Myoelectric Control and Neuromusculoskeletal Modeling: Complementary Technologies for Rehabilitation Robotics

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Abstract

Stroke and spinal cord injury (SCI) are a leading cause of disability in the United States, and researchers have pursued using robotic devices to aid rehabilitation efforts for resulting upper-extremity impairments. To date, however, robotic rehabilitation of the upper limb has produced only limited improvement in functional outcomes compared to traditional therapy. This paper explores the potential of myoelectric control and neuromusculoskeletal modeling for robotic rehabilitation using the current state of the art of each individual field as evidence. Continuing advances in the fields of myoelectric control and neuromusculoskeletal modeling offer opportunities for further improvements of rehabilitation robot control strategies. Specifically, personalized neuromusculoskeletal models driven by a subject's electromyography signals may provide accurate predictions of the subject's muscle forces and joint moments which, when used to design novel control strategies, could yield new approaches to robotic therapy for stroke and SCI that surpass the efficacy of traditional therapy.

Keywords

Robotic rehabilitation, upper limb motor impairment, electromyography, neuromusculoskeletal modeling

Introduction

Approximately 270,000 people who have sustained a spinal cord injury are living in the United States, with over 40% of survivors reporting incomplete tetraplegia [1]. Additionally, an estimated 7 million adults in the United States self-report having had a stroke, with stroke being a leading cause of long-term disability [2]. Loss of upper-limb function due to neurological injury significantly limits the ability of survivors to live and work independently. Intensive motion therapy after either spinal cord injury or stroke has been shown to have a positive effect on sensory-motor recovery in the upper-extremities [3].

Rehabilitation robots, both end-effector and exoskeleton types, are capable of delivering intensive upper-limb movement therapy using a range of control strategies that aim to maximally engage the participant [4]. An advantage of exoskeleton type robots over end-effector type robots is that a one-to-one correspondence exists between the robot's joints and the subject's joints. Assist-as-needed type controllers, which provide movement assistance only when the participant is unable to complete the movement independently, have been shown to promote recovery of movement coordination to a greater degree than controllers that move a passive limb throughout the arm's workspace [5,6]. Despite significant advances in both robotic hardware and controller technologies in recent years, robotic rehabilitation outcomes only match outcomes for traditional therapy when the number of repetitions is matched between the two strategies [7]. A recent meta-analysis comparing robotic therapies and conventional therapy showed no statistically significant improvements in performing activities of daily living after robotic therapy [8].

To address the limited progress robots have made in improving upper-extremity rehabilitation outcomes, this review examines a promising new approach of combining myoelectric control with neuromusculoskeletal (NMS) modeling to develop novel robot controllers that may lead to significant functional recovery. Myoelectric control takes in electromyogram (EMG) signals from the subject, which are often used to determine user intent as inputs to a control law. NMS modeling can convert these measured EMG signals into muscle forces and moments, accounting for the complex nonlinear physiological and biomechanical relationships involved in the conversion. Combining myoelectric control with NMS modeling could facilitate the development of physiologically based control strategies that can decode user intent and determine assistive robotic torques. This review analyzes progress in assist-as-needed robot control strategies, myoelectric control, and NMS modeling individually while keeping in mind the broader goal of combining the three areas into more effective rehabilitation robot control strategies, illustrated in Fig. 1. The studies surveyed in this paper are summarized in Table 1.

Control Techniques for Robotic Rehabilitation

Robots are used for upper-extremity rehabilitation because they are well suited to deliver high repetitions of precise movements and capture quantitative measures of movement coordination (see Blank et al. for a recent survey [5]). Despite these capabilities, existing robotic rehabilitation strategies offer limited benefits in clinical and functional outcomes when compared to conventional therapy [7,8]. Recently, a significant research focus in the field of robotic rehabilitation has been the development of novel control strategies that attempt to elicit improvements in motor coordination by modulating the robot behavior in response to the capabilities of the participant. This research has been performed with robotic devices including exoskeletons with varying degrees of freedom (DOF), for movements in two and three dimensions. Controllers have been tested with able-bodied participants, as well as those with SCI or stroke (see Table 1, top section, for a summary).

Impedance controllers are the basis for a large class of robotic rehabilitation control strategies. Impedance controllers modulate the dynamic relationship between force and motion and ensure safe physical interactions between the human user and the robot. In contrast, a position-based control scheme results in the robot following a prescribed trajectory while the human user simply “rides along.” Impedance controllers are preferred in rehabilitation applications because they facilitate the user’s engagement and participation in movement execution. An impedance control framework typically relies on a reference trajectory, and the controller provides force feedback based on that reference trajectory. Because of this approach, if a participant is able to complete the motion, the controller provides no force, and in this way, it acts as an “assist-as-needed” strategy. Pure impedance control still permits slacking on the part of the participant because the robot will follow the reference trajectory regardless of the participant’s contribution to movement execution. Various adaptations of “assist-as-needed” type controllers have been proposed to prevent slacking, with most approaches requiring an estimate of the ability of the participant to complete the movement, and then modulating the gains on the controller based on this estimate to promote engagement [9,10].

More generalized control strategies beyond the “assist-as-needed” paradigm have been proposed and evaluated in the context of robotic rehabilitation, including resistive and error augmenting controllers [11,12]. Studies discussed in this paper focus on assist-as-needed controllers, which provide a more intuitive connection to NMS modeling; however, other controllers for robotic rehabilitation could be adapted to incorporate myoelectric control and NMS modeling.

Clinical evaluation of these assist-as-needed type controllers for rehabilitation of the upper limb has been conducted in both stroke and SCI populations. In one study involving 17 participants with incomplete SCI, an assist-as-needed controller implemented on an upper-limb exoskeleton robot was compared to a subject-triggered controller [6]. The assist-as-needed controller allowed a variable amount of error on the motion and adapted the reference trajectory in real-time to challenge the participant. Recalculating the reference trajectory in real-time allowed the participant to deviate from the reference trajectory without a restoring force if the new motion was towards the goal. Despite demonstrating participant engagement and increasing levels of challenge with the novel controller, no statistically significant improvement in function was observed in the assist-as-needed control group compared to the subject-triggered control group after therapy intervention. More recently, an assist-as-needed controller was applied to rehabilitation of the upper limb of individuals following stroke [13]. The impedance-type controller implemented in this study included an adaptation law to vary the error gain, and a forgetting factor to limit slacking. This controller was tested in a therapy regimen with 6 stroke-impaired individuals, and there were no statistically significant improvements in functional ability outcomes. Further, the study did not use a control group receiving conventional therapy. Mounis et al. developed a method to estimate the functional ability of a subject based on the Wolf Motor Function Test using an exoskeleton and proposed a decaying control law based on this estimate. Results show success in estimating the functional ability similar to clinical evaluations, but the subsequent controller was only evaluated in a simulation environment and not with robotic hardware [14].

Additional novel control strategies to promote participant engagement in robotic rehabilitation have recently been proposed though not yet evaluated with motor impaired populations. One strategy suggests ways to adapt the task, assistance, and visual feedback based on the participant's ability [15]. Another proposed control strategy uses machine learning to determine a subject's ability to complete a task and adjusts the assistance based on the determined ability of the subject [16]. Because these controllers rely on reference trajectories, they do not attempt to determine user intent but rather only attempt to predict user capability. To improve robotic rehabilitation, researchers will likely need to incorporate control strategies that directly detect user intent. One promising approach is the use of the individual's own muscle excitations, measured with electromyography (EMG), as a means to use physiological signals for intent detection.

Myoelectric Control: Utilizing Physiological Signals

Myoelectric control relies on the detection of electrical activity from muscles, often through the use of surface electrodes placed on the skin over the muscle belly, to determine the intended action of the human and transform this action into corresponding commands to the support robot. These EMG signals serve as the inputs to a given control strategy that generates the resulting action to be taken by the robot. This approach is commonly used in human-robot interaction and human intent detection applications ranging from the intuitive control of prosthetic limbs to assistive exoskeletons (see Bi et al., 2019 for a review) [17]. Use of EMG signals as inputs to a robot control system presents a number of technological challenges for implementation. These include ensuring consistent placement of electrodes over time; variable EMG signal quality, especially in impaired populations; and development of model-based or machine learning approaches to convert signals to useful control inputs [17]. Despite these challenges, myoelectric control is increasingly used for the purpose of decoding motion and intent, predicting movements, and controlling assistive and therapeutic robotic devices.

Decoding focuses on analyzing EMG signals along with limb kinematics to determine how the EMG signals map to movement. This operation can be performed to determine mappings between EMG and joint positions, joint velocities, or joint torques. Liu et al. demonstrated the ability to decode shoulder, elbow, and wrist angles in both able-bodied and stroke-impaired populations [18]. Decoding operations can also be used to predict the participant's attempt to move via increased EMG signal amplitudes, or intended movement directions for isometric movements [19]. Decoding is a process that can be done offline (after data has been collected), or it can be used for real-time intent detection and classification as part of a robot control scheme. A recent example demonstrated the detection of movement onset in one of two pre-defined directions based on EMG signals from seven muscles of the upper limb as a proof of concept for real-time control of an assistive exoskeleton [20]. While the study documented the viability of the algorithm for offline use, the authors discussed its applicability for real-time control of an exoskeleton. Others have used high-density EMG and classification algorithms to decode twenty arm and finger/thumb movements in stroke-impaired individuals [21].

Motion prediction takes things a step further, attempting to predict the intended *future* motion of the limb based on real-time acquisition of EMG-signals. Like decoding, motion prediction maps EMG-signals to joint angles, velocities, or torques, with the objective being real-time movement prediction based on time-varying EMG signals acquired from a set of electrodes. This real-time prediction remains an open problem, with some recent progress showing the viability of recursive algorithms to predict both basic and dynamic wrist motions that resemble those involved in activities of daily living. Despite the intention for prosthesis control, this work has only been demonstrated in an offline mode and remains to be implemented in real-time [22].

Myoelectric control of a robot uses the decoding and predicting concepts described above to interpret the intentions of the participant and subsequently command a robot to achieve the desired movement. Most work in myoelectric control has been for prosthetics and powered orthotics applications, where EMG signals are acquired from intact muscles of the amputee and used to control a prosthetic arm [23] or an assistive exoskeleton for achieving hand dexterity [24]. In most applications of myoelectric control, the EMG signals are used as direct inputs to a controller, or machine learning algorithms are used to classify EMG signal features and determine the intended action to be taken.

Only recently have groups started to use EMG signals as an input to a rehabilitation robot intended to restore function, primarily with the goal of maintaining user engagement like that achieved through impedance type assist-as-needed controllers. Sarasola-Sanz et al. noted that using pathological EMG signals from the paretic limb of an individual post-stroke would likely lead to pathological motion, so they examined using EMG signals from the healthy limb and mirroring the signal to assist movements of the paretic limb in a rehabilitation scenario [25]. Lambelet et al. developed the eWrist, a portable wrist exoskeleton that combines force and myoelectric control in an assist-as-needed control strategy [26]. Pilot evaluation with able-bodied participants demonstrated the validity of the approach, but additional work remains to evaluate the benefit of myoelectric control of the eWrist for rehabilitation applications. In related work, McDonald et al. demonstrated the potential of EMG sensing for intended movement direction detection in individuals with SCI using an upper limb exoskeleton, but they did not incorporate the approach into a rehabilitation control scheme [19]. Teramae et al. developed a myoelectric plus assist-as-needed controller that estimates user torque with EMG-signals and combines this estimation with a model predictive control scheme, recalculating a new optimal trajectory at each instant in time [27]. Despite the potential of these personalized, EMG-based control strategies, degraded performance has been observed when these techniques are applied to individuals with stroke or spinal cord injury [19]. This degraded performance motivates the need for more accurate prediction of motion from EMG signals in individuals with stroke or spinal cord injury, especially to achieve real-time robot myoelectric control in a rehabilitation setting.

Neuromusculoskeletal Modeling: Combining Myoelectric Control with Physics
NMS modeling uses physics and physiological models to map EMG signals into individual muscle forces or moments and potentially into motion predictions. For a more detailed overview

of NMS modeling, the reader is directed to [28]. For upper extremities, NMS modeling has been used for both motion prediction and control involving various number of DOFs and for individuals with intact limbs and for those with amputations (see Table 1, top section, for a summary). Because of its basis in physics and physiology, NMS modeling can provide a more accurate and robust prediction of motion than machine learning methods [29,30]. NMS modeling also allows for extrapolation to situations outside of available data because of its grounding in laws of physics and principles of physiology, something machine learning techniques cannot achieve.

Recent work using NMS models for motion prediction has focused on motion in the wrist and hand, with work on 2 and 3 DOF systems. In 2015, a simplified NMS model was used to predict 2 DOF motions in the wrist and hand using a limited number of EMG-signals [31]. Though this technique was used for myoelectric prosthesis control, the results can be extrapolated to other areas such as robotic exoskeletons. In 2017, this work was expanded to include a third DOF to predict wrist and hand motion offline [32]. Other recent motion prediction work has focused on evaluating different model variations, specifically for EMG-to-activation dynamics [33]. Given their ability to estimate internal forces and moments, which are closer physically to body motion than are EMG signals, NMS models are likely to be better suited than machine learning models for use in myoelectric controls schemes. Physics-based NMS models interpolate and extrapolate well from experimental data whereas machine learning models only interpolate well.

Combining rehabilitation robots, myoelectric control and NMS modeling has the potential to create more effective, robust, and personalized robotic rehabilitation treatments. While studies have already examined myoelectric control for rehabilitative robotics, the fact that EMG based motion classifiers perform worse for individuals with motor impairments is concerning for further progress in the field. In contrast, personalized NMS models allow for physically and physiologically accurate mapping of EMG signals to joint moments and motion for both able-bodied individuals and those with motor impairments.

How, then, could rehabilitation robots, myoelectric control, and NMS modeling be combined to support the design of personalized rehabilitation interventions? One approach is based on the concept of “computational neurorehabilitation,” a term coined by Reinkensmeyer et al. describing the use of computational models to predict how neuroplasticity and motor learning would occur in an individual patient over time as a result of a rehabilitation intervention [34]. An advantage of this approach is that the robot control strategy could be adapted gradually over time to support the patient’s changing needs throughout the therapy process. An associated disadvantage is that an explicit model is required of how the patient’s neural control strategy adapts over time, which is a challenging modeling problem, especially when representing specific patients. An alternate approach involves predicting a potentially achievable neural adaptation that would produce a desired functional outcome, and then seeking to drive the central nervous system in that direction through robotic rehabilitation [35]. This approach would not predict gradual neural control changes over time, and it requires assumptions about which aspects of a patient’s neural control strategy are, and are not, changeable through therapy. However, it involves a simpler predictive modeling approach that can already represent specific patients and has the potential to predict personalized rehabilitation strategies in the near future [36,37]. Both approaches provide exciting avenues for future research at the intersection of rehabilitation robots, myoelectric control, and NMS modeling.

While the prediction capabilities of NMS modeling are important, these models must have real-time capabilities if they are to be used for robot control purposes. Because of the complexity of a typical model, this problem is not trivial. However, recent work has shown promise in achieving real-time control using NMS models. Crouch et al. successfully implemented their 2 DOF model as a controller in a virtual environment and had subjects complete a path tracing task with EMG-signals as the only control input [38]. Boungiorno et al. examined whether a simplified model with only one subject-specific parameter per muscle could provide accurate motion predictions. Their results showed that the simplified model functioned comparably to a more complex model and would be more suitable for real-time control applications [39]. Sartori et al. achieved real-time control of a physical prosthetic device using NMS modeling with a 3 DOF wrist and hand model [40]. Recently, Blana et al. showed the feasibility of real-time control of finger movements using an NMS model [41].

While the above studies achieved real-time control, results were achieved with able-bodied individuals rather than those with stroke or SCI. Similar to the machine learning techniques discussed above, it is important to examine NMS modeling capabilities for stroke and spinal cord injury rehabilitation applications. Multiple recent studies have reported work in this area for lower-limb control [36,42,43]. However, the authors could not find any studies examining the application of NMS modeling to upper-limb robotic rehabilitation for individuals with a stroke or spinal cord injury. The extensive work modeling lower-extremity motion has demonstrated that personalized NMS models can correctly predict motion for individuals with stroke or spinal cord injury [36,42]. Recently, Durandau et al. not only predicted motion with an NMS model but also successfully controlled a lower-extremity exoskeleton with a controller based on an NMS model in individuals with stroke and spinal cord injury [43].

Conclusion and Future Directions

This review has focused on the most recent work in the areas of rehabilitative robotics, myoelectric control, and NMS modeling. While novel assist-as-needed control algorithms have been shown to engage neurologically impaired individuals during upper-limb robotic rehabilitation, clinical studies have not demonstrated statistically significant improvements in functional outcomes as a result of these interventions. Measuring an individual’s muscle activity via electromyography has been shown to be a viable method of detecting movement intent and predicting intended arm movements; however, the machine learning algorithms on which these methods are based do not perform as well when used with individuals who have suffered neurological injuries like stroke and spinal cord injury. NMS models can predict internal muscle forces and moments from EMG and kinematic measurements, providing robot control inputs that are closer physically to body motion than EMG signals. To date, NMS modeling-based control algorithms have not been implemented for real-time control of upper limb rehabilitation robots, though recent studies have shown promise in using NMS modeling to predict motion and control lower-extremity exoskeletons for individuals with stroke or SCI.

The physiological basis of NMS modeling provides many other potential benefits to the field of rehabilitative robotics. Rather than simply providing assistive torques based on deviations from a reference trajectory, control strategies based on NMS modeling might produce new robotic rehabilitation control methods that can facilitate both movement compensation and movement restoration, either based on assist-as-needed controllers or for other paradigms that introduce challenge (e.g. error augmentation, resistance). From a compensation standpoint, an NMS model-based control strategy could calculate the user-provided torque and determine the robotic torque necessary to achieve the desired movement. From a restoration standpoint, an NMS model-based control strategy could determine the EMG-signals required for the desired motion and develop a personalized strategy aimed at restoring those proper EMG-signals.

As an example, model-based control methods that utilize a subject's real-time EMG and kinematic data could facilitate the design of personalized assist-as-needed robot controllers that eliminate the "slacking" problem and the need for predefined motion trajectories [44]. Recent improvements in EMG-driven modeling now make it possible to construct subject-specific neuromusculoskeletal models that can reproduce a subject's experimentally measured motion when driven by the subject's experimentally measured EMG signals [36,37,45]. One possible way to use such models to design personalized assist-as-needed robot controllers that eliminate slacking and the use of predefined motion trajectories is outlined below:

1. Have the subject perform a specified task as well as possible without robotic assistance while collecting experimental EMG and kinematic data.
2. Personalize an EMG-driven neuromusculoskeletal model to the subject's EMG and movement data. The personalized model will be able to predict the subject's experimentally measured motion when the subject's experimental EMG data are used as inputs. The personalized EMG-driven model will also automatically account for the subject's abnormal neural control strategy.
3. Predict minimal changes in the subject's EMG signals such that the subject completes the desired task, and calculate the corresponding changes in the subject's joint moments. The personalized EMG-driven model would be used to develop these predictions, which represent the subject's minimal neural control changes that will achieve the desired task. While the predicted EMG signals will likely remain abnormal, they will also likely be more achievable by the subject than would healthy EMG signals.
4. Create a linear regression model that estimates the predicted changes in the subject's joint moments as a function of the subject's EMG signals. This model will be different from existing proportional myoelectric control approaches that scale a single EMG signal to calculate the applied robot control torque at a particular joint [46].
5. Develop an assist-as-needed robot controller where the applied robot control torques are calculated by the linear regression model based on the subject's current EMG signals. If the subject "slacks" and does not generate sufficiently large EMG signals, then the robot control torques needed to complete the task will not be generated. Furthermore, knowledge of a pre-defined motion trajectory will not be required.
6. Over time, gradually withdraw the assistive robot control torques with the hope that the subject will gradually learn the minimal EMG changes needed to achieve the task.

While the personalized robot controller design approach outlined above holds promise, significant research is still needed to bring together the neuromusculoskeletal modeling and experimental elements required to implement it.

Future work in rehabilitation robotics should begin developing and testing control strategies that combine myoelectric control with NMS models. As discussed here, the area of NMS modeling in upper-extremity rehabilitation has been largely unexplored yet shows great potential to achieve better functional outcomes than the current state-of-the-art robotic rehabilitation as well as traditional therapy.

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Tables and Figures

Table 1: Recent studies examining robotic rehabilitation, myoelectric control, or neuromusculoskeletal modeling.

	Study	Joints	EMG	Population	NMS Model	Control	Control Implementation
Robotic Rehabilitation	Pehlivan 2015 [9]	E,W	N	H	N	C	R
	Frullo 2017 [6]	E,W	N	C	N	C	R
	Stroppa 2017 [16]	S,E	N	H	N	C	R
	Agarwal 2019 [15]	H	N	H	N	C	R
	Mounis 2019 [14]	S,E	N	S	N	C	S
	Oliveira 2019 [13]	S,E,W	N	S	N	C	R
Myoelectric Control	Zhang 2012 [21]	E.W.H	Y	S	N	P	NA
	Lambelet 2017 [26]	W	Y	H	N	C	R
	Meeker 2017 [24]	H	Y	S	N	P	R
	Bakshi 2018 [22]	W	Y	H	N	P	NA
	Sarasola-Sanz 2018 [25]	S,E,W,H	Y	S,H	N	P	NA
	Teramae 2018 [27]	E	Y	H	N	C	R
	Trigili 2019 [20]	S,E	Y	H	N	P	NA
	Liu 2020 [18]	S,E,W	Y	S,H	N	P	NA
	McDonald 2020 [19]	E,W	Y	C,H	N	P	NA
NMS Modeling	Crouch 2015 [31]	W,H	Y	H	Y	P	NA
	Crouch 2016 [38]	W,H	Y	H	Y	C	S
	Pan 2017 [32]	W,H	Y	H	Y	P	NA
	Sartori 2018 [40]	W,H	Y	A,H	Y	C	R
	Blana 2020 [41]	H	Y	H	Y	C	R

Joints: S = shoulder, E = elbow, W = wrist, H = hand involved in the study

EMG: Y = yes, N = no if EMG signals were acquired from the participants

Population: H = able-bodied/intact, S = stroke, C = spinal cord injury, A = amputee

NMS (neuromusculoskeletal) Model: Y = yes, N = no if NMS models were used

Control: C = control action is computed, P = prediction of movement only

Control Implementation: When control action is computed, was implementation S = simulation only, or R = with robotic hardware

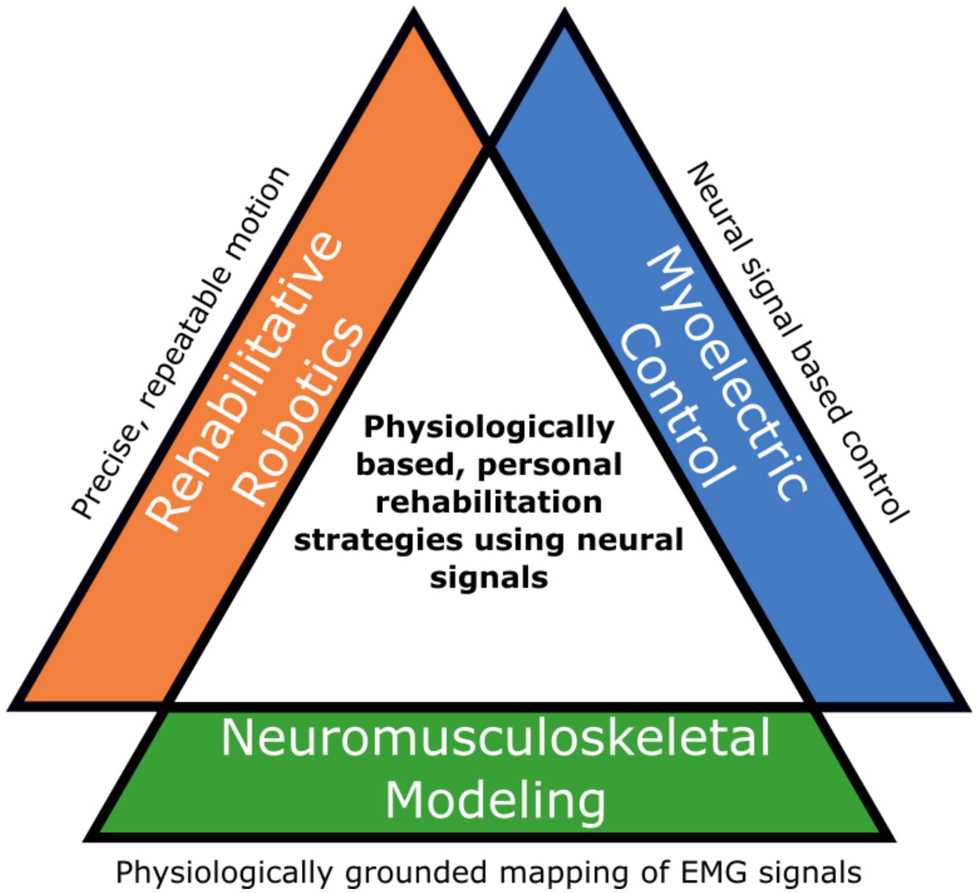

Figure 1: Venn diagram showing the intersection of robotic rehabilitation, myoelectric control, and neuromusculoskeletal modeling.