The 7th International Conference on Multibody System Dynamics
June 9-13, 2024, Madison, WI, USA

A holistic human motor control model for predictive control of assistive robots

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Abstract
Humans are highly dexterous and agile in their interactions with the environment. To develop assistive robots that aid humans in their interactions, the first step is to understand, and model, the human motor control system. Here I present a holistic mathematical model for human motor control, which encompasses multiple levels of control, from high-level decision-making to low-level muscle and skeletal dynamics. This holistic model incorporates various known neural and biomechanical processes, which increases its biofidelity and predictive power. The model also runs faster than real-time, making it a suitable choice for the predictive control of assistive robots.

Introduction
Tool use and dexterous motor function are at the core of humans' daily activities, and the ultimate objective of assistive robots is to aid humans in such physical tasks. To achieve this goal, understanding, and modeling, how humans control their movement is the necessary first step. Such a predictive model can then provide the robot with the necessary information to anticipate how the user will act, and more importantly, how they will react to the "disturbances" that come from the robot. The challenge is that human movements are the emerging behavior of a complex dynamical system that constitutes the neural, muscular, skeletal, and sensory systems, which interact with the environment in a closed-loop manner. Further, motor adaptation and neuroplasticity also affect how the sensorimotor apparatus responds to a stimulus over time. Existing musculoskeletal models can predict movements well in a given context, such as steady-state gait [1], but they rely on non-linear optimization algorithms—a slow process that lacks biofidelity and is often incapable of extrapolating beyond the optimized contexts (e.g. responding to disturbances). Instead, we need a *holistic*, *biofidelic*, and *real-time-solvable* model of human movements for the predictive control of robots.

Here I present a novel model for human movement with these requirements in mind. This *holistic* model of human movement encompasses multiple levels of detail in the human sensorimotor system; it is based on neuroscientific theories such as internal models and optimal sensorimotor integration for decision-making and action planning, as well as biomechanically plausible details of the neuromusculoskeletal system. Therefore, this model enables distinguishing the contributions of various levels of the sensorimotor system in movement control.

Model description
This holistic model consists of multiple modules (Figure 1**A**), representing different "levels" of control that work together cohesively in a close-loop manner (Figure 1**B**). The highest level of control is an abstract computational module that deals with action planning and decision-making. These abstract decisions are made based on a low-dimensional *internal model* that resides in a simplified *task space*. This module receives delayed sensory feedback from the arm and the environment from which it optimally infers the current states of its internal model. Using these estimated states, an optimally tuned feedback control gain calculates the abstracted muscle forces in the task space. This feedback gain is solved offline to minimize effort and movement accuracy [2]. The abstract and low-dimensional muscle force commands are then expanded into high-dimensional physiological muscle space in a middle level, by utilizing coordinated muscle activity bundles, often known as "muscle synergies" [3]. This mid-level controller uses the memorized action of each synergy in the task space to solve for synergy activations, which are then used to calculate individual muscle activities [4]. Finally, the low-level biomechanical model, which represents the nonlinear dynamics of the muscles, arm, and the environment, receives muscle activities and produces movements in the physical world. The sensory information about the kinematics of the hand (the physical task space) is fed back to the higher-level module to close the loop.

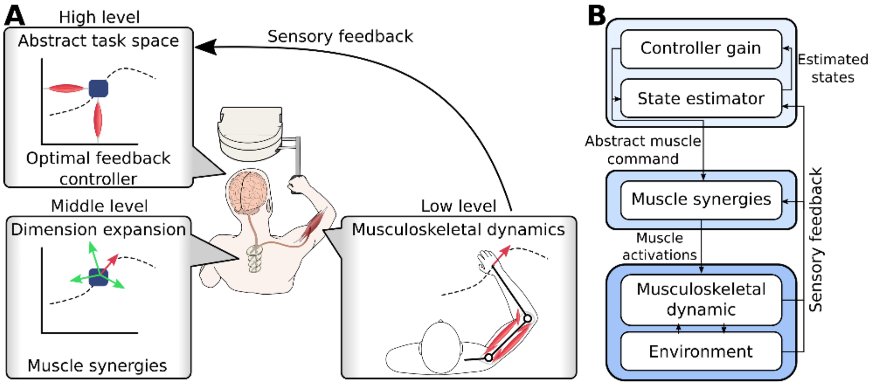
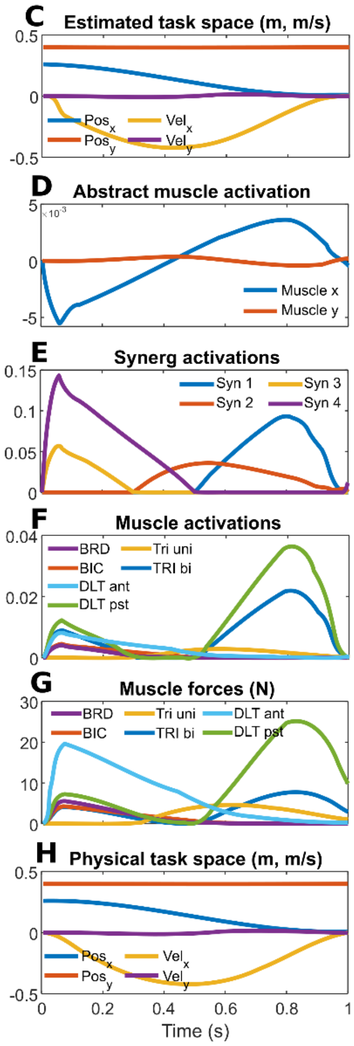


Figure 1. **A**. Overview of the holistic model, consisting of multiple modules. **B**. Model block diagram. **C-H**. Simulation results.



Results

I simulated a 2-Degree-of-Freedom planar arm model that was actuated by 6 hill-type muscles with activation/excitation dynamics (Figure 1**C-H**). The right hand moved 25cm to the left ($-x$ direction). The sensory feedback coming from the *physical* task space was used to estimate the states of the internal model in the *abstract* task space (panel **C**), from which abstract muscle activations were calculated optimally (panel **D**). These low-dimensional muscle activations were expanded into the full muscle space in a two-stage expansion: first, the synergy activations were calculated (panel **E**), which were then used to combine the synergies to calculate the muscle activations (panel **F**). The muscle activation dynamics and hill-type model gave muscle forces (panel **G**), which then drove the planar arm in the 2D physical space (panel **H**). The hand kinematics was used as the sensory feedback to close the loop with 50 ms delay.

The input to this feedback motor control model was only the target position; the arm kinematics and muscle activities emerged as the movement progressed because of the closed-loop control. No reference trajectory was needed. Additionally, the model could robustly respond to perturbations due to the feedback control structure, and in a human-like manner (not shown). Because the control model replicates neural processes, the model runs in $\sim 110\ ms$ to simulate a 1.1-s simulation (10 times faster than real-time).

Conclusion

The presented holistic model is a vital component of the predictive control of robots, as it can predict how a human behaves in novel scenarios without any prior data. The model also captures responses to perturbations, which are an inevitable aspect of human-robot interactions. Lastly, the model is faster than real-time, which is an essential requirement for deployment as control-oriented models of robots.

References

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