRI in specific application areas, such as rehabilitation [9], ergonomics [10], teleimpedance [11], and human movement analysis and synthesis [12]. These informative

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surveys, however, had limited connections between pHRI and human modeling.

To understand how to combine human modeling with pHRI, we systematically examine: human neuromusculoskeletal and sensorimotor control modeling (Sections II and III), pHRI modeling (Section IV), applications of human modeling in pHRI (Section V), and future directions (Section VI).

II. Neuromusculoskeletal Modeling With pHRI

Over the last three decades, several (neuro)musculoskeletal models have been developed for different body segments, like upper extremity [13], lower extremity [14], and full body [15], [16] models. Some of the state-of-the-art models and software resulting from the recent developments are OpenSim [17], AnyBody [18], Mujoco [19] and MyoSim/MyoSuite [20]. In this survey, we focus on three important biological systems necessary to generate human movement in which pHRI can improve our understanding and be used to assist/augment human performance. They are the nervous, muscular and skeletal systems.

The *nervous system* consists of tracts and circuits of neurons forming the nerves and processing centers of the Central Nervous System (CNS, i.e., the brain and spinal cord). Nerves serve as the primary paths for signal transmission in biological systems, which have inherent transmission delays. Pools of alpha motor neurons in the spinal cord innervate groups of muscle fibers forming motor units for the generation of coordinated movement. An alpha motor neuron in a motor unit processes all synaptic inputs (analogous to control signals in robotics) approximately as an *integrate-and-fire system* [21] to generate trains of neural impulses to contract the innervated muscle fibers. When the synaptic inputs come from the proprioceptors, which sense the length/velocity (e.g., muscle spindle) or tension resulting from the same muscle fibers, a neural reflex circuit is formed (e.g., spinal reflexes), which are essential for the rapid involuntary movement control.

Quantifying the reflex responses is crucial in characterizing the motor abilities/impairments (e.g., posture maintenance) of an individual/patient. Precise robotic haptic devices have been instrumental in estimating the reflex gains [22] and time delays [23] based on observed human dynamic responses to introduced perturbations during position/force control tasks.

The *muscular system* consists of over 650 skeletal muscles which function as contractile wire actuators for transducing neural impulses into mechanical tension. The interface between the nervous and muscular systems is the motor unit described above. Muscle fibers are ultimately composed of strings of sarcomeres which are nano-scale biological motors. The innervated muscle fibers receive the neural impulses from the alpha motor neurons as inputs and become activated, i.e., an electrical activation level, which is governed by *muscle activation dynamics* [24]. The muscle activation level then causes the muscle to contract and generate tension that is applied to the bone, governed by *musculotendon contraction dynamics*. Muscle is typically represented by a Hill-type model [25], in which a musculotendon unit is composed of an active contractile element in parallel to a passive elastic element, which is connected in series at a pennation angle to a passive elastic nonlinear spring as a tendon.

The parameters of the Hill-type muscle model determine the subject-specific characteristics and mechanical properties of the muscle, which are important in the context of pHRI. On the other hand, there are tremendous opportunities to identify these parameters and personalize muscle models for different individuals using robot arms or exoskeletons through pHRI [26]. Typically, individualized muscle parameters can be identified by solving an optimization problem to minimize the difference between a measured output at the joint level, e.g., joint torque, and its corresponding estimate based on a human model [9]. For instance, an estimated joint torque can be calculated using the muscle activation and contraction dynamics of selected muscles with EMG signals as input, while the actual joint torque can be directly measured by wearable exoskeletons [27] or obtained indirectly by the force measured at an extremity through inverse dynamics [28].

The *skeletal system* consists of over 200 bones (analogous to links in robotics) and forms the structural frame that supports all the other organs including muscles. Bones articulate with each other forming joints. Bones are pulled upon by muscles, modelled above as musculotendon units, causing motion about or along the joints (relative rotations and translations), which generates human movement. The tendon functions as an interface between the muscular and skeletal systems connecting muscles to bones. The transmission of the musculotendon unit tension to joint torque is characterized by the muscle's moment arm(s) about the joint(s) it spans, which are also dependent on the joint position. Since musculotendon units can only pull, they act in agonist and antagonist muscle pairs to actuate joints bidirectionally.

Mechanical impedance of the combined musculoskeletal system is an important property for pHRI, which can be estimated by robotic devices connected to the human body through perturbations [29]. The correlations between the perturbations and the resulting reactive motion or force deviations can be used to estimate the endpoint impedance at the extremities [30] and the joint impedance of individual joints [31], [32]. However, perturbations interrupt the operator and the continuous impedance estimation. Instead, as muscle activation has a linear relation with muscle stiffness, it can be measured by the EMG sensor and used as input for models [5], [30], which encode causal relation between different stiffnesses (muscle, joint and extremity) and are calibrated offline with the perturbation method in advance, to enable online continuous estimation of joint or extremity stiffness.

III. Sensorimotor Control Modeling With pHRI

While neuromusculoskeletal models represent the physical part of human body (analogous to plants in robotics), it is also important to gain insight into the control of the neuromusculoskeletal system. Human (sensori)motor control regulates the control process of human movement. The CNS (analogous to controllers in robotics) integrates multimodal sensory information (exteroception and proprioception), and

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elicits neural control signals to drive and recruit muscles and generate coordinated movements [33]. Sensorimotor control models can help understand and predict human behavior in pHRI. Reciprocally, pHRI has also been extensively used as a tool to experimentally study sensorimotor control models.

A. Movement Control

One of the most fundamental tasks of human sensorimotor control is to coordinate body movements. Typically, different mathematical models of movement control can be fit into an optimal feedback control framework [34] where a cost function prescribes how the CNS derives the motor commands for muscles. Planar manipulandum robots are often used to experimentally validate such mathematical models. For example, some of the well-known early models studied in this manner were the minimum-jerk model [35] and minimum-torque-change model [36], which resulted in smooth trajectories as observed by the robotic measurement device.

Due to the physiological implausibility of CNS to measure endpoint jerk or joint torque, more recent models are based on signal-dependent noise [37]. The noise level in the motor commands tends to increase with the motor command level [38] and minimizing the noise results in experimentally observed smooth movements. This also conforms with *Fitts' law* [39] that describes the speed-accuracy tradeoff, where faster movements tend to be more inaccurate as they require larger muscle activations and thus induce more noise. Another major tradeoff in human sensorimotor control modeling is the cost-benefit tradeoff, which results from CNS maximizing the perceived benefit of reaching the target quickly while simultaneously minimizing the movement cost by not going too fast. For example, recent studies used robots to study a model based on the cost-benefit tradeoff [40] or a model unifying speed-accuracy and cost-benefit tradeoffs [41].

B. Internal Models

To alleviate the issues of inherent noise and delay in the sensorimotor system, CNS has and manages inverse models to generate feedforward commands, and forward models to predict the effects (state estimation) of the overall motor commands (feedforward and feedback commands), and the internal models can be gained and improved from experience and training [42]. In [43], a manipulandum robot was used to change the arm external environment dynamics by adding force fields at the human hand and the observed adaptation of the arm trajectory corroborated the existence of an inverse model to compensate for the altered arm-environment dynamics. Forward models were also evidenced in [44] with pole balancing experiments where human subjects used a real manipulandum as an interface to control/balance a virtual pole on a screen and a 7-DoF anthropomorphic arm with different control strategies including predictive control was used as a control subject for comparisons.

C. Impedance Control

When unpredictable disturbances or perturbations arise in the human movement which is very common in the context of pHRI, any delayed responses (e.g., internal models or reflex responses) can lead to instability and task failure. To address this, humans use impedance control to provide zero-time-delay responses. PHRI can also be used to study how CNS adapts body impedance to external perturbations.

One of the key strategies used by CNS is that the limb endpoint stiffness can be directionally adjusted to counteract external perturbations [45], [46]. In these studies, a planar manipulandum was used to generate planar perturbations. In [6], the endpoint stiffness adaptation study was expanded by using a 7-DoF robot arm to provide 3D perturbations. The study in [5] used the same robot to model the relationship between the arm endpoint stiffness and the 7-dimensional joint stiffness. In [47], a 7-DoF haptic interface robot was employed to examine how human sensorimotor control reacts to force feedback and how that affects the arm endpoint impedance transferred to the remote robot in bilateral teleimpedance.

D. Mutual Benefits

Many concepts and models for interpreting motor functions reviewed here originated from robotics and control theory, and pHRI plays an important role in studying human motor control. The robotic devices can be used to precisely control the conditions in the experiments by altering the environment dynamics (force fields and perturbations) and varying time delay, noise or task parameters, and to measure human movement and impedance. Anthropomorphic arms and humanoid musculoskeletal robots [4] can be used as desired robotic counterparts to validate the proposed new human sensorimotor models by making full use of the knowledge of the robot state and the measurement of all the variables. In addition, pHRI can be used to allow human subjects to interact with controlled virtual environments for comparative experiments. In neuroscience studies, these are often carried out with a planar manipulandum plus a 2D screen, where simplified planar human arm models are often used [29]. In the future, more advanced robotic devices like multi-DoF robot arms or exoskeletons can be used together with VR headsets to create specialized platforms/environments and design sophisticated experiments to study human motor control with high-fidelity 3D human models [48].

Obtaining better human sensorimotor models through pHRI can in turn guide the design and development of more human-friendly pHRI systems in terms of criteria, such as safety, ergonomics and comfort [49], based on the knowledge of how humans would respond to robots. The pHRI system can be controlled in a way that the criteria-related cost functions of human motor control are optimized while guaranteeing the completion of the primary task, and that the robot impedance is adapted to facilitate the completion of the task and the interaction with the human partner by considering human body impedance. The internal models can be utilized to guide the design of a pHRI system to help humans learn new or regain motor skills for training or rehabilitation purpose. Having high-fidelity human

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sensorimotor models will also enable realistic pHRI simulations to avoid possibly risky and cumbersome pHRI experiments.

IV. Human-Robot Interaction Modeling

In many situations, humans and robots get in close proximity interactions, such as exoskeletons sitting on the human body or humans collaborating closely with a humanoid or other robot. Human movement will change under the influence of the robot, and it is also expected to change over time [50]. Models of humans alone are not enough to describe the situation, but the effect of the robot has to be considered in the model. Models of pHRI play roles at different levels to inform robot behavior and form: 1) Design level, 2) Planning level, 3) Trajectory level, 4) Control level.

On the design level, a combined human-robot model could play an important role in design optimization of collaborative or wearable robots, taking their trajectories in pHRI into account for choosing optimal design parameters [51]. The design level defines the key characteristics of a particular pHRI. In this respect, human models can be helpful both for simulation in the prototyping stage and for the personalization of robots to a specific user. For example, a human model can be used to design an exoskeleton to fit a particular user and task [52]. At the planning level, the robot decides its goal and chooses what kind of goals and behavior to take according to the detected human intent [53]. This detection can be made by combining contacts and force with other biomechanical variables estimated from human modeling.

The trajectory and control levels are concerned with human movement prediction and online robot movement execution depending on the detected human's intent through physical interaction [54] or biosensors (such as EMG and FMG) [55], [56]. The robot generates and adapts the desired trajectories to better fit human intent at the trajectory level, whereas at the control level, the aim is to obtain adaptive control of the desired trajectories. A big challenge is that humans constantly adjust their movement under the effect of the robot and will further adapt while getting familiar with it. Biomechanical metrics can inform about the status of the adaptation [57].

One of the key elements of pHRI at all four levels is the exchange of forces and motion between the human and the robot [58]. While the motion can be derived with the robot kinematic model at the contact point, the contact force can be either measured by force/torque sensors [59], joint torque sensors, or estimated using the robot dynamic model [60]. Importantly, their exchange relation can be regulated with the impedance control approach [61], where the interaction point on the robotic link is modeled as a virtual spring-mass-damper system. The stiffness, inertia and damping parameters can then be varied online to accommodate the desired human-robot interaction. Impedance controllers are principally employed at the control level [62], however, the impedance can also be important at the trajectory and planning levels [54].

While the exchanged force and motion are the most common interfaces to model and control pHRI, interactions through other channels can provide additional enhancement of pHRI modeling. For example, EMG signals can be utilized to estimate the user's joint torque for Assist-As-Needed (AAN) control of a rehabilitation robot [63] or human limb impedance for skill transfer from human to robot [64]. Human's multi-modal status including other biomechanical variables can enhance pHRI in high-level behavioral planning [65]. Recent studies propose integrating the trajectory and control levels into one framework of interaction modeling for robots closely interacting with humans, using neural networks [66] for collaborative robot guidance tasks or assimilation control [67] for an exoskeleton. Such extensions of human-robot interface channels are expected to be increasingly integrated to move towards better performance and ease of use at different levels.

V. Applications of Human Models in pHRI

There are many applications for human modeling in pHRI, but three typical application areas will be discussed: 1) Ergonomics through cobots and exoskeletons, 2) Rehabilitation through assistive devices, and 3) Control of prosthetic limbs.

A. *Ergonomics Through Cobots and Exoskeletons*

A human skeletal model was used to estimate ergonomics and indicate the best working configurations for humans [68]. However, the method was not integrated into the robot control for human-robot collaboration. A similar approach proposed to integrate a human skeletal model into a real-time robot control system in order to adapt the human co-worker posture during the collaborative task execution based on minimizing joint torque [1]. Instead of a skeletal model, the Rapid Entire Body Assessment (REBA) model was applied, which heuristically accounted for human body ergonomics, trading off detailed insight for simplicity [69].

While skeletal and heuristic models can be used for rough estimates of ergonomics-related metrics, they do not incorporate the muscular system. Instead, more detailed musculoskeletal models have been used to estimate muscle forces and muscular manipulability for ergonomic human-robot co-manipulation control [70], [71]. These works also labelled shared human-robot workspace using information from musculoskeletal models to visualize ergonomic postures.

Unlike joint torques and muscle forces, which provide information about instantaneous effort, it is the accumulation of effort that results in fatigue. Human muscle fatigue models based on measured EMG data [72] or simulated muscle activity [73] were used to estimate the fatigue of human co-workers in order to inform the robot controller how to adjust the collaborative task execution and optimize the ergonomics. A method for grouping muscles based on the direction of the applied external load was exploited to form a mapping between task execution of the required load direction and muscle groupings, which enabled the robot control to change directions when a certain group of muscles were fatigued to involve a non-fatigued group of muscles [74].

While human models can provide estimates of present (e.g., muscle force) and past effort (fatigue) for robots to act reactively,

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they can also be used for future predictions for robots to act in a predictive manner. In the work [75], the robot learned the model of human-robot interaction dynamics via neural networks. The learned model was then used in Model Predictive Control (MPC) to optimize the impedance control parameters with the aim of minimizing human effort as defined by interaction forces. The method in [54] used MPC for a collaborative robotic arm to adapt the movement trajectories based on the inferred human intent. The controller incorporated the human physical behavior model through Gaussian Processes and measured interaction forces based on which the robot predicted where the human wanted to move.

Besides application to direct collaboration with robotic arms, human models can be applied also to teleoperation and mobile robots. The approach in [76] implemented a personalized center-of-pressure model of the operator's human skeleton to control the movement of a teleoperated mobile platform. The approach in [77] used a musculoskeletal model to estimate fatigue of the human operator's arm during teleoperation based on which the control system would temporarily decouple the remote robot from the haptic device, which can reconfigure the arm to a more ergonomic posture.

Aside from the external assistance of (mobile) robotic arms, human modeling can also be applied in wearable robots (i.e., exoskeletons) to support human workers. For example, in [52], the design of a passive exoskeleton involved the use of a spinal musculoskeletal model of the human worker to assist in heavy object manipulation and reduce the risk of back pain. Models can also be used in the control of active exoskeletons. For example, the method in [78] used a musculoskeletal model to transform muscle activity measured by EMG into assistive joint torque of an active exoskeleton.

B. Rehabilitation Through Assistive Devices

The estimates from human models, especially joint torque, can be used to instruct calculating robot control commands with direct applications in robot-assisted rehabilitation. Recent work employed real-time EMG-driven musculoskeletal modeling to create adaptive myoelectric controllers for upper limb arm exosuits [79], which enabled the worn exosuit to automatically modulate the level of elbow flexion-extension torques across a large range of hand-lifted weights with no *a priori* assumptions on the weight to be lifted. More recently, real-time EMG-driven models were used to control bilateral ankle exoskeletons, which provided adaptive assistance across a range of walking speeds including transitions across speeds [80]. This approach was also demonstrated on neurologically impaired individuals including incomplete spinal cord injury patients and post-stroke individuals affected by knee and ankle joint paresis [81]. Results showed the ability to measure weak and compromised residual EMG signals from paretic muscles (which could not yield detectable ankle and knee joint motion) and concurrently predict the resulting muscle force and joint torque, which could be used in real-time to command exoskeletons and restore voluntary motion in otherwise immobilized limbs.

Other examples include patient-specific musculoskeletal models integrated into real-time robot control to guide rehabilitation therapy, which could be done either by a robot autonomously [82], [83] or by a therapist through teleoperation [84], [85]. A further categorization can be made based on the type of assistive robot: exoskeleton [79], [80], [81] and external robotic manipulator [2], [84], [85]. For instance, The work in [2] proposed to use a novel strain map that exploited latent space to abstract musculoskeletal model data related to tissue functions into an intuitive map for safe physical therapy through pHRI.

In all the examples, the ability to interface humans with real-time (neuro)musculoskeletal models enables inferring the dynamics of biomechanical variables, such as muscle force or tendon strain, which could not be viably measured in intact patients in vivo [86]. The availability of such information can provide indications on how a patient's motor capacity varies over time in response to robotic therapy, thereby enabling better personalization of the rehabilitation treatment.

C. Control of Prosthetic Limbs

Technological progress has led to powered prosthetic limbs, which have the potential to actively assist amputees in dynamic and dexterous tasks. However, despite progress in form factor, sensing, actuation and osseointegration, active-powered prostheses cannot match the performance of biological limbs, hampering the translation of such technology to everyday life. Advances in real-time neuromechanical modeling are leading to model-based control that can potentially bridge the existing divide between artificial and biological limbs.

Muscle reflexes are important for fast responses through *feedback-based control* paradigm. Musculoskeletal models driven by synthetic reflexive activations were employed to control powered prosthetic and orthotic devices [87]. This feedback-based control approach enabled the generation of biomimetic responses that displayed stumble recovery to drive the control of active devices. More recently, muscle reflexes were established that received center of mass (COM) feedback in modeling ankle responses improved generation of artificial torque profiles in response to anterior-posterior perturbations [88]. For upper-limb prostheses, a neuromorphic model of muscle reflex was proposed for compliant control of a prosthetic hand [89], in which the reflex model emulated pools of spiking motor neurons and a muscle spindle with spiking afferents. However, feedback-based control is susceptible to sensor noise which is detrimental to proper torque generation.

An alternative is employing *feedforward-based control* formulation based on a central pattern generator as well as concepts of muscle synergies typically for cyclic movements, such as locomotion, that require rhythmic patterns of muscle activation primitives. Increasing evidence supports the hypotheses that EMG-extracted synergies well represent the neural coordinative structures, explicitly encoded in the CNS, that are used to reduce the computational burden in the neuromuscular control of complex motor tasks [90]. Sets of 4 to 5 synergies were extracted using methods such as non-negative factorization to drive forward musculoskeletal models and generate realistic estimates of lower

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extremity joint torques [91] for the simultaneous control of lower limb exoskeletons [92]. However, synergy structures need to be defined *a priori* for a given movement and cannot generalize to a large repertoire of neuromechanically diverse movements, which may limit the applicability of prosthetic limbs.

To maximize generalizability across movements, *myoelectric model-based control* with advanced processing techniques can be used to access the neural information underlying an individual's movement. This control paradigm enables deriving experimental estimates of subject-specific and context-dependent neuromuscular strategies with no direct need for making *a priori* assumptions on feedback or feedforward neural control mechanisms such as reflex rules or predefined synergies [9]. In this scenario, EMG estimates of neuromuscular excitations have been used to drive neuromusculoskeletal models during a variety of dynamic motor tasks as well as neuromuscular and orthopedic conditions and predict a range of neuromuscular variables. This approach was successfully employed to establish myoelectric controllers for powered wrist-hand prostheses [93], which enabled establishment of biomimetic interfaces that synthesized the musculoskeletal function of an individual's phantom limb controlled by EMG-derived neural excitations. In the context of lower limb prostheses, using an EMG-driven musculoskeletal model, a below-knee amputee was able to track a desired joint motion of his virtual foot defined by graphical display [94]. A subject with amputation performed under the Agonist-antagonist Myoneural Interface surgical paradigm used an EMG-driven neuromusculoskeletal model to control a powered ankle prosthesis in the stance phase of walking [95].

VI. Discussion

There are several central challenges in human modeling. First, many internal biomechanical variables can not be directly measured. Second, from the innermost nervous system to the outermost skeletal system, there are many redundancies, i.e., many motor neurons control one muscle and multiple muscles drive one joint. These two challenges render variable estimation and parameter identification hard in a human model. Third, there is large variability in the neuromusculoskeletal and senorimotor control models among different individuals, and both of the two models change over time (nonstationarity). PHRI provides an important means to create/control various special experiment conditions for making model parameters more observable, and to build platforms for studying how personal neuromotor response adapts to robotic assistance. Wearable robots may help solve the personalization and nonstationarity issues to update these models for individuals by continuously sensing the human status, and simultaneously use the updated models to augment human performance.

As introduced in Section II, three biological systems can be included in a human model. How the systems should be modeled depends on the requirements of the specific application, i.e., the interested biomechanical variables used for the robot control and the model accuracy and speed. For instance, if only joint torque needs to be estimated for an ergonomic pHRI study, only the skeletal system is needed. If reflex gain and time delay need to be considered for posture stabilization in a rehabilitation study, all three systems have to be modeled. However, the more details of a system and more systems are modeled, the slower the calculation efficiency of the human model would be, which can be an important issue for online applications, like the control of prosthetic limbs. How to simplify a human model while maintaining the estimation accuracy of interested variables is another challenge. To this end, quantification of the sensitivity of different model components to the estimation accuracy of different variables is a promising future research direction.

Moreover, it is worth mentioning two different ways of using human models. One is inverse analysis where the measured human motion dynamics (e.g., body movement and external force) in the skeletal system is used to estimate the variables in the muscular or nervous system (e.g., muscle activity) causing the movement. It is *a posteriori* analysis for human movement that has already happened, which can not be generalized to novel situations for prediction purpose. This type of analysis is often carried out offline, e.g., ergonomic evaluation of a pHRI task after a recorded experiment. The other one is forward analysis where the measurement in the muscular system, typically EMG data, is used to derive the resulting muscle force and motion dynamics, which is *a priori* analysis and can be used for predicting what human movement will happen in advance, e.g., predictive control of prosthetic limbs. However, forward analyses are not suitable for applications which require a large number of EMG electrodes which are prone to large sensor noise and artifacts, such as full-body applications. How to incorporate the internal models (in Section III) in the robot predictive control can be investigated to reduce the number of EMGs.

Finally, unlike human impedance that stems from the viscoelastic properties of muscles and tendons and can provide instantaneous response in highly dynamic tasks for stability, robot impedance is usually rendered through control which inherently suffers from computation and/or communication delays that can deteriorate the stability. When a human body is coupled with an impedance-controlled robot in pHRI, human impedance has to be incorporated in a stability analysis of the coupled system, and can also be considered when optimizing task performance or human fatigue.

References

[1] W. Kim, J. Lee, L. Peternel, N. Tsagarakis, and A. Ajoudani, "Anticipatory robot assistance for the prevention of human static joint overloading in human–robot collaboration," *IEEE Robot. Automat. Lett.*, vol. 3, no. 1, pp. 68–75, Jan. 2018.

[2] J. M. Prendergast, S. Balvert, T. Driessen, A. Seth, and L. Peternel, "Biomechanics aware collaborative robot system for delivery of safe physical therapy in shoulder rehabilitation," *IEEE Robot. Automat. Lett.*, vol. 6, no. 4, pp. 7177–7184, Oct. 2021.

[3] G. Clark and H. B. Amor, "Learning ergonomic control in human–robot symbiotic walking," *IEEE Trans. Robot.*, vol. 39, no. 1, pp. 327–342, Feb. 2023.

[4] Y. Asano, K. Okada, and M. Inaba, "Design principles of a human mimetic humanoid: Humanoid platform to study human intelligence and internal body system," *Sci. Robot.*, vol. 2, no. 13, 2017, Art. no. eaaq0899.

[5] C. Fang, A. Ajoudani, A. Bicchi, and N. G. Tsagarakis, "Online model based estimation of complete joint stiffness of human arm," *IEEE Robot. Automat. Lett.*, vol. 3, no. 1, pp. 84–91, Jan. 2018.

Authorized licensed use limited to: TU Delft Library. Downloaded on August 18,2023 at 10:08:12 UTC from IEEE Xplore. Restrictions apply.

[6] A. Naceri, T. Schumacher, Q. Li, S. Calinon, and H. Ritter, "Learning optimal impedance control during complex 3D arm movements," *IEEE Robot. Automat. Lett.*, vol. 6, no. 2, pp. 1248–1255, Apr. 2021.

[7] A. E. Block, S. Christen, R. Gassert, O. Hilliges, and K. J. Kuchenbecker, "The six hug commandments: Design and evaluation of a human-sized hugging robot with visual and haptic perception," in *Proc. IEEE/ACM Int. Conf. Hum.-Robot Interaction*, 2021, pp. 380–388.

[8] J. Borgstedt, F. E. Pollick, and S. Brewster, "Hot or not? exploring user perceptions of thermal human-robot interaction," in *Proc. IEEE 31st Int. Conf. Robot Hum. Interactive Commun.*, 2022, pp. 1334–1340.

[9] M. Sartori, D. G. Llyod, and D. Farina, "Neural data-driven musculoskeletal modeling for personalized neurorehabilitation technologies," *IEEE Trans. Biomed. Eng.*, vol. 63, no. 5, pp. 879–893, May 2016.

[10] M. Lorenzini, M. Lagomarsino, L. Fortini, S. Gholami, and A. Ajoudani, "Ergonomic human-robot collaboration in industry: A review," *Front. Robot. AI*, vol. 9, 2023, Art. no. 262.

[11] L. Peternel and A. Ajoudani, "After a decade of teleimpedance: A survey," *IEEE Trans. Hum.-Mach. Syst.*, vol. 53, no. 2, pp. 401–416, Apr. 2023.

[12] D. Kulić, G. Venture, K. Yamane, E. Demircan, I. Mizuuchi, and K. Mombaur, "Anthropomorphic movement analysis and synthesis: A survey of methods and applications," *IEEE Trans. Robot.*, vol. 32, no. 4, pp. 776–795, Aug. 2016.

[13] K. R. Holzbaur, W. M. Murray, and S. L. Delp, "A model of the upper extremity for simulating musculoskeletal surgery and analyzing neuromuscular control," *Ann. Biomed. Eng.*, vol. 33, pp. 829–840, 2005.

[14] S. L. Delp, J. P. Loan, M. G. Hoy, F. E. Zajac, E. L. Topp, and J. M. Rosen, "An interactive graphics-based model of the lower extremity to study orthopaedic surgical procedures," *IEEE Trans. Biomed. Eng.*, vol. 37, no. 8, pp. 757–767, Aug. 1990.

[15] S. R. Hamner, A. Seth, and S. L. Delp, "Muscle contributions to propulsion and support during running," *J. Biomech.*, vol. 43, no. 14, pp. 2709–2716, 2010.

[16] Y. Nakamura, K. Yamane, Y. Fujita, and I. Suzuki, "Somatosensory computation for man-machine interface from motion-capture data and musculoskeletal human model," *IEEE Trans. Robot.*, vol. 21, no. 1, pp. 58–66, Feb. 2005.

[17] A. Seth et al., "Opensim: Simulating musculoskeletal dynamics and neuromuscular control to study human and animal movement," *PLoS Comput. Biol.*, vol. 14, no. 7, 2018, Art. no. e1006223.

[18] M. Damsgaard, J. Rasmussen, S. T. Christensen, E. Surma, and M. De Zee, "Analysis of musculoskeletal systems in the anybody modeling system," *Simul. Model. Pract. Theory*, vol. 14, no. 8, pp. 1100–1111, 2006.

[19] E. Todorov, T. Erez, and Y. Tassa, "MuJoCo: A physics engine for model-based control," in *Proc. IEEE/RSJ Int. Conf. Intell. Robots Syst.*, 2012, pp. 5026–5033.

[20] H. Wang, V. Caggiano, G. Durandau, M. Sartori, and V. Kumar, "MyoSim: Fast and physiologically realistic MuJoCo models for musculoskeletal and exoskeletal studies," in *Proc. IEEE Int. Conf. Robot. Automat.*, 2022, pp. 8104–8111.

[21] D. Farina, F. Negro, S. Muceli, and R. M. Enoka, "Principles of motor unit physiology evolve with advances in technology," *Physiol.*, vol. 31, no. 2, pp. 83–94, 2016.

[22] W. Mugge, D. A. Abbink, A. C. Schouten, J. P. Dewald, and F. C. Van Der Helm, "A rigorous model of reflex function indicates that position and force feedback are flexibly tuned to position and force tasks," *Exp. Brain Res.*, vol. 200, pp. 325–340, 2010.

[23] Y. Yang et al., "Nonlinear connectivity in the human stretch reflex assessed by cross-frequency phase coupling," *Int. J. Neural Syst.*, vol. 26, no. 08, 2016, Art. no. 1650043.

[24] D. G. Lloyd and T. F. Besier, "An EMG-driven musculoskeletal model to estimate muscle forces and knee joint moments in vivo," *J. Biomech.*, vol. 36, no. 6, pp. 765–776, 2003.

[25] F. E. Zajac, "Muscle and tendon: Properties, models, scaling, and application to biomechanics and motor control," *Crit. Rev. Biomed. Eng.*, vol. 17, no. 4, pp. 359–411, 1989.

[26] M. Toigo, M. Flück, R. Riener, and V. Klamroth-Marganska, "Robot-assisted assessment of muscle strength," *J. Neuroeng. Rehabil.*, vol. 14, pp. 1–10, 2017.

[27] P. Lian, Y. Ma, L. Zheng, Y. Xiao, and X. Wu, "A three-step hill neuromusculoskeletal model parameter identification method based on exoskeleton robot," *J. Intell. Robotic Syst.*, vol. 104, no. 3, 2022, Art. no. 44.

[28] G. Durandau, D. Farina, and M. Sartori, "Robust real-time musculoskeletal modeling driven by electromyograms," *IEEE Trans. Biomed. Eng.*, vol. 65, no. 3, pp. 556–564, Mar. 2018.

[29] E. Burdet, R. Osu, D. Franklin, T. Yoshioka, T. Milner, and M. Kawato, "A method for measuring endpoint stiffness during multi-joint arm movements," *J. Biomech.*, vol. 33, no. 12, pp. 1705–1709, 2000.

[30] A. Ajoudani, C. Fang, N. Tsagarakis, and A. Bicchi, "Reduced-complexity representation of the human arm active endpoint stiffness for supervisory control of remote manipulation," *Int. J. Robot. Res.*, vol. 37, no. 1, pp. 155–167, 2018.

[31] Y. Z. Yahya, I. W. Hunter, T. F. Besier, A. J. Taberner, and B. P. Ruddy, "Shoulder joint stiffness in a functional posture at various levels of muscle activation," *IEEE Trans. Biomed. Eng.*, vol. 69, no. 7, pp. 2192–2201, Jul. 2022.

[32] H. Y. Huang, A. Arami, I. Farkhatdinov, D. Formica, and E. Burdet, "The influence of posture, applied force and perturbation direction on hip joint viscoelasticity," *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 28, no. 5, pp. 1138–1145, May 2020.

[33] D. W. Franklin and D. M. Wolpert, "Computational mechanisms of sensorimotor control," *Neuron*, vol. 72, no. 3, pp. 425–442, 2011.

[34] E. Todorov and M. I. Jordan, "Optimal feedback control as a theory of motor coordination," *Nature Neurosci.*, vol. 5, no. 11, pp. 1226–1235, 2002.

[35] T. Flash and N. Hogan, "The coordination of arm movements: An experimentally confirmed mathematical model," *J. Neurosci.*, vol. 5, no. 7, pp. 1688–1703, 1985.

[36] Y. Uno, M. Kawato, and R. Suzuki, "Formation and control of optimal trajectory in human multijoint arm movement," *Biol. Cybern.*, vol. 61, no. 2, pp. 89–101, 1989.

[37] C. M. Harris and D. M. Wolpert, "Signal-dependent noise determines motor planning," *Nature*, vol. 394, no. 6695, pp. 780–784, 1998.

[38] K. E. Jones, A. F. d. C. Hamilton, and D. M. Wolpert, "Sources of signal-dependent noise during isometric force production," *J. Neuriophysiol.*, vol. 88, no. 3, pp. 1533–1544, 2002.

[39] P. M. Fitts, "The information capacity of the human motor system in controlling the amplitude of movement," *J. Exp. Psychol.*, vol. 47, no. 6, pp. 381–391, 1954.

[40] E. M. Summerside, R. Shadmehr, and A. A. Ahmed, "Vigor of reaching movements: Reward discounts the cost of effort," *J. Neuriophysiol.*, vol. 119, no. 6, pp. 2347–2357, 2018.

[41] L. Peternel, O. Sigaud, and J. Babič, "Unifying speed-accuracy trade-off and cost-benefit trade-off in human reaching movements," *Front. Hum. Neurosci.*, vol. 11, 2017, Art. no. 615.

[42] D. M. Wolpert and M. Kawato, "Multiple paired forward and inverse models for motor control," *Neural Netw.*, vol. 11, no. 7/8, pp. 1317–1329, 1998.

[43] M. Kawato, "Internal models for motor control and trajectory planning," *Curr. Opin. Neurobiol.*, vol. 9, no. 6, pp. 718–727, 1999.

[44] B. Mehta and S. Schaal, "Forward models in visuomotor control," *J. Neuriophysiol.*, vol. 88, no. 2, pp. 942–953, 2002.

[45] D. W. Franklin, G. Liaw, T. E. Milner, R. Osu, E. Burdet, and M. Kawato, "Endpoint stiffness of the arm is directionally tuned to instability in the environment," *J. Neurosci.*, vol. 27, no. 29, pp. 7705–7716, 2007.

[46] D. W. Franklin et al., "CNS learns stable, accurate, and efficient movements using a simple algorithm," *J. Neurosci.*, vol. 28, no. 44, pp. 11165–11173, 2008.

[47] L. M. Doornebosch, D. A. Abbink, and L. Peternel, "Analysis of coupling effect in human-commanded stiffness during bilateral tele-impedance," *IEEE Trans. Robot.*, vol. 37, no. 4, pp. 1282–1297, Aug. 2021.

[48] C. E. Sunesson, D. T. Schøn, C. N. P. Hassø, F. Chinello, and C. Fang, "Predictor: A physical emulator enabling safety and ergonomics evaluation and training of physical human-robot collaboration," *Front. Neurorobot.*, vol. 17, 2023, Art. no. 1080038.

[49] S.-H. Hyon, J. G. Hale, and G. Cheng, "Full-body compliant human–humanoid interaction: balancing in the presence of unknown external forces," *IEEE Trans. Robot.*, vol. 23, no. 5, pp. 884–898, Oct. 2007.

[50] E. M. van Zoelen, K. van denM. Bosch,M. Rauterberg, E. Barakova, and M. Neerincx, "Identifying interaction patterns of tangible co-adaptations in human-robot team behaviors," *Front. Psychol.*, vol. 12, 2021, Art. no. 645545.

[51] K. M. Monika Harant and Matthias B. Näf, "Multibody dynamics and optimal control for optimizing spinal exoskeleton design and support," *Multibody Syst. Dyn.*, vol. 57, no. 2, pp. 389–411, 2023.

[52] J. Babič et al., "Spexor: Design and development of passive spinal exoskeletal robot for low back pain prevention and vocational reintegration," *SN Appl. Sci.*, vol. 1, pp. 1–5, 2019.

Authorized licensed use limited to: TU Delft Library. Downloaded on August 18,2023 at 10:08:12 UTC from IEEE Xplore. Restrictions apply.

[53] D. P. Losey, C. G. McDonald, E. Battaglia, and M. K. OMalley, "A review of intent detection, arbitration, and communication aspects of shared control for physical humanrobot interaction," *Appl. Mech. Rev.*, vol. 70, no. 1, Jan. 2018.
[54] K. Haninger, C. Hegeler, and L. Peternel, "Model predictive impedance control with Gaussian processes for human and environment interaction," *Robot. Auton. Syst.*, vol. 165, 2023, Art. no. 104431.
[55] M. R. U. Islam, A. Waris, E. N. Kamavuako, and S. Bai, "A comparative study of motion detection with FMG and sEMG methods for assistive applications," *J. Rehabil. Assistive Technol. Eng.*, vol. 7, 2020, Art. no. 2055668320938588.
[56] S. Jiang, Q. Gao, H. Liu, and P. B. Shull, "A novel, co-located emg-fmg-sensing wearable armband for hand gesture recognition," *Sensors Actuators A: Phys.*, vol. 301, 2020, Art. no. 111738.
[57] G. Marinou, L. Sloot, and K. Mombaur, "Towards efficient lower-limb exoskeleton evaluation: Defining biomechanical metrics to quantify assisted gait familiarization," in *Proc. IEEE RAS/EMBS Int. Conf. Biomed. Robot. Biomechatronics, Seoul*, 2022, pp. 1–8.
[58] W. He, C. Xue, X. Yu, Z. Li, and C. Yang, "Admittance-based controller design for physical humanrobot interaction in the constrained task space," *IEEE Trans. Automat. Sci. Eng.*, vol. 17, no. 4, pp. 1937–1949, Oct. 2020.
[59] J. G. Hale and F. E. Pollick, ""sticky hands": Learning and generalization for cooperative physical interactions with a humanoid robot," *IEEE Trans. Syst., Man, Cybern., Part C. (Appl. Rev.)*, vol. 35, no. 4, pp. 512–521, Nov. 2005.
[60] E. Magrini, F. Flacco, and A. De Luca, "Control of generalized contact motion and force in physical human-robot interaction," in *Proc. IEEE Int. Conf. Robot. Automat.*, 2015, pp. 2298–2304.
[61] N. Hogan, "Impedance control: An approach to manipulation: Parts 1, 2, 3," *J. Dyn. Syst., Meas. Control*, vol. 107, pp. 1–24, 1985.
[62] S. Haddadin and E. Croft, "Physical humanrobot interaction," in *Springer Handbook of Robotics*. Berlin, Germany: Springer, 2016, pp. 1835–1874.
[63] T. Teramae, T. Noda, and J. Morimoto, "EMG-based model predictive control for physical humanrobot interaction: Application for assist-as-needed control," *IEEE Robot. Automat. Lett.*, vol. 3, no. 1, pp. 210–217, Jan. 2018.
[64] C. Yang, C. Zeng, P. Liang, Z. Li, R. Li, and C.-Y. Su, "Interface design of a physical humanrobot interaction system for human impedance adaptive skill transfer," *IEEE Trans. Automat. Sci. Eng.*, vol. 15, no. 1, pp. 329–340, Jan. 2018.
[65] Y. Hu, N. Abe, M. Benallegue, N. Yamanobe, G. Venture, and E. Yoshida, "Toward active physical human–robot interaction: Quantifying the human state during interactions," *IEEE Trans. Hum.-Mach. Syst.*, vol. 51, no. 3, pp. 367–378, Jun. 2022.
[66] S. Cremer, S. K. Das, I. B. Wijayasinghe, D. O. Popa, and F. L. Lewis, "Model-free online neuroadaptive controller with intent estimation for physical humanrobot interaction," *IEEE Trans. Robot.*, vol. 36, no. 1, pp. 240–253, Feb. 2020.
[67] G. Li, Z. Li, and Z. Kan, "Assimilation control of a robotic exoskeleton for physical human-robot interaction," *IEEE Robot. Automat. Lett.*, vol. 7, no. 2, pp. 2977–2984, Apr. 2022.
[68] P. Maurice et al., "Human movement and ergonomics: An industry-oriented dataset for collaborative robotics," *Int. J. Robot. Res.*, vol. 38, no. 14, pp. 1529–1537, 2019.
[69] A. G. Marin, M. S. Shourijeh, P. E. Galibarov, M. Damsgaard, L. Fritzsch, and F. Stulp, "Optimizing contextual ergonomics models in human-robot interaction," in *Proc. IEEE/RSJ Int. Conf. Intell. Robots Syst.,*2018, pp. 1–9.
[70] L. F. C. Figueredo, R. C. Aguiar, L. Chen, S. Chakrabarty, M. R. Dogar, and A. G. Cohn, "Human comfortability: Integrating ergonomics and muscular-informed metrics for manipulability analysis during human-robot collaboration," *IEEE Robot. Automat. Lett.*, vol. 6, no. 2, pp. 351–358, Apr. 2021.
[71] L. Peternel, D. T. Schøn, and C. Fang, "Binary and hybrid work-condition maps for interactive exploration of ergonomic human arm postures," *Front. Neurorobot.*, vol. 14, 2021, Art. no. 590241.
[72] L. Peternel, N. Tsagarakis, D. Caldwell, and A. Ajoudani, "Robot adaptation to human physical fatigue in human–robot co-manipulation," *Auton. Robots*, vol. 42, pp. 1011–1021, 2018.
[73] C. Messeri, A. Bicchi, A. M. Zanchettin, and P. Rocco, "A dynamic task allocation strategy to mitigate the human physical fatigue in collaborative robotics," *IEEE Robot. Automat. Lett.*, vol. 7, no. 2, pp. 2178–2185, Apr. 2022.
[74] L. Peternel, C. Fang, N. Tsagarakis, and A. Ajoudani, "A selective muscle fatigue management approach to ergonomic human-robot co-manipulation," *Robot. Comput.- Integr. Manuf.*, vol. 58, pp. 69–79, 2019.
[75] L. Roveda et al., "Model-based reinforcement learning variable impedance control for human-robot collaboration," *J. Intell. Robotic Syst.*, vol. 100, no. 2, pp. 417–433, 2020.
[76] Y. Wu, P. Balatti, M. Lorenzini, F. Zhao, W. Kim, and A. Ajoudani, "A teleoperation interface for loco-manipulation control of mobile collaborative robotic assistant," *IEEE Robot. Automat. Lett.*, vol. 4, no. 4, pp. 3593–3600, Oct. 2019.
[77] L. Peternel, C. Fang, M. Laghi, A. Bicchi, N. Tsagarakis, and A. Ajoudani, "Human arm posture optimisation in bilateral teleoperation through interface reconfiguration," in *Proc. IEEE RAS/EMBS 8th Int. Conf. Biomed. Robot. Biomechatronics (BioRob).*, 2020, pp. 1102–1108.
[78] S. Yao, Y. Zhuang, Z. Li, and R. Song, "Adaptive admittance control for an ankle exoskeleton using an EMG-driven musculoskeletal model," *Front. Neurorobot.*, vol. 12, 2018, Art. no. 16.
[79] N. Lotti et al., "Adaptive model-based myoelectric control for a soft wearable arm exosuit: A new generation of wearable robot control," *IEEE Robot. Automat. Mag.*, vol. 27, no. 1, pp. 43–53, Mar. 2020.
[80] G. Durandau, W. F. Rampeltshammer, H. v. d. Kooij, and M. Sartori, "Neuromechanical model-based adaptive control of bilateral ankle exoskeletons: Biological joint torque and electromyogram reduction across walking conditions," *IEEE Trans. Robot.*, vol. 38, no. 3, pp. 1380–1394, Jun. 2022.
[81] G. Durandau et al., "Voluntary control of wearable robotic exoskeletons by patients with paresis via neuromechanical modeling," *J. Neuroeng. Rehabil.*, vol. 16, pp. 1–18, 2019.
[82] P. K. Jamwal, S. Hussain, Y. H. Tsoi, and S. Q. Xie, "Musculoskeletal model for path generation and modification of an ankle rehabilitation robot," *IEEE Trans. Hum.-Mach. Syst.*, vol. 50, no. 5, pp. 373–383, Oct. 2020.
[83] K. Li, M. Tucker, R. Gehlhar, Y. Yue, and A. D. Ames, "Natural multicontact walking for robotic assistive devices via musculoskeletal models and hybrid zero dynamics," *IEEE Robot. Automat. Lett.*, vol. 7, no. 2, pp. 4283–4290, Apr. 2022.
[84] M. Tröbinger et al., "Introducing garmi-a service robotics platform to support the elderly at home: Design philosophy, system overview and first results," *IEEE Robot. Automat. Lett.*, vol. 6, no. 3, pp. 5857–5864, Jul. 2021.
[85] S. Balvert, J. M. Prendergast, I. Belli, A. Seth, and L. Peternel, "Enabling patient-and teleoperator-led robotic physiotherapy via strain map segmentation and shared-authority," in *Proc. IEEE-RAS 21st Int. Conf. Humanoid Robots*, 2022, pp. 246–253.
[86] M. Sartori and G. S. Sawicki, "Closing the loop between wearable technology and human biology: A new paradigm for steering neuromuscular form and function," *Prog. Biomed. Eng.*, vol. 3, no. 2, 2021, Art. no. 023001.
[87] M. Afschrift, F. De Groote, and I. Jonkers, "Similar sensorimotor transformations control balance during standing and walking," *PLoS Comput. Biol.*, vol. 17, no. 6, 2021, Art. no. e1008369.
[88] A. Q. L. Keemink, T. J. H. Brug, E. H. F. van Asseldonk, A. R. Wu, and H. Van Der Kooij, "Whole body center of mass feedback in a reflex-based neuromuscular model predicts ankle strategy during perturbed walking," *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 29, pp. 2521–2529, 2021.
[89] C. M. Niu, Q. Luo, C.-h. Chou, J. Liu, M. Hao, and N. Lan, "Neuromorphic model of reflex for realtime human-like compliant control of prosthetic hand," *Ann. Biomed. Eng.*, vol. 49, pp. 673–688, 2021.
[90] E. Bizzi and V. C. Cheung, "The neural origin of muscle synergies," *Front. Comput. Neurosci.*, vol. 7, 2013, Art. no. 51.
[91] M. Sartori, L. Gizzi, D. G. Lloyd, and D. Farina, "A musculoskeletal model of human locomotion driven by a low dimensional set of impulsive excitation primitives," *Front. Comput. Neurosci.*, vol. 7, 2013, Art. no. 79.
[92] M. R. Tucker et al., "Control strategies for active lower extremity prosthetics and orthotics: A review," *J. Neuroeng. Rehabil.*, vol. 12, no. 1, pp. 1–30, 2015.
[93] M. Sartori, G. Durandau, S. Došen, and D. Farina, "Robust simultaneous myoelectric control of multiple degrees of freedom in wrist-hand prostheses by real-time neuromusculoskeletal modeling," *J. Neural Eng.*, vol. 15, no. 6, 2018, Art. no. 066026.
[94] S. K. Au, P. Bonato, and H. Herr, "An EMG-position controlled system for an active ankle-foot prosthesis: An initial experimental study," in *Proc. IEEE 9th Int. Conf. Rehabil. Robot.*, 2005, pp. 375–379.
[95] T. Shu et al., "Modulation of prosthetic ankle plantarflexion through direct myoelectric control of a subject-optimized neuromuscular model," *IEEE Robot. Automat. Lett.*, vol. 7, no. 3, pp. 7620–7627, Jul. 2022.

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