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MYOELECTRIC CONTROL OF ROBOTIC LEG PROSTHESES AND EXOSKELETONS: A REVIEW

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ABSTRACT

Myoelectric signals from the human motor control system can improve the real-time control and neural-machine interface of robotic leg prostheses and exoskeletons for different locomotor activities (e.g., walking, sitting down, stair ascent, and non-rhythmic movements). Here we review the latest advances in myoelectric control designs and propose future directions for research and innovation. We review the different wearable sensor technologies, actuators, signal processing, and pattern recognition algorithms used for myoelectric locomotor control and intent recognition, with an emphasis on the hierarchical architectures of volitional control systems. Common mechanisms within the control architecture include 1) open-loop proportional control with fixed gains, 2) active-reactive control, 3) joint mechanical impedance control, 4) manual-tuning torque control, 5) adaptive control with varying gains, and 6) closed-loop servo actuator control. Based on our review, we recommend that future research consider using musculoskeletal modeling and machine learning algorithms to map myoelectric signals from surface electromyography (EMG) to actuator joint torques, thereby improving the automation and efficiency of next-generation EMG controllers and neural interfaces for robotic leg prostheses and exoskeletons. We also propose an example model-based adaptive impedance EMG controller including muscle and multibody system dynamics. Ongoing advances in the engineering design of myoelectric control systems have implications for both locomotor assistance and rehabilitation.

1. INTRODUCTION

Lower-limb prostheses and exoskeletons can be subcategorized into passive, semi-powered, or powered devices [1, 2]. The development of powered (also called robotic) prostheses and exoskeletons for real-world applications requires that such devices be self-contained (i.e., untethered), have similar dimensions and inertial properties as the biological limbs [3], and have different joint mechanical impedances (e.g., stiffness and damping) for different locomotion modes [4]. Unlike passive and semi-powered devices, robotic leg prostheses and exoskeletons can uniquely generate net positive mechanical power to accelerate the human-machine (so-called biomechatronic) system using hydraulic, pneumatic, or electric actuators.

The optimal engineering design of an adaptive and robust controller for these robotic devices, especially while physically interacting with humans and real-world environments, remains a significant challenge, to which researchers are actively working on to better assist movement and rehabilitation [5]. To date, most devices have used a hierarchical control architecture, including high-level and lower-level controllers. The high-level controller, also called the supervisory controller, is in charge of recognizing the user's locomotor intent (e.g., walking upstairs). The lower-level controllers are used to control the robotic device based on the high-level control decisions [5, 6].

Traditionally, individual controllers have been designed and optimized for variety of locomotion modes like level-ground walking, ramp ascent and descent, stair ascent (see Fig.1), and sit-to-stand [7–9]. Finite state machines using mechanical and/or inertial sensors have struggled with effectively transitioning between different locomotor activities [10]. Consequently, these systems have typically limited the user's mobility and overall quality-of-life [10]. Errors in identifying the user's locomotor intent can be reduced by incorporating myoelectric signals into the robot control system [10, 11]. Surface electromyography (EMG) has been the most commonly used sensor for myoelectric control. Motivated to inform the design of next-generation locomotor control systems, we reviewed the state-of-the-art in myoelectric (EMG) controllers for robotic leg prostheses and exoskeletons, with an emphasis on the hierarchical architectures of volitional control systems.

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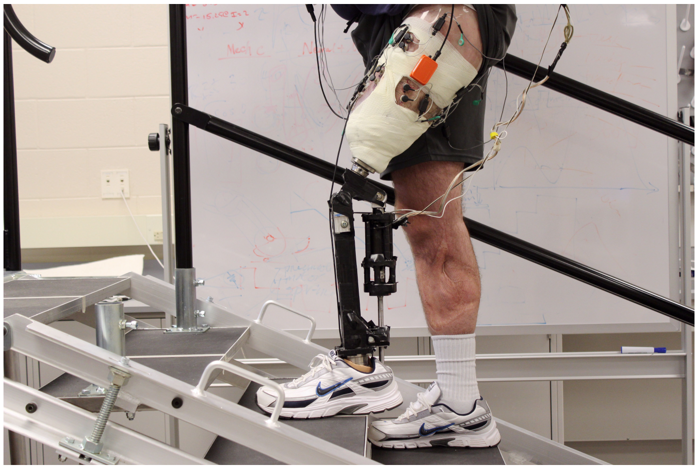

FIGURE 1: STAIR CLIMBING WITH A ROBOTIC PROSTHESIS USING MYOELECTRIC CONTROL. PHOTO COURTESY OF HELEN HUANG (UNIVERSITY OF NORTH CAROLINA AT CHAPEL HILL AND NORTH CAROLINA STATE UNIVERSITY, USA)

2. BACKGROUND OF CONTROLLERS

Before discussing the design and performance of different myoelectric controllers, we first introduce the general control approaches used by robotic leg prostheses and exoskeletons, including echo control, finite-state machines, and volitional control. Echo control systems mainly target users with unilateral mobility impairments. This controller uses closed-loop position control by which the robotic limb tracks the contralateral unaffected biological leg trajectories using mechanical and/or inertial sensors with a one-half stride delay [12]. While echo control systems are relativity straightforward and easy to implement, the controller is not real-time and significantly limits the human-machine dynamic interactions (e.g., the user passively rides the robotic device during locomotion); this muscle inactivity can also result in further weakening. In contrast, finite-state machines use kinematic and/or force information [13], and a pattern recognition algorithm, to recognize the intended locomotion mode. Each finite-state is predefined by system variables that adjust the device mechanics like robot joint kinematics [14, 15]. Historically, myoelectric signals were mainly used to transition between different finite-state locomotion modes [14] and were not used for direct volitional control.

Myoelectric controllers can allow robotic prostheses and exoskeletons to respond reliably to the user's locomotor intent, even for small nonrhythmic movements like driving a car or repositioning the legs while seated [2, 16]. Since improper operation can lead to falls and potentially severe injuries, EMG controls should be especially safe, predictable, real-time, and robust to disturbances. Recently, researchers have used biological muscle activations from the residual limb for neural control of robotic prostheses [8, 10, 13, 15, 17–21]. Incorporating EMG signals into the robot control system has been shown to significantly reduce misclassifications of locomotion modes in lower-limb amputees [22, 23].

3. CONTROL REQUIREMENTS

Here we review the different wearable sensors, signal processing, pattern recognition algorithms, and actuator technologies used by myoelectric locomotor control systems.

Wearable Sensors. Control systems for robotic leg prostheses and exoskeletons have used different wearable sensor technologies, including mechanical, inertial, vision, and myoelectric (EMG). Mechanical sensors can provide position, velocity, acceleration, force, and torque measurements of the joints and/or limbs. Some examples include rotary potentiometers for angle measurements, uniaxial load cells for force measurements [13], inertial measurement units (i.e., combined accelerometers and gyroscopes), and vertical-axis force-sensing resistors to measure foot-ground contact [11, 16, 24]. Some researchers have recently used computer vision for sensing and classifying human walking environments [25–29].

Unlike mechanical and inertial sensors, EMG signals can sense the joint movement in advance since muscles have a small amount of bioelectrical delay [30], therein allowing for predictive control. EMG signals from residual muscles [13], combined with a neuromuscular reflex model, have been used to control a robotic ankle prosthesis directly and reliably [10]. However, EMG signals are sensitive to electrode positioning, skin-electrode impedance, movement artifacts, muscle fatigue, and perspiration [18, 24]. Consequently, the performance of myoelectric control systems can deteriorate [31]. A method for adapting the controller to contain these changes is required before a viable EMG control uses in clinical environments. Kinematic and force and/or torque information can be used to complement myoelectric signals via multisensor data fusion [11, 32].

EMG Signal Processing. To achieve high-quality EMG signals, the electrodes should remain fixed to the skin [22]. Raw EMG signals should be amplified, filtered, and digitized before use in the robot control algorithm. The amplitude of the signal is generally measured in millivolts (mV) and a differential amplifier with desired gains is used. Since high accelerations can occur during ambulation (e.g., especially during foot-ground contact), movement artifacts can corrupt the myoelectric signals. High-pass filters are often used to reduce the effects of such artifacts. The signals are then digitized and sent to an onboard microprocessor. Myoelectric signals are rectified since human muscles get positive tension by activation [10].

Pattern Recognition Algorithms. To estimate the desired joint trajectory, the user's locomotion mode can be predicted using myoelectric signals and a pattern recognition algorithm. By identifying patterns in the EMG signals, the intended locomotor activity can be predicted [22] (i.e., since different locomotor activities can be estimated by specific joint trajectories). Along with EMG signals, mechanical signals can be processed and used for pattern recognition [22]. Pattern recognition algorithms like linear discriminant analysis and dynamic Bayesian networks [11, 22]) have been used to identify patterns in myoelectric signals. However, these algorithms can cause long delays, especially when transitioning from one locomotor activity to another [35]. Successful intent classifiers have been developed using human-socket junction forces, foot-ground contacts, myoelectric signals,

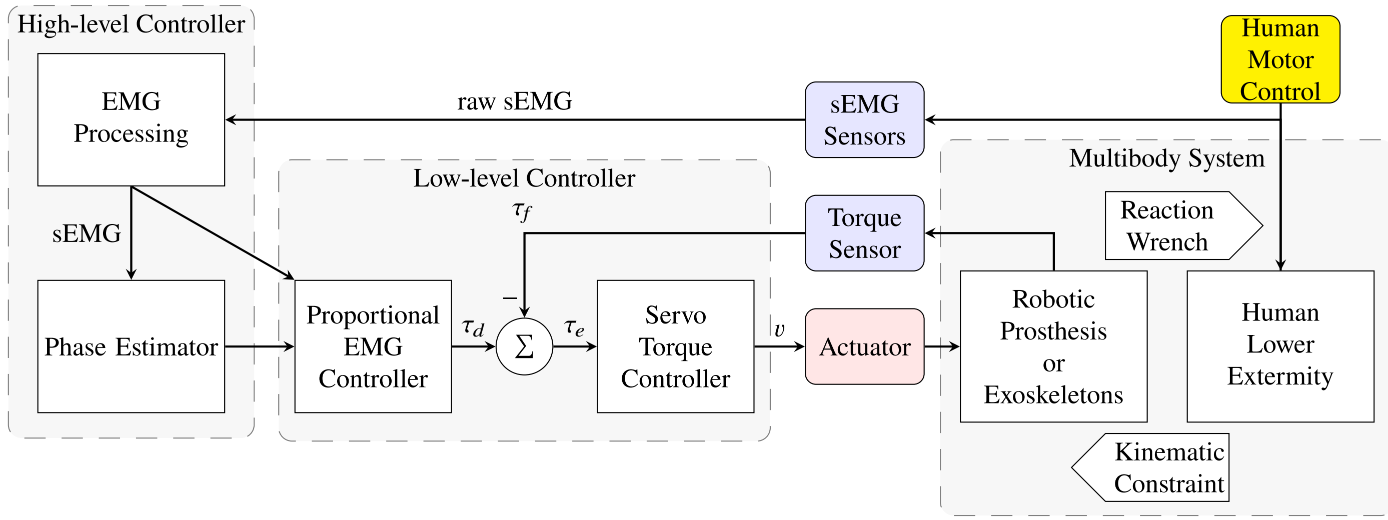

FIGURE 2: HIGH-LEVEL PROPORTIONAL MYOELECTRIC CONTROL AND LOW-LEVEL SERVO CONTROL WTIH TORQUE FEEDBACK [33].

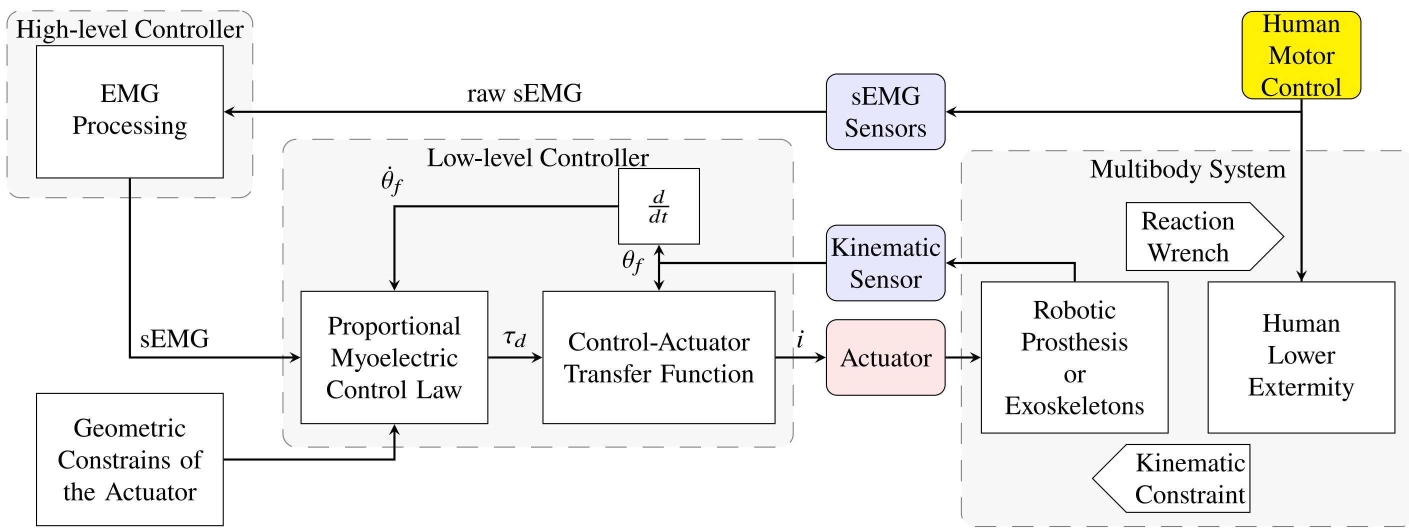

FIGURE 3: HIGH-LEVEL PROPORTIONAL MYOELECTRIC CONTROL AND LOW-LEVEL SERVO CONTROL WITH KINEMATIC FEEDBACK [18].

and the kinematics of contralateral limb [24]. Including EMG signals and time history data into the control system has been shown to significantly lower classification errors during human-prosthesis locomotion [22, 24]. Researchers have demonstrated that unilateral transtibial amputees can predict locomotor activities using myoelectric signals from the unaffected biological knee joint [36].

Robotic Actuators. Modeling the actuator dynamics can play an important role in designing a high-performance robot control system [25]. There are three broad categories of actuators used in robotic leg prostheses and exoskeletons, including electric motors, pneumatic artificial muscles, and hydraulic cylinders. Brushed DC motors coupled with precision ball-screw assemblies have been the most common actuation system used in robotic prostheses [18, 25]. In pneumatic artificial muscle systems, one actuator supplies flexion torques while another generates extension torques [17]. The oldest actuation system used in robotic prostheses and exoskeletons is fluid-powered technologies. However, hydraulic systems suffer from slow response times and require cumbersome hydraulic equipment [37].

4. CONTROL ARCHITECTURES

Combining data from onboard mechanical and/or inertial sensors with surface EMG can accurately interpret the user's intended movement [11]. Such "neuromuscular-mechanical data fusion" has been shown to provide more robust and intuitive control during human-prosthesis ambulation with seamless transitions between different locomotion modes and the ability to volitionally reposition the lower-limbs [7, 10, 11, 34]. This control system design uses the summation of EMG and kinematic measurements (i.e., joint angles and angular velocities [11]) with a constant controller gain as the command torque for the robotic system. The amount of gain is usually determined by experimen-

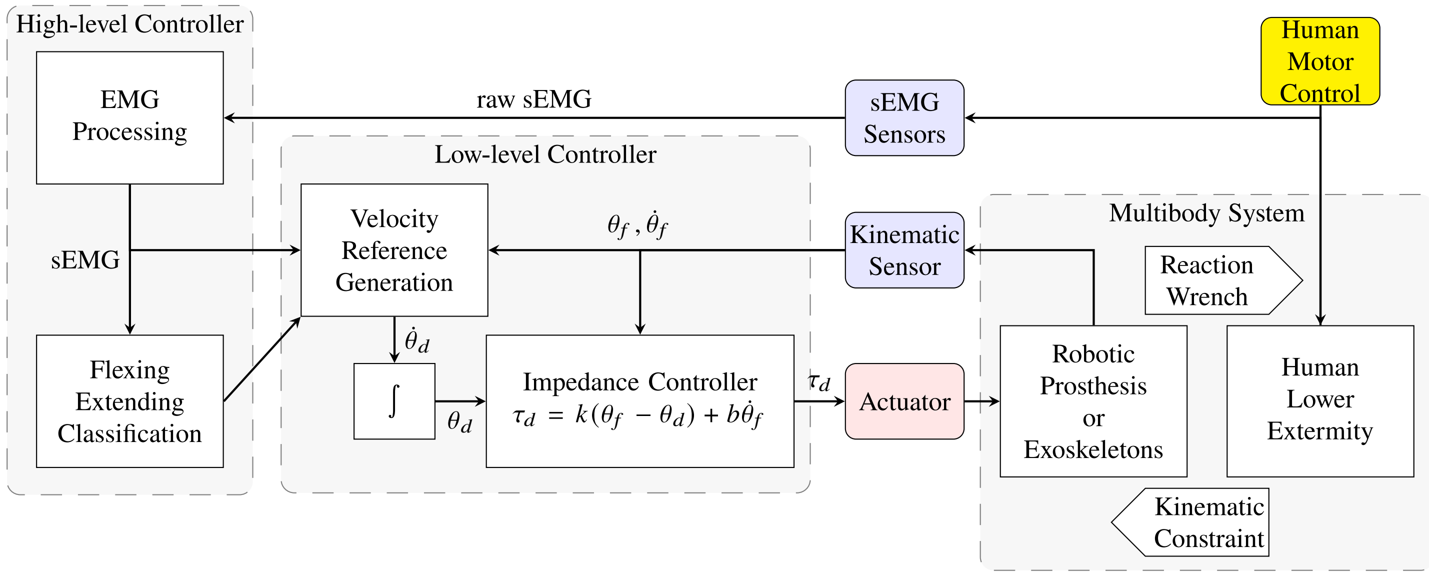

FIGURE 4: VOLITIONAL MYOELECTRIC IMPEDANCE CONTROL WITH A HIGH-LEVEL CLASSIFICATION AND REFERENCE OF ANGLE BY INTEGRATION OF VELOCITY [9].

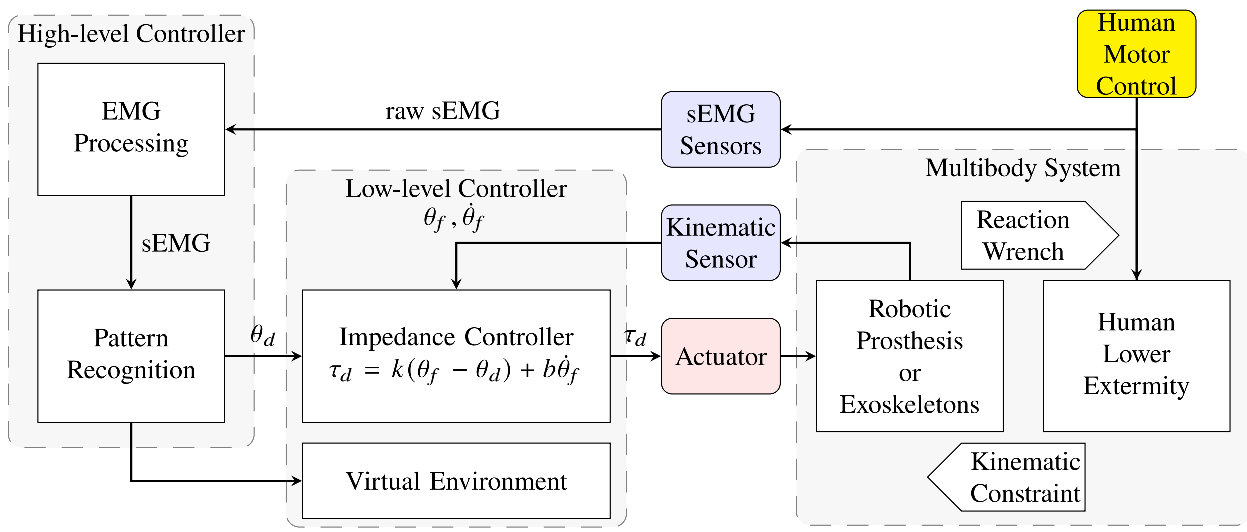

FIGURE 5: IMPEDANCE CONTROLLER USED TO GENERATE JOINT TORQUE COMMANDS BY COMPARING A VIRTUAL ENVIRONMENT (LOW-LEVEL) WITH REFERENCES FROM A PATTERN RECOGNITION ALGORITHM (HIGH-LEVEL) [34].

tal trial-and-error. The controller then regulates the actuator joint torques proportional to the processed EMG signals in real-time [33, 38]. Experimentally, proportional myoelectric controllers have been shown to reduce muscle activities and metabolic costs during walking compared to control systems that used recorded biological torque profiles [39].

The most straightforward control algorithm is an open-loop feed-forward torque control model. This robot controller does not include kinematic or kinetic feedback and only uses proportional myoelectric signals. The output torque τ_d is typically based on the least-squares fit during walking, which is a summation of the lower-limb joint angles, angular velocities, and processed EMG signals with specific gains [13], which has limitations. In contrast, active-reactive control algorithms have been used to simulate the underlying control mechanisms of the biological joints. The "active" actuation of the joint simulates the user's effort to drive the joint and the "reactive" response simulates the joint's reaction to the motion due to mechanical impedance. In this controller design, the EMG signals are represented as a sign signal or an on-off switch. This control system allows for direct neural control over the robotic device and dynamic interactions with the physical environment by modulating the joint mechanical impedance according to the combined muscle activations of users [16].

Rather than using a constant controller gain on EMG signals, manual-tuning torque controllers allow the user to manu-

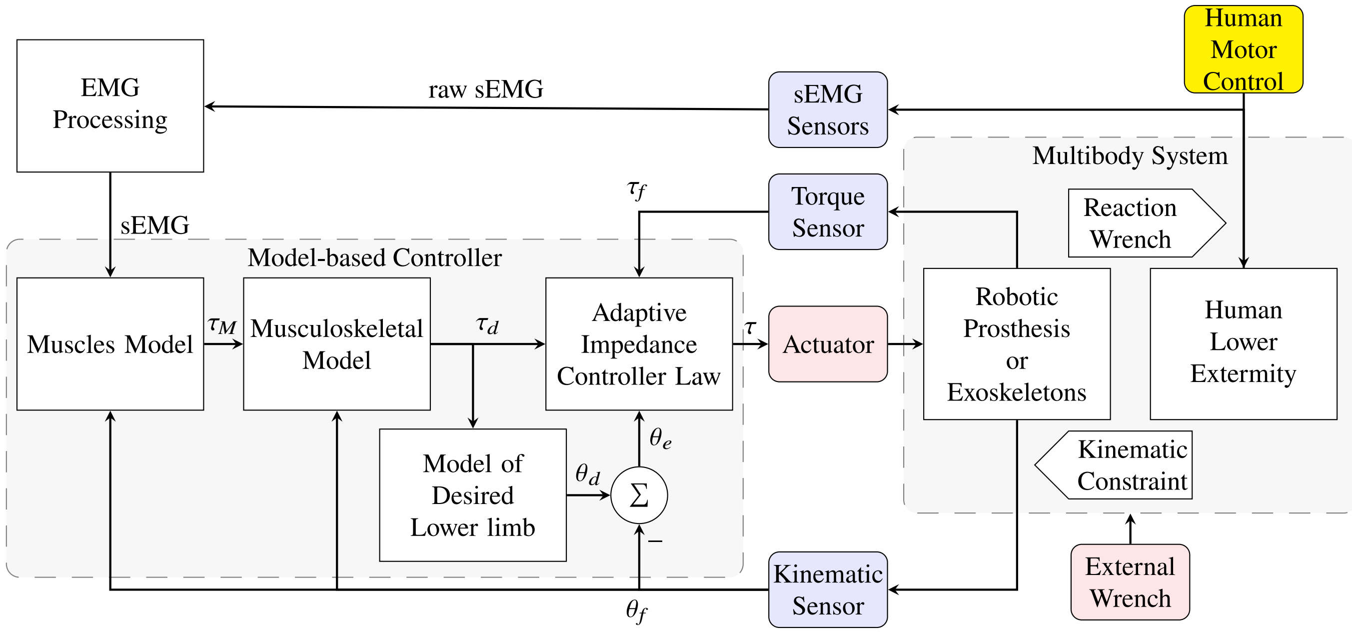

FIGURE 6: PROPOSED MYOELECTRIC ADAPTIVE-IMPEDANCE CONTROL ALGORITHM USING HUMAN MUSCULOSKELETAL MODELING.

ally increase or decrease the actuator gains in real-time [15, 20]. However, this method opposes the automatic control system design philosophy of robotic leg prostheses and exoskeletons for real-world deployment. By adding low-level servo controls to decrease error torque τ_e, researchers can significantly improve the controllability of the robotic device (see Fig.2) and decrease errors in the actuator control resulting from external disturbances [33]. An alternative application is low-level feedback servo-actuator control and high-level feed-forward myoelectric torque control (Fig.3). The high-level controller outputs to the servo-actuator are the desired joint torques τ_d. The low-level control outputs are the desired motor currents i in Fig.2-5, which are generated using an actuator model, motor torque constants, and servo amplifier gains. To improve the actuator transient response, the system can include torque feedback with a small proportional gain [18, 33].

There are several limitations to using fixed controller gains for mapping EMG to actuator joint torques. Designing an intelligent system that dynamically adapts the controller gains to the EMG signal amplitudes can result in better volitional control performance via incorporating the nonlinear relation between biological muscles and the generated movement dynamics. Researchers have shown that using such adaptive controllers can decrease human-exoskeleton walking metabolic costs compared to using fixed controller gains, thereby improving the overall locomotor efficiency [40].

Impedance control is the most common low-level controller used by robotic leg prostheses and exoskeletons. This method controls the joint mechanical impedance such that the robotic device accepts flow inputs θ_d (motion) and produces effort outputs τ_d (forces). The architecture of the control is typically based on healthy biomechanical data. The sum of muscle activations can determine the joint mechanical impedance. Therefore, when both the flexion and extension muscles are strained, the joint mechanical impedance is high, and when the muscles are relaxed, the joint mechanical impedance is low. Researchers have estimated actuator joint torques using a linear two-state impedance control (low-level) and a form of proportional myoelectric torque control united with a joint mechanical impedance (high-level) [13, 41–45].

The control architecture in Fig.4 shows an example of mechanical impedance control. The motorized joint is controlled with a virtual stiffness and damping that simulates the non-impaired biological joint mechanical impedance properties. Volitional movement of the robotic device is then controlled by the stiffness set-point angle of the mechanical impedance controller as a function of the measured myoelectric signals [9]. Using this control framework, Ha et al. modeled the human knee joint as a virtual spring-damper system to distinguish how a robotic leg prosthesis responds to forces and torques transmitted by the user and physical environment [9].

Impedance control has been used to control a virtual knee-ankle prosthesis independently and an experimental robotic knee prosthesis with structure of real-time feedback [34]. The controller predicted the user's desired ambulation mode (high-level), which in turn, managed the joint mechanical impedance (low-level) [34]. Since joint mechanical impedance between different locomotor activities can sometimes be relatively similar (e.g., ramp descent and level-ground walking), some misclassifications went unnoticed by the amputee user (Fig.5). Many users have preferred to start with lower proportional controller gains on EMG signals [17, 20]. Then, as users adapted their muscle activations and became more confident with practice, they gradually preferred higher controller gains. Evidence of learning and adaptation suggests that volitional EMG control systems may have distinct advantages over other high-level controller designs for robotic exoskeletons and prostheses (e.g., activity recognition-based controllers). Note that users typically required visual feedback to volitionally control the robotic device [17, 20].

5. DISCUSSION AND FUTURE DIRECTIONS

Myoelectric control of robotic leg prostheses and exoskeletons is an active but challenging area of research. Each of the control system designs described here have advantages (e.g., model-less, straightforward implication, and structure) and drawbacks (e.g., inaccurate control signals and EMG-torque relations, and require manual adjusting gain). Based on our review, it seems unlikely that one approach would satisfy all real-world applications, and thus combining different controllers seems more appropriate. Previous studies have typically assumed a simple proportional relationship between the myoelectric signals and actuator joint torques. Future work should consider incorporating muscle kinematics and dynamics from musculoskeletal simulations into the control system design to improve accuracy and robustness [46]. In such an approach, identifying and validating the dynamic model (e.g., body segment parameters, foot-ground contact, and muscle dynamic parameters) would be required. Researchers could identify the muscle parameters using optimal control theory (e.g., the muscle activities and joint torques could be the optimization inputs and the muscle dynamic parameters could be the variables [47]).

Two methods of modeling biological muscles include mathematical models from biomechanics (as previously mentioned) and machine learning algorithms. Mathematical muscle models typically consist of "Hill-type" muscle models. Although researchers can develop and use dynamic models of the human lower-limbs, solving the forward dynamic computations of such musculoskeletal models can be time-consuming and thus impede real-time control of the robotic device. Alternatively, machine learning algorithms like artificial neural networks can automatically and efficiently compute the nonlinear relationships between myoelectric and kinematic and kinetic signals [48, 49]. However, additional research is warranted to determine the efficacy of using machine learning algorithms for this novel application.

A mixture of top-down volitional control and bottom-up reflex control can allow for seamless locomotion mode transitions and direct neural control over the robotic device during nonrhythmic movements. To reiterate, the high-level controller estimates the user's intended locomotor activity in real-time based on myoelectric signals (and/or mechanical and inertial data) and the low-level controller ensures the actuator joint torques produce the desired motion [6]. Future research could consider using an adaptive gain or a model-predictive controller approach. By using this control system design and musculoskeletal modeling and simulations (i.e., instead of simple proportional EMG-torque mappings), robotic leg prostheses and exoskeletons may achieve actuator dynamics and control that are more similar to their biological counterparts (Fig.6).

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