ASSISTANCE REGULATION IN WEARABLE ASSISTIVE DEVICES

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I. INTRODUCTION

Muscle loss and motor skill degradation, two common outcomes of old age and neurological diseases such as stroke affect millions of individuals around the world. In fact, it is estimated that over 200000 Canadians suffer a variety of impairments due to strokes alone [1]. Motor skill impairments in particular can substantially limit the ability of many such individuals to work, participate in recreational activities, or even perform the activities of daily living. Assistive devices (ADs) have been shown to increase the autonomy and quality of life of these individuals, and to reduce home care costs and caregiver burden [2].

Devices such as canes, walkers, and powered exoskeletons are all examples of the broad class of devices classified as ADs. However, powered ADs such as actuated orthoses and exoskeletons have been the focus of substantial recent research [3-13]. In addition to the benefits described above, these devices also have the potential to lower rehabilitation therapy costs, and to promote neuromuscular recovery. However, this last benefit – promoting neuromuscular recovery – is unlikely to be realized using the muscle amplification control strategies commonly employed on many powered ADs [5-8, 10-12].

Muscle amplification control strategies typically result in ADs that amplify the user's strength and drastically minimize the effort required to complete a particular task. Prolonged use of such devices may result in unintentional detrimental effects such as muscle atrophy or reduced functional capacity – these devices may provide users with too much assistance. Furthermore, it is also well known that maintaining an appropriate level of exercise intensity is fundamental in facilitating neuromuscular recovery during rehabilitation therapy [14]. Thus, it is important to account for user effort regulation when designing an AD controller. This ensures that the AD provides the user with the immediate assistance required to perform the desired motion or task, and promotes functional recovery (or helps sustain functional capacity) as a result of prolonged use.

This paper presents the concept of a powered AD controller designed to help facilitate functional recovery via direct regulation of user effort and task-independent assistance modulation. Section II provides an overview of common AD control strategies, while Section III presents the proposed controller – the assistance regulator - and its realization for a powered knee orthosis. Simulation results are presented and discussed in Section IV, and the paper concludes with a summary of the results and a brief discussion of future work in Section V.

II. CHALLENGES IN ASSISTIVE DEVICE CONTROL

The desired motion of an AD is typically prescribed in real-time using user-supplied input signals such as interaction forces measured at user-device interfaces or surface electromyography (sEMG) signals [3-13]. The key challenge in assistive device control is in predicting the user's desired motion (i.e., the desired trajectory of the user's joint that corresponds to what the user is thinking about doing). Accurate estimates of desired motion provide a means for systematically prescribing the appropriate assistance magnitude and timing. However, both interaction forces and sEMG signals are poor predictors of desired motion. In fact, sEMG signals are best used as predictors of user effort [3-4, 10-11] or muscle force/joint torque [5-7, 9].

The challenges in predicting desired motion have in part led to the muscle amplification control strategies commonly used on many powered ADs [3, 5-7, 10-12]. Some muscle amplification strategies use sEMG signals to predict joint torques, and command actuator torques proportional to the estimated joint torques [5-7]. Simpler approaches such as commanding actuator torques proportional to sEMG signal amplitudes have been presented in [10-11]. Alternatively, more complex methods employing learning algorithms to learn the relationship between sEMG signals and the user's intended motion have also been considered in [3]. However, we note that few researchers directly address the importance of regulating user effort in designing AD controllers. Accordingly, most AD controllers may not be efficient at promoting functional recovery and extended use may result in unanticipated detrimental effects.

III. ASSISTANCE REGULATION IN WEARABLE ASSISTIVE DEVICES

This section presents the knee joint and orthosis models used for simulation purposes and a new AD controller designed specifically to help regulate user effort. The proposed controller – the assistance regulator (AR) – consists of a modified AD impedance control algorithm previously presented in [13] and relies on measurements of the user's joint torque to modulate the assistance provided to the user. For the sake of simplicity, the following presentation assumes that these joint torque measurements are readily available. In practice, these measurements may be obtained from empirically derived muscle models that relate joint torques (or muscle forces) to sEMG signals [5-7, 9].

Knee and Orthosis Models

Consider the situation in which a user sitting on a chair uses a 1 DOF powered orthosis to assist knee flexion and extension. Both the lower leg and orthosis may be modelled as parallel 2nd order rotational systems [4]:

$$J_k\ddot{\theta}_k + b_k\dot{\theta}_k + m_k g l_k \sin(\theta_k) = -\tau_{int} + \tau_{knee} \quad (1)$$

$$J_e\ddot{\theta}_e + b_e\dot{\theta}_e + m_e g l_e \sin(\theta_e) = \tau_{int} + \tau_m \quad (2)$$

where J, b, m, g and l represent the moment of inertia, viscous damping coefficient, mass, gravitational acceleration, and the center of mass offset, respectively, and τ_{int}, τ_m and τ_{knee} represent the reaction torque due to the interaction force, the torque applied by the motor, and the knee torque generated by the user's muscles, respectively. The subscripts k and e indicate the knee joint and exoskeleton properties, respectively.

In practice, the reaction torque can be estimated using a force sensor at the user-device interface. However, during simulation, the interaction force is modeled as:

$$\tau_{int} = P(\theta_k - \theta_e) + D(\dot{\theta}_k - \dot{\theta}_e) \quad (3)$$

where P and D correspond to the expected stiffness and damping at the user-device interface.

The user's behavior was modeled using the human motor behavior model described in [15]. We note that models of this type have been validated using motor adaption experiments and are primarily suitable for explaining steady state behavior after motor adaptation [16].

Assistance Regulation using a Virtual Impedance Model

The virtual impedance model shown below specifies the desired dynamic behavior of the orthosis. This model can be integrated in real-time to specify the reference trajectory of the orthosis. Assuming a rigid connection at the user-device interface, perfectly tracking this reference trajectory implies that the orthosis - and by extension the knee joint itself - exhibits a particular impedance.

$$K_1\ddot{\theta}_{ref} + K_2\dot{\theta}_{ref} + K_3\theta_{ref} = \tau_{int} + \tau_{virtual} \quad (5)$$

where K_1, K_2 and K_3 are constants chosen to achieve the desired knee joint dynamic behavior, and $\tau_{virtual}$ is an additional term used to modify the behavior of the controller. In particular, defining $\tau_{virtual}$ as shown below provides a convenient means for regulating the user effort (via regulation of knee torque).

$$\tau_{virtual} = \begin{cases} 0 & \text{if } \sigma_l < \tau_{knee} < \sigma_u \\ \beta(\tau_{knee} - \sigma_l) - \alpha\dot{\theta}_e & \text{if } \tau_{knee} \le \sigma_l \\ \beta(\tau_{knee} - \sigma_u) - \alpha\dot{\theta}_e & \text{if } \tau_{knee} \ge \sigma_u \end{cases} \quad (6)$$

where α, β, σ_l and σ_u refer to the damping gain, proportional gain, and lower and upper assistance triggers, respectively. In general, the assistance triggers would correspond to limits on the maximum and minimum allowable muscle-generated joint torque. For the simulation experiments considered in this paper, the upper and lower assistance triggers correspond to the maximum and minimum allowable knee torques, respectively, for any arbitrary motion the user attempts to generate.

Substituting (6) into (5) indicates that the controller provides no assistance anytime the user's knee torque is bounded between the two trigger values. However, as soon as the user's knee torque falls outside the trigger range, the user is provided with additional assistance in proportion to the difference between the user's knee torque and the corresponding trigger's magnitude. Thus, (6) attempts to regulate the user's knee torque to lie within the torque range specified by the upper and lower assistance triggers.

High values of β would result in rapid changes to the assistance provided to the user that would make the AD difficult to control. Accordingly, (6) contains damping terms that are used to help minimize oscillations, and reduce the likelihood of an unstable interaction developing between the user and the AD.

IV. SIMULATION RESULTS AND DISCUSSION

The primary goal of the simulation experiments was to compare the difference between using our AR and the muscle amplifying controller described in [6]. The user's impairment was modelled by limiting the user's knee torque to +/-1.5 Nm, while σ_u, σ_l, β and α were set to 1 Nm, -1 Nm, 30 and 7 Nm·s/rad, respectively.

Figures 1 and 2 provide results for large and small amplitude knee motions. It is clear from Figure 1 that both the muscle amplifying controller and the assistance regulator allow the user to track his/her desired motion quite easily. However, it is important to note that the AR was supposed to regulate the user's knee torque to lie approximately between +/-1 Nm, while the muscle amplifying controller gains were tuned to maximize muscle effort during the large amplitude motion test. Accordingly, the muscle amplifying controller provokes more user effort than the AR in the large amplitude motion test. However, the AR does succeed in helping regulate the user's knee torque to approximately 1.15 Nm after the initial transient period.

Figure 2 provides results for a small amplitude motion test conducted using the same controller gains. Again, both the AR and muscle amplifying controller track the desired motion of the user. In this case, however, the muscle amplifying controller provides excessive assistance, while the AR maintains the knee torque close to the desired value of 1 Nm. These results indicate that the AR is capable of regulating the desired level of user effort even when there is a drastic change in the torque requirements of the activity.

Higher values of β could be used to reduce the steady-state knee torque regulation error. However, we note that strict regulation of the user's knee torque is not essential to the fundamental goal of regulating the user's effort as a means of maintaining a sufficient exercise intensity level that may help promote functional recovery in the long run. Additionally, excessively large values of β may result in an unstable interaction between the user and the device.

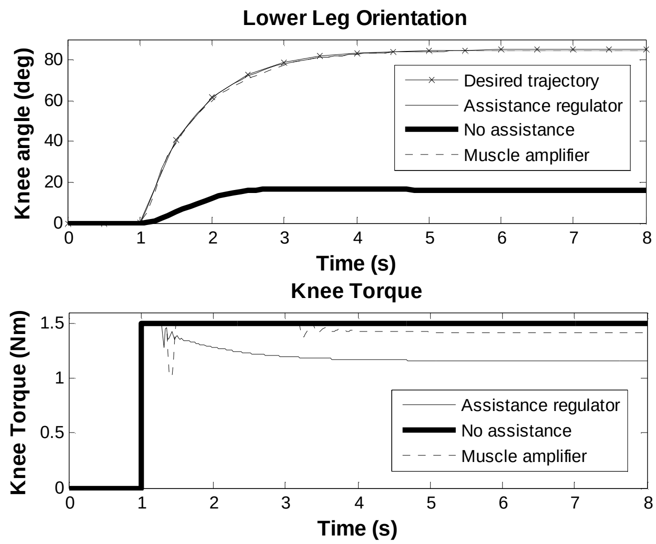

Figure 1: Large Amplitude Knee Motion

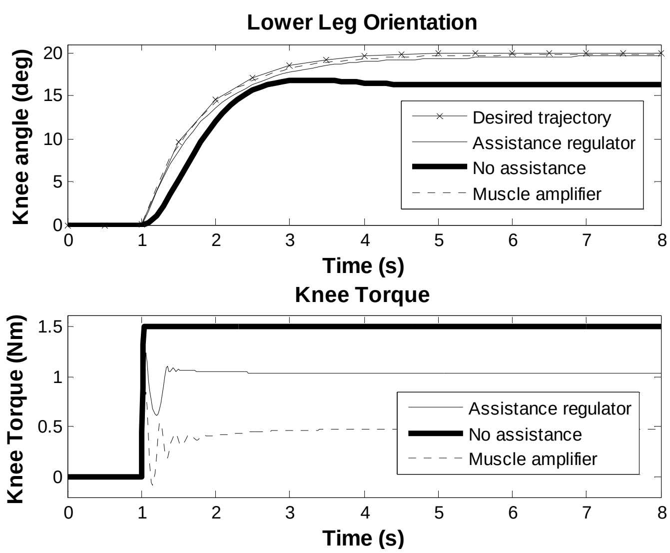

Figure 2: Small Amplitude Knee Motion

The sEMG-driven forearm AD controller described in [4] is perhaps the only similar AD controller designed for active assistance regulation. In [4], the reference trajectory of an impedance controller was manipulated in order to provide the user with more assistance anytime a therapist specified sEMG signal threshold was exceeded. Thus, the controller regulated user effort in the sense that the user was required to provide the effort required to sustain any motion whenever this threshold was not exceeded.

However, the controller did not allow for precise regulation of user effort, and was vulnerable to factors like muscle co-contraction and the joint angle dependence of muscle force. Additionally, another drawback of this approach – and of similar approaches such as in [13] – was the researchers' choice to use fixed impedance controller gains.

Fixed impedance controller gains, like fixed amplification gains, are undesirable since they generate a fixed input-output relationship between the user's joint torque and angle. Since the user's joint torque capacity remains constant regardless of the activity's torque requirements, low gains will ensure sufficient user effort during the completion of one task, but the same gains may be insufficient for assisting the user in completing a higher intensity task. High gains will ensure sufficient assistance during the completion of high-intensity tasks, but the same gains will provide excessive assistance for low-intensity tasks; the performance of the muscle amplifying controller in Figures 1 and 2 above is a perfect example of this behavior.

These tradeoffs can be overcome by using different gains for different tasks. However, using task-dependent controller gains introduces its own challenges. ADs are usually designed to assist users in a wide range of tasks with highly variable torque requirements. Thus, simply defining the appropriate gains for each task is itself a significant challenge. Furthermore, using task-dependent controller gains introduces additional control complexity and sensing and computation overheard due to the need to identify what task the user is performing and which controller gains need to be used at any given instant. In contrast, the AR presented in this paper avoids these challenges because it automatically adapts to the torque requirements of the task. As a result, the tradeoff between using low and high impedance (or amplification gains) is avoided altogether.

V. CONCLUSIONS AND FUTURE WORK

Regulating user effort and ensuring sufficient exercise intensity are two important factors that can aid in facilitating functional recovery. This paper has presented a new AD controller designed specifically for addressing these two challenges. Unlike the muscle amplifying controllers typically used on many ADs, simulation results with our proposed controller, the assistance regulator, indicated that our controller successfully regulated the user's joint torque with small steady-state errors, and automatically adapted to the torque requirements of the task. In the future, an experimental apparatus currently under development will be used to validate the simulation experiments. Additionally, these experiments will be used to determine how factors such as inaccuracies in joint torque estimates and noisy interaction force measurements affect the overall performance of the controller.

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