Towards Adaptive Impedance Control for Upper-limb Prostheses

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I. Motivation and Background

Consider the simple task of holding an umbrella on a rainy and windy day. Forces arise from the *physical interaction* between the umbrella, the human hand, and any perturbation imposed by the wind. To ensure a stable interaction with the umbrella and the wind, humans increase their limb impedance (i.e., stiffness, damping, and inertia) by co-activating antagonist muscles [2]. Other tasks, e.g., placing a peg in a hole, may require limb compliance to limit the interaction forces and afford lower manipulation precision. The importance of enabling such adaptive behaviour on a robot manipulator physically interacting with the environment is well-known in the robotics community [3]. In physical human-robot interaction (pHRI), modulation of the robot's impedance is desirable for robustly and safely interacting with humans. This requirement is pronounced in motor prostheses control, the long-term motivation for the work described here, for two reasons: the robot (prosthesis) physically interacts with the environment; the human motor intent has to be implemented on the prosthesis.

While there has been considerable progress in designing upper-limb prostheses that have hardware compliance, none allow the user to voluntarily modulate the impedance of a single Degree of Freedom (DoF) of the robot. This is due to the difficulties in decoding the human motor intent from surface electromyographic (sEMG) signals. In fact, despite being the most widely used non-invasive human-machine interface, surface electromyography provides noisy low-bandwidth signals. Another major difficulty is the non-unique association between changes in muscle activations (i.e., sEMG signals) and the changes in joint kinematics and dynamics. Due to the high complexity and redundancy of the neural musculoskeletal system, the same motion can be performed at different levels of contraction of the muscles (i.e., joint impedance).

State-of-the-art methods for the control of commercial prostheses learn a direct mapping from sEMG signals of antagonist muscles to desired joint kinematics [4] in an offline training phase. While effective for up to 2-DoF control, these methods do not represent or use information about the human joint impedance in the controllers. As a result, performance deteriorates in practical settings, when physical interactions with the environment require the user to continuously adapt muscle contractions to control the prosthesis. In such settings, the features of the EMG signals change drastically from those observed during training.

Methods developed to provide simultaneous control of joint kinematics and impedance often employ sEMG-driven muscle-tendon units (MTUs) to include domain knowledge about muscle contraction dynamics. The MTUs provide an estimation of the muscle-tendon forces and impedance from which the joint kinematics, and impedance can be obtained. However, existing methods only use partial information from these models [5], [6]. Typically, only the MTUs forces are used to compute the joint net torque and derive the joint kinematics. Joint stiffness from MTUs is ignored and estimated as a polynomial function of sEMG signals; damping is omitted or computed as a function of stiffness. Moreover, the estimated joint impedance is not directly used to implement a variable impedance controller, but stiffness and damping are tuned during a calibration stage to ensure the controller's stability. This approach requires multiple calibration phases often separate from the optimization of the MTUs, and it creates a mismatch between the dynamics of the muscle-tendon model (i.e., the intended human impedance) and the dynamics of the robot. This affects the user's control performance and limits the transparency of the control methods.

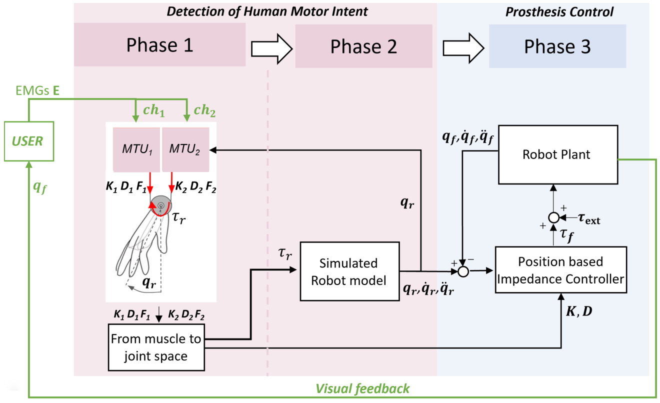

Fig. 1: Overview of framework architecture.

II. Framework overview

Toward addressing the aforementioned limitations, we present AIC-UP, an sEMG-driven framework (Fig. 1) that *provides the user with three Degrees of Control (DoC) for a DoF*. AIC-UP makes the following contributions:

- It decodes the human motor intent about wrist flexion-extension as joint kinematics, stiffness, and damping, and implements the motor intent on a simulated 1-DoF robot (i.e., robot plant). The *detection of human*

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motor intent block includes the MTUs and maps the sEMG signals ch_1 and ch_2 to an estimate of the user's motor intent as joint position q_r, joint stiffness K, and damping D. The inertia is assumed to be the natural inertia of the robot. The *prosthesis control* block executes the estimated motor intent through a robot system based on a variable position-based impedance controller, allowing online motion control and adaptation of the simulated robot's impedance. The robot's plant joint position q_f is the visual feedback given to the user. The variable impedance controller implicitly allows the user to counter external perturbations using K and D predicted from the MTUs. Notice that the MTUs are virtually attached to the "simulated robot model", which is unaffected by external perturbations. If τ_{ext} is not null, q_f will start drifting from q_r. The subject may use the visual feedback to modulate the motor commands and achieve the desired control behaviour. As the simulated robot model and the (simulated) robot plant, we choose to use a generic manipulator, the Puma robot 560 and control its second DoF.

- In a departure from existing work, we ensure that the *human intended dynamics* (first block) matches the robot's dynamics (second block), by using K and D estimated from the MTUs to implement the dynamic behaviour of the robot plant. This design choice enhances the transparency of the control methods.
- We tackle the ill-posed problem of estimating the value of the MTUs' parameters by making structural assumptions on MTUs, and by designing an optimization framework that includes the impedance controller. The join position q_f, which is affected by K and D, is used as the optimizations signal.

III. Experimental Evaluation

AIC-UP's performance is evaluated during online reaching tasks in static and dynamic environments with eight able-bodied subjects and a transradial amputee. We investigated whether the users could *exploit stiffness and damping adaptation to counter perturbations in the form of force fields that push the simulated wrist away from a target*. We compared AIC-UP to a baseline method comprising a neural network that learns and predicts the joint kinematics from sEMG signals followed by a fixed-gain high stiffness controller to track the estimated motion on the robot [4]. Our framework and the baseline are trained on the same dataset, i.e., the sEMG signals from the wrist flexor and extensor, and the corresponding reference wrist flexion-extension; this includes repetitions of the wrist flexion-extension at low and high levels of coactivation of muscles. Following the online control testing with able-bodied subjects, we experimentally demonstrated that:

- AIC-UP supports online adaptation of the simulated robot kinematics and dynamics in response to external disturbances.
- AIC-UP performance is comparable to that of the baseline in the absence of perturbations, and substantially better in the presence of perturbations.

  Moreover, we investigate the users' perception of controllability provided by the two methods. The users' feedback, consistent with the quantitative results, indicated that AIC-UP provides improved performance compared with the baseline. Here "controllability" refers to robustness and responsiveness to fast-changing features of the sEMG signals, and to the user's ability to stabilise the system after an external perturbation.

Although our framework was only tested with a single amputee, the corresponding results matched those of the able-bodied participants. This is a promising result, especially considering the participant's difficulties in perceiving differences in muscle co-contraction due to amputation. This result indicates that our framework may provide more intuitive control and implement features crucial for enhancing controllability. For more details about the framework and results, see [1].

IV. Conclusions and Future Work

We have presented a novel framework AIC-UP that supports the control of joint kinematics, stiffness, and damping, and we have provided experimental evidence that AIC-UP allows for superior controllability of the joint in the presence or absence of unexpected perturbations. Current and future work will address multi-DoF control. The extension to multiple DoFs of the wrist is straightforward within the framework, but experimental validation would be needed to investigate suitable input activations to additional MTUs and prove controllability in more challenging conditions. While upper-limb prostheses control is the motivating application domain, the framework is relevant to other rehabilitation devices, to other pHRI scenarios (e.g., teleoperation), and to robot manipulation applications (e.g., the design of variable impedance controllers).

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