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 car 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.

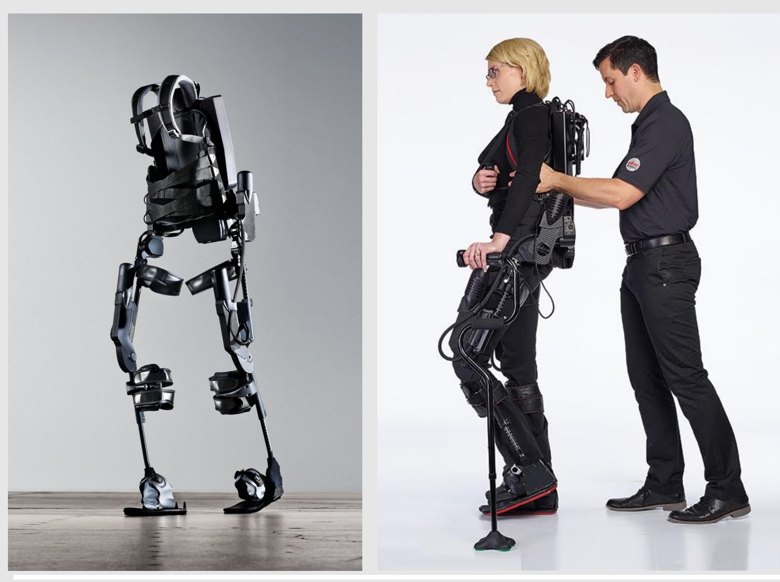
The proposed work will create software-enabled, task-specific support for assistive biomedical devices. The algorithms will keep the assisted person safe while leaving the user free to both move and exert effort.

Why? Ability to exert effort, freedom to move freely, and maintaining safety are key features of a successful human-machine interface. Lack of user effort has been shown to lead to overreliance and limit or even reverse learning. In rehabilitation settings, patient effort is particularly important, because it is critical for therapeutic impact. During assistance, operators want to maintain freedom to move and control the device. No matter the objective , users need to remain safe.

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. It has and will continue serving as an important testbed for the developed algorithms.



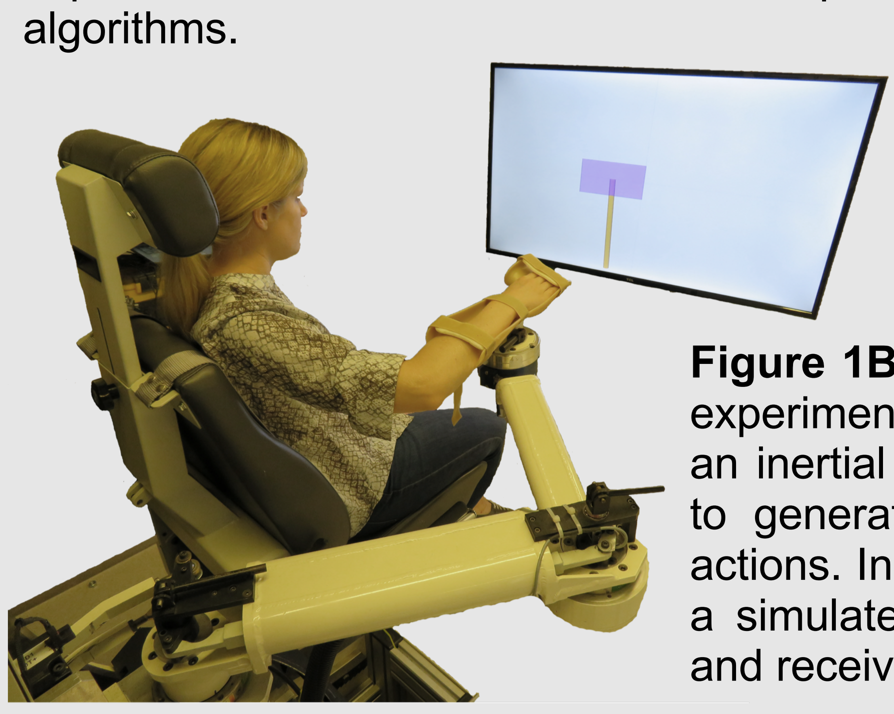


Figure 1B: Upper limb robotic platform used during experiments. It provides haptic feedback to simulate an inertial model via admittance control and is able to generate enough force to overpower a user's actions. In our experiments we asked users to invert a simulated cart-pendulum system, providing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

Filter-Based Shared Control

Skill-sensitivity

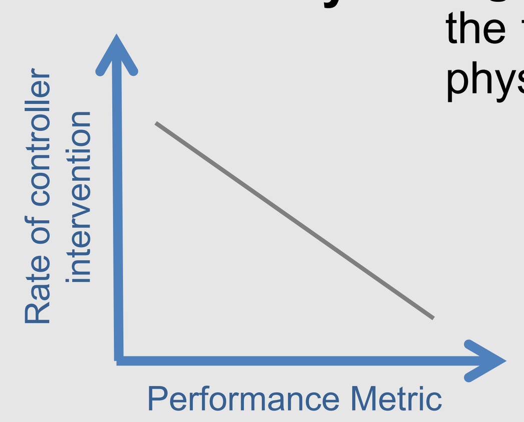
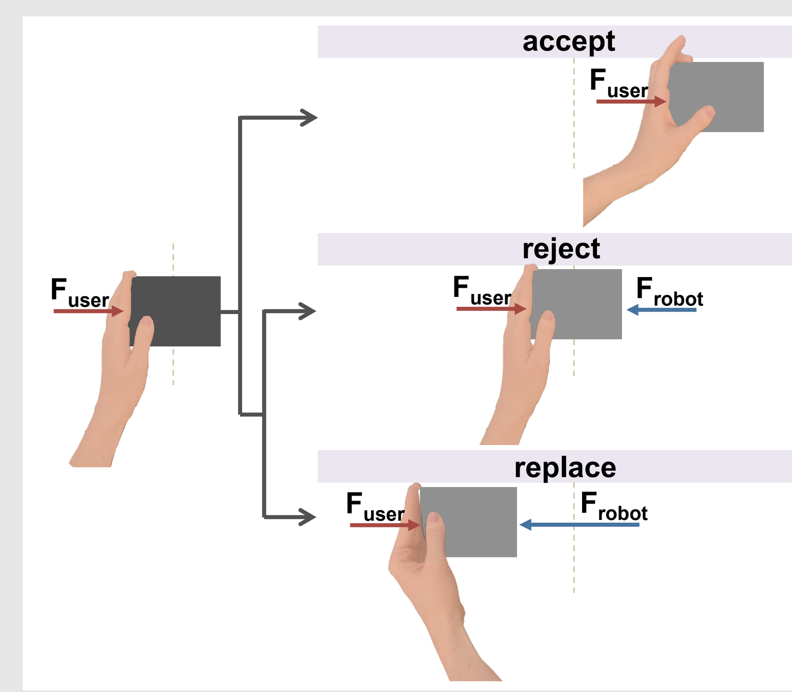


Figure 2: We create a shared control paradigm based on the filtering of user inputs. The robot assists with tasks by physically accepting, rejecting, or replacing user actions. We show that our filter-based approach is sensitive to user skill level, meaning it engages less, the better a user is at a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



Simulated Results:

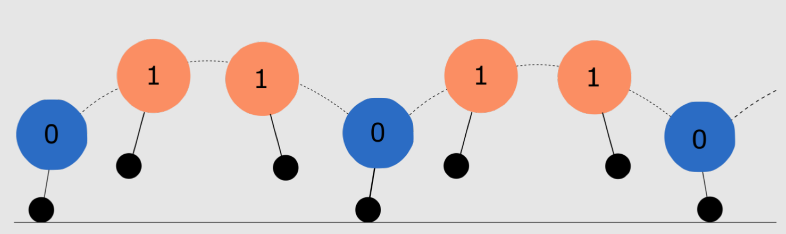
Skilled user – 0% intervention;
noise input – ~50% intervention.

Experimental Results:

Performance Metric	Magnitude of Pearson Correlation Coefficient
Success Rate	0.20, *p < 0.001*
Balance Time	0.13, *p = 0.003*
Time to Success	0.21, *p < 0.001*

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 (generated without any *a priori* knowledge of system dynamics).



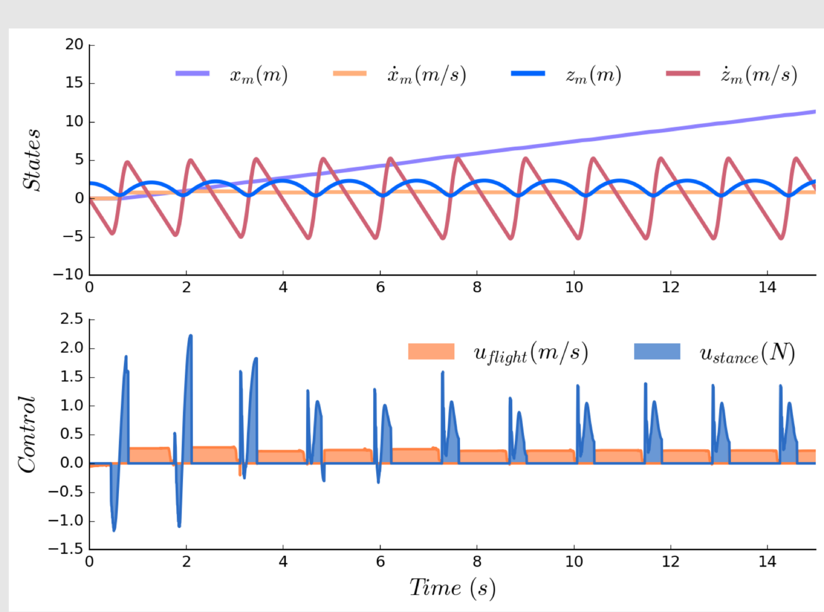
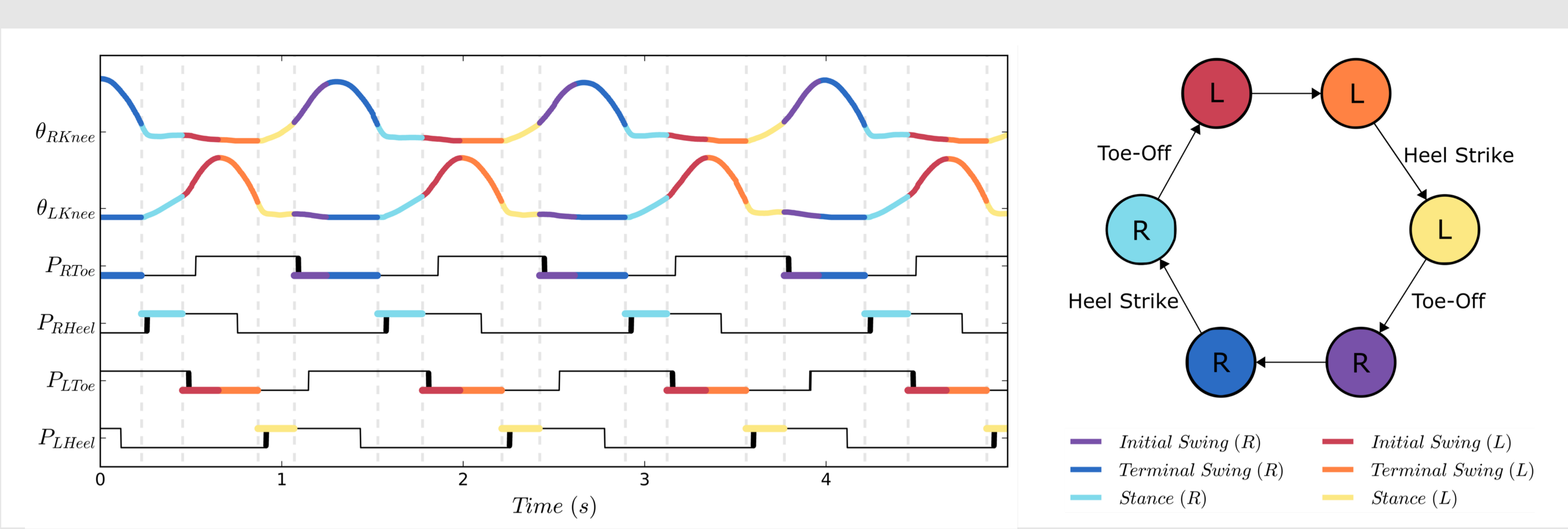


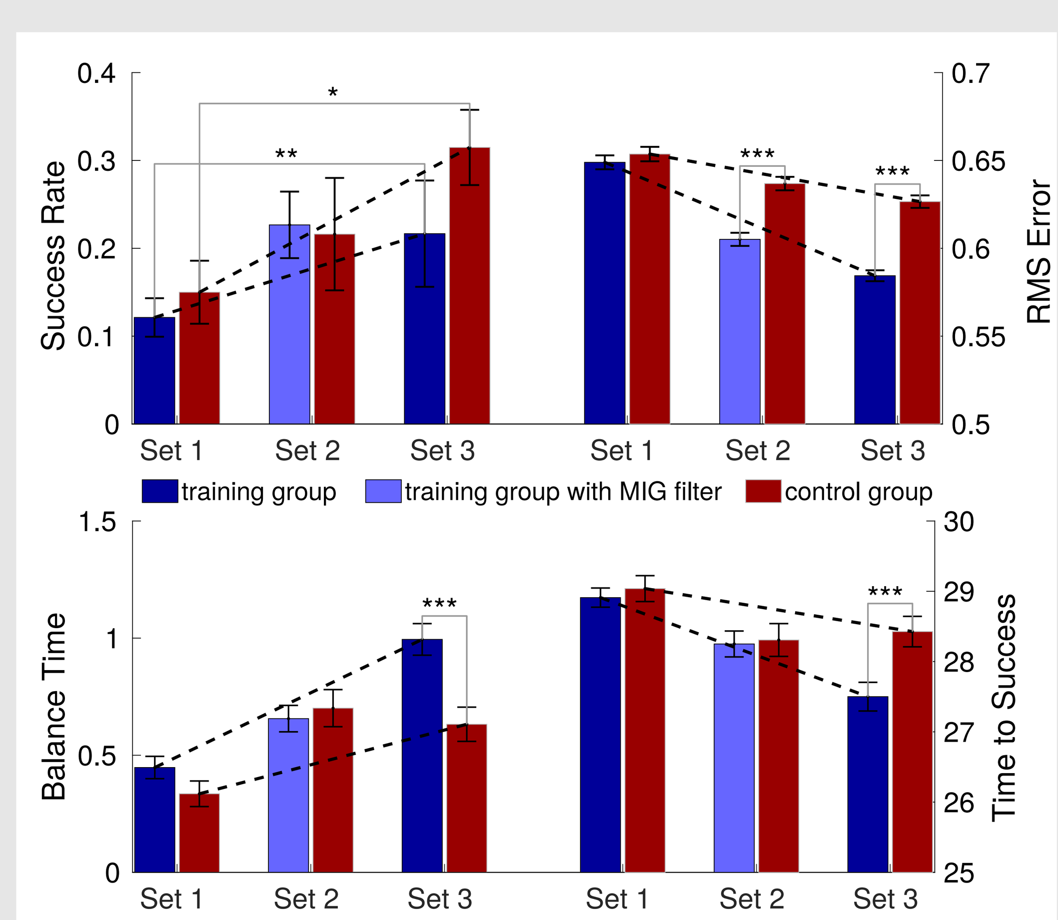
Figure 4B: We apply the same model-learning algorithms to data of human walking. Visible below is gait partitioning of an individual walking freely in the Ekso Bionics exoskeleton. Such segmentation is generated from only 30s of kinematic data.



How should devices support motion without dictating how a task is done? How should algorithms support maximal intentionality of an operator while keeping them safe?

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 guidance of the filtering scheme. This might be due to the fact that the interface only rejects bad decisions, rather than enforcing good ones, making the operator responsible for any success.

Safety-Oriented Assistance with Minimal Interference

Figure 5A: The filtering shared control paradigm can be used for assistance to ensure safety without interfering with the task. We tested it on a simulated SLIP hopper. Note that the shared control in combination with a stable controller can keep balanced even a simulated unskilled hopper generating actions based on Gaussian noise. Trajectory visible on the left.

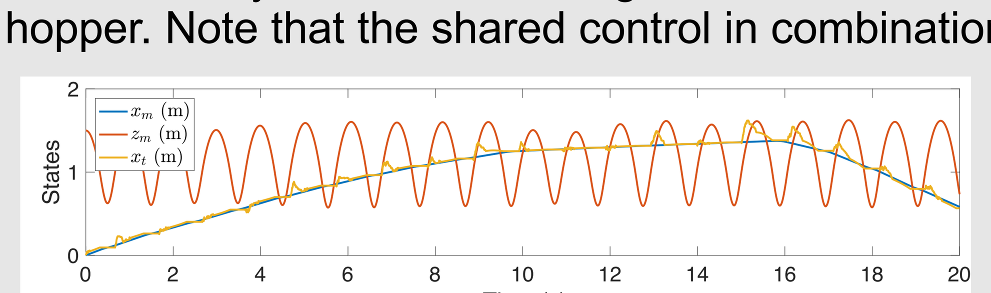


Figure 5B: For a simulated low-skill hopper (left), the shared control paradigm keeps it upright with only 40% intervention. And for a skilled hopper (right), the paradigm allows the hopper to change speed and direction with minimal intervention (~20%). These results suggest that such shared control could provide users with the desired combination of safety and flexibility.