NRI: Task-Based Assistance For Software-Enabled Biomedical Devices

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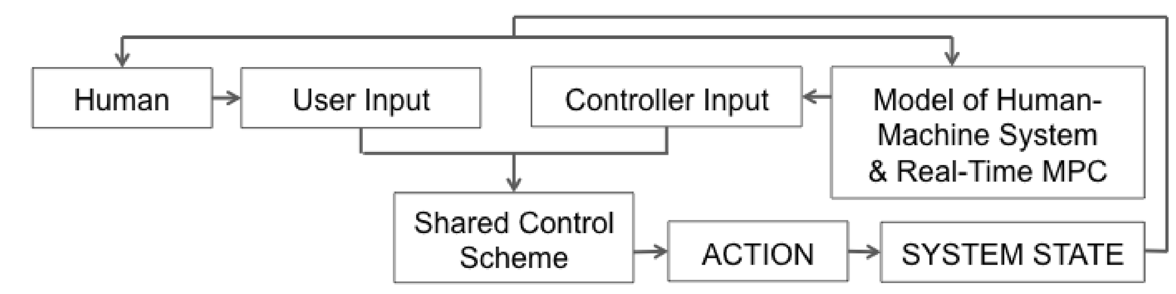
Aim: Human-machine interfaces have become necessary to ensure safe, reliable interaction with complex systems in activities ranging from driving a wheelchair to rehabilitation therapy. Effective interfaces can reduce the cognitive load on a human operator by planning efficient routes, automating obstacle avoidance, managing low level controls of robotics, and filtering input signals. Interfaces may also provide feedback aimed to improve task performance and training, even after neurological injury. However, such interfaces must be able to manage substantial uncertainty that stems from the unpredictable nature of human behavior.
The proposed work will create software-enabled, task-specific support for assistive biomedical devices. The algorithms will enable devices to support motion when the goal is motor learning or relearning.

Why? Approaches to designing kinesthetic feedback for robotic training platforms lie on a spectrum from antagonistic and resistive strategies that are dynamically updated based on user performance to passive assistive strategies in which users have a consistent guide during training. Training regimens at either end of the spectrum have been shown to be appropriate depending on the type and relative difficulty of the task.

How? The proposed work will develop algorithms to control physical hardware that will modify human operator motion. We will use haptic force generation both to create cues and to act on a person during motion to impact task performance. The generality of the approach (requiring only a physical model and task encoded as an objective function) will enable a broad spectrum of assistance previously implausible.



Experimental Platforms

Figure 1A: The Ekso Bionics exoskeleton provides the means to assist a person during balance and locomotion. In the ideal case, it would adapt to the users' natural gait pattern and allow them to maneuver freely. The exoskeleton has and will continue serving as an important testbed for the developed algorithms.

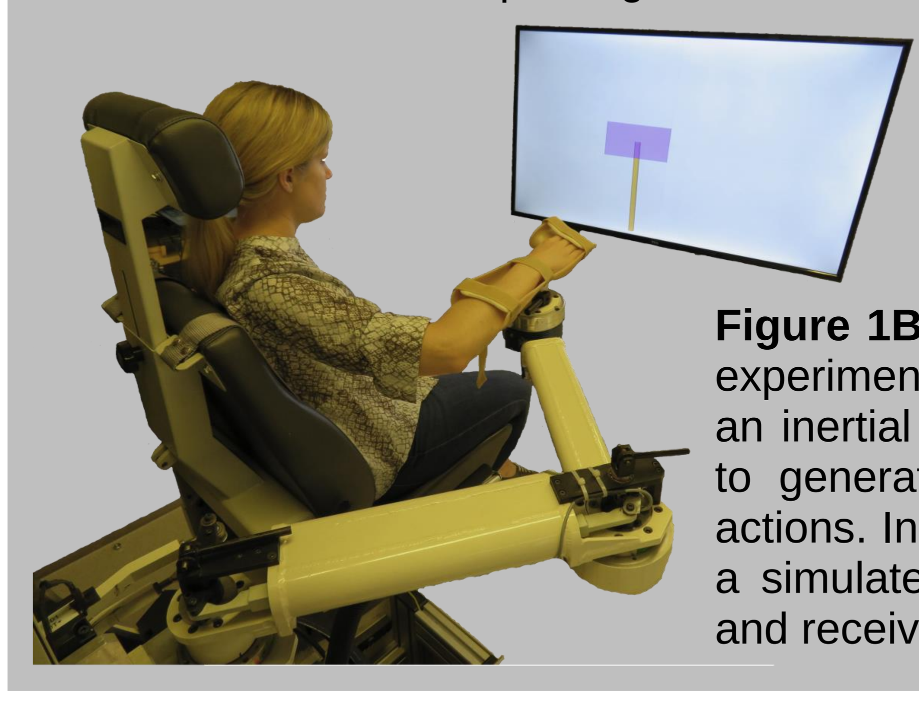
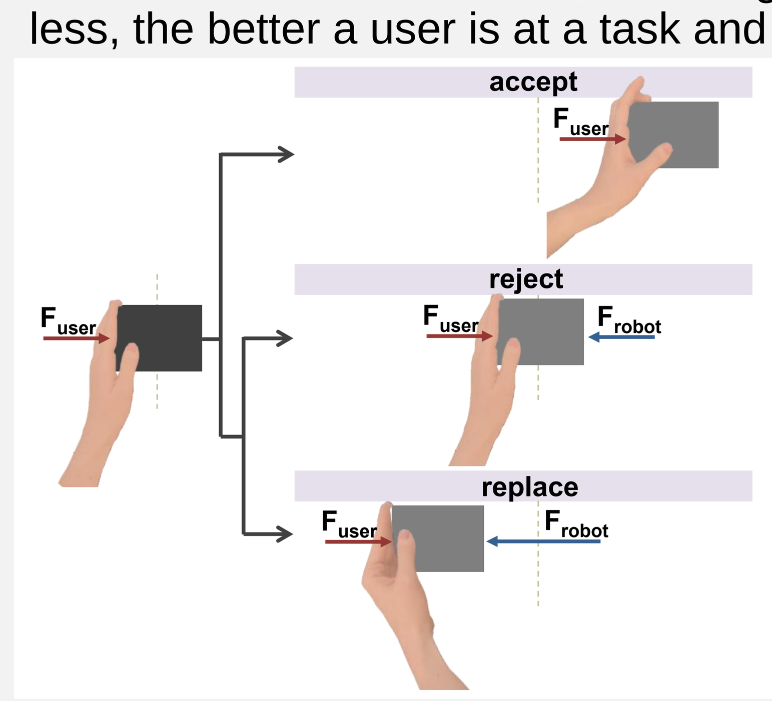


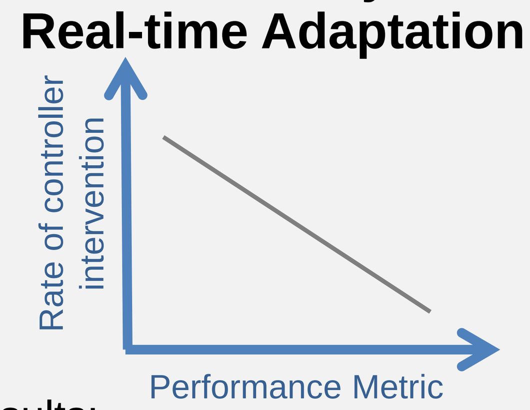
Figure 1B: Upper limb robotic platform used during experiments. It provides haptic feedback to simulate an inertial model via admittance control and is able to generate enough force to overpower a user's actions. In our experiments we asked users to invert a simulated cart-pendulum system, providing input and receiving guidance through the robot.

Hybrid Shared Control

Figure 2: We create a shared control paradigm based on the filtering of user inputs. The robot assists with tasks by physically accepting, rejecting, or replacing user actions.
We show that our filter-based approach is sensitive to user skill level, meaning it engages less, the better a user is at a task and *vice versa*.



Skill-sensitivity & Real-time Adaptation



Experimental Results:

Correlation to Initial Skill

Measure	r	p
Success Rate	$\mathbf{-0.235}$	5.898×10^{-9}
Balance Time	$\mathbf{-0.427}$	$< 2.2 \times 10^{-16}$
Time to Success	$\mathbf{0.2444}$	1.2898×10^{-9}
Error	$\mathbf{0.302}$	4.308×10^{-14}
Ergodicity	$\mathbf{0.282}$	2.078×10^{-12}

Correlation to Trial by Trial Performance

Measure	r	p
Balance Time	$\mathbf{-0.616}$	$< 2.2 \times 10^{-16}$
Time to Success	$\mathbf{0.602}$	$< 2.2 \times 10^{-16}$
Error	$\mathbf{0.677}$	$< 2.2 \times 10^{-16}$
Ergodicity	$\mathbf{0.706}$	$< 2.2 \times 10^{-16}$

Data-driven Learning of Human-Machine Systems

Figure 4A: To control a dynamic human-machine system, such as an exoskeleton, we need to be able to quickly learn an approximation of its dynamics and generate stable control based on the learned model. Here, we use the Koopman Operator and machine learning techniques to approximate the hybrid dynamics of a SLIP model. The top cartoon illustrates how we differentiate hybrid modes. The bottom plots show a SLIP trajectory generated using model-predictive control and a data-driven model (created without any *a priori* knowledge of system dynamics).

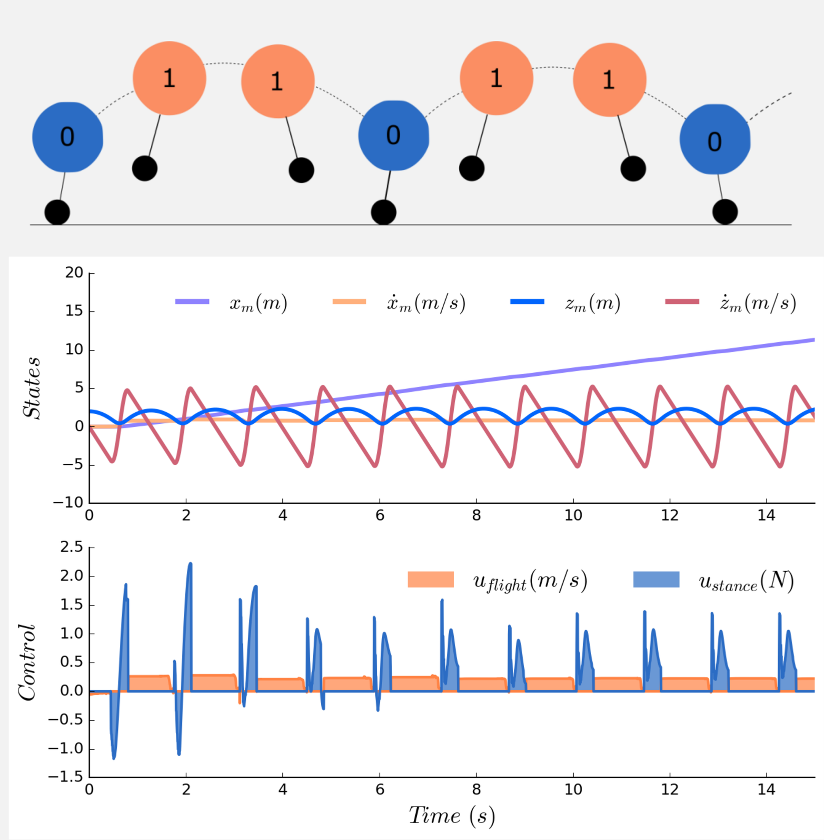
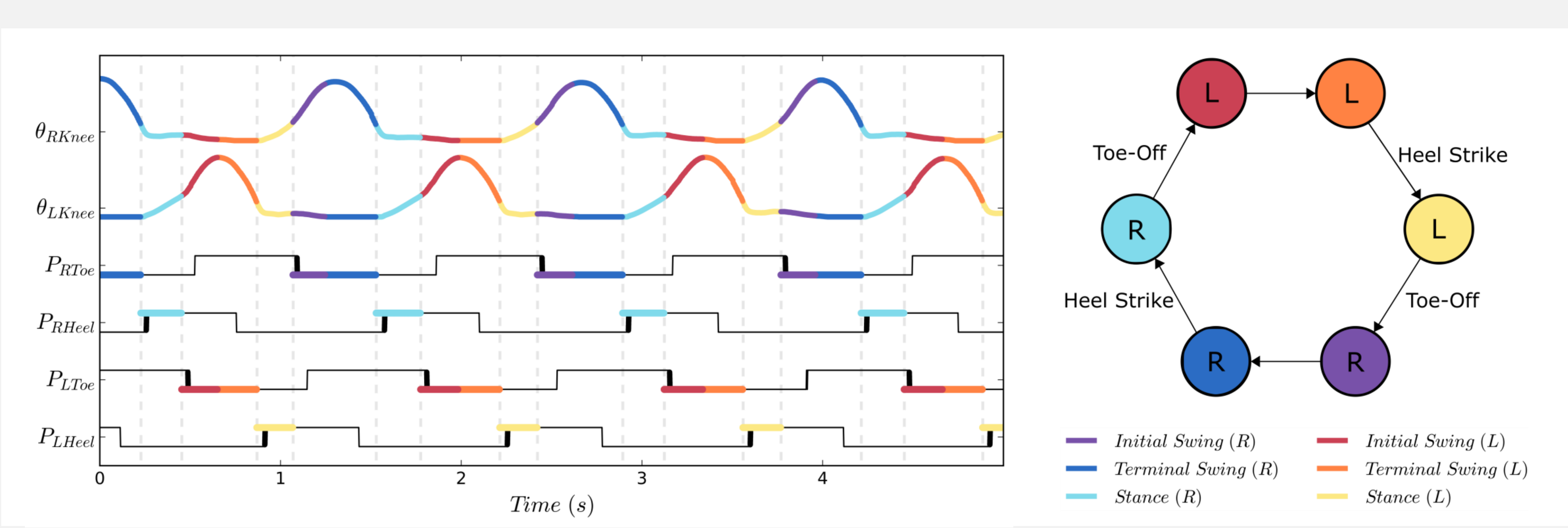


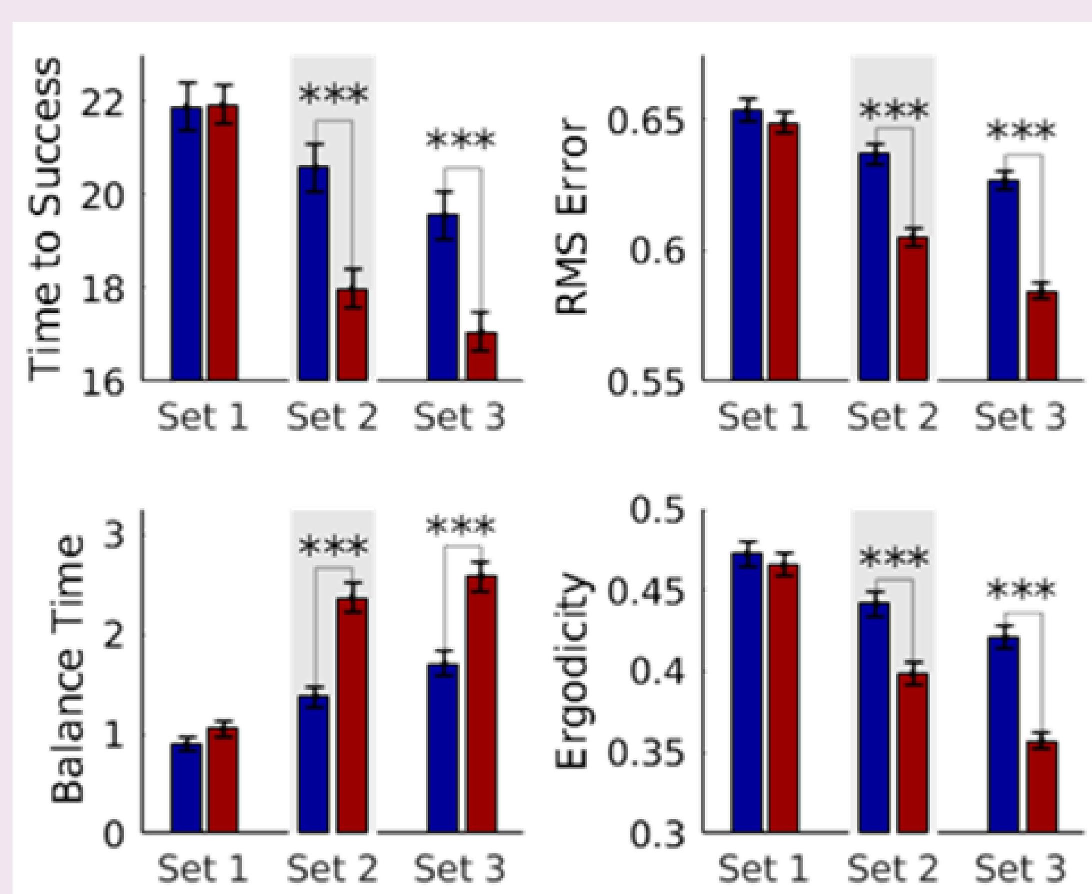
Figure 4B: We apply the same model-learning algorithms to data of human walking. Visible below is gait partitioning of an individual walking freely in the Ekso Bionics exoskeleton. Such segmentation is generated from only 30s of kinematic data.



How should devices support motion when the goal is motor learning or relearning? How can we design feedback without dictating how a task is done?

Accelerated Training Through Forceful Interaction

Figure 3: We used the the NACT3D, pictured in Fig. 1B, to filter out physical inputs from a user to assist with cart-pendulum inversion. The robotic filtering of user inputs led to accelerated learning of the task. Average performance data for all study participants (N=27) for the considered task metrics is visible on the left. The key point is that performance improves more quickly when subjects train using the hybrid shared controller as assessed across 4 different task metrics. This might be due to the fact that the interface only rejects bad decisions, rather than enforcing good ones---providing feedback without explicit guidance.



Increased Skill Retention

Figure 5A: Participants trained in week 1 retain high performance level in week 2 as measured by RMS error and ergodicity. The trained group retains their initial performance level while the control group continues to improve—eventually reaching the same level of performance as the trained group. It appears the feedback helped with retention because the learning was more structure.

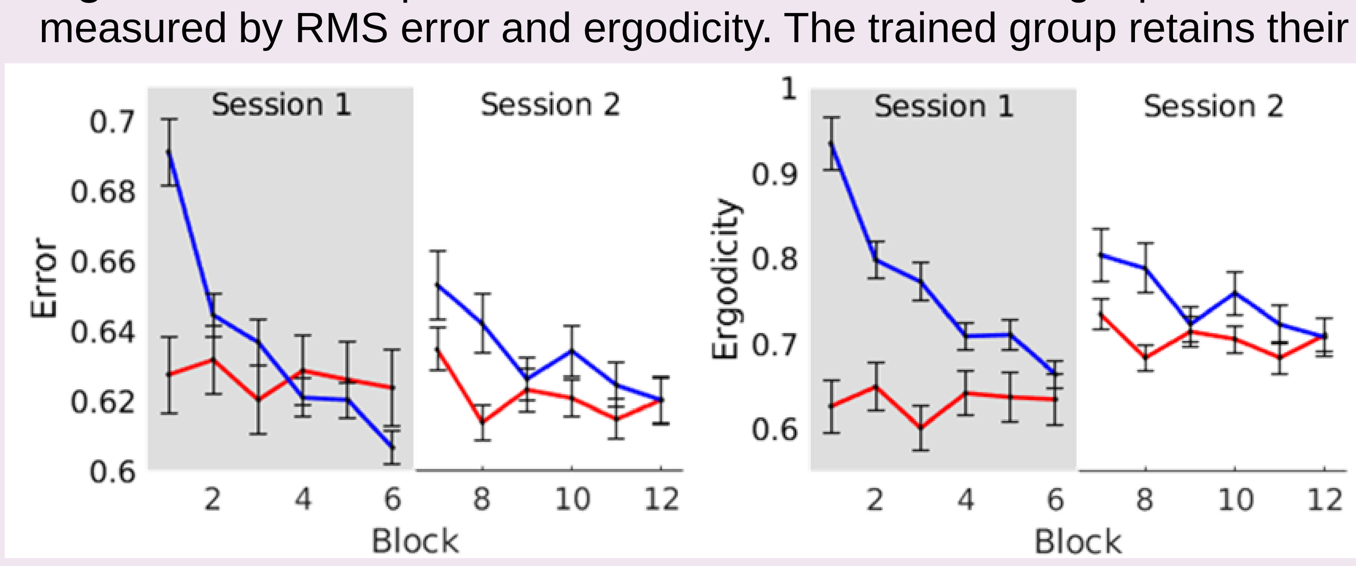


Figure 5B: The automation was able to assist subjects in completing the cart-pendulum inversion task when the hybrid shared controller was engaged. Subjects perform better in terms of time to success and balance time compared to controls and their own unassisted trials. However, task-specific measures lacked the granularity to detect training effects.